Brain-Computer Interfaces
based on
Multisensory Event-Related Potentials

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Brain-Computer Interfaces
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Multisensory Event-Related Potentials

Brain-Computer Interfaces gebaseerd op Multisensorische Event-Related Potentials

(met een samenvatting in het Nederlands)

Proefschrift

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1

Introduction

Inspired by the amazing developments in computer technology and neuroscience, moviemakers have brought visions to life in which peoples' thoughts can be read and used to control their environments: for example the movies Firefox (Eastwood 1982; based on the novel from Thomas 1977), The Matrix (Wachowski and Wachowski 1999), and The Final Cut (Naim 2004). To many people this might appear as the ultimate way of being in control, when one simply has to think rather than do (physical) effort to control oneself or objects around us. All our thoughts originate in the brain, and since mental activity generates brain signals, it should theoretically be possible to derive thoughts by measuring and extracting these signals with technology.

Although 'mind reading' devices are science fiction, systems that measure and interpret brain signals do already exist. Such systems are often referred to as Brain-Computer Interfaces (BCIs). An interface is defined as the supporting hardware and software through which the exchange of symbols and actions between humans and computers occur (Hartson and Hix 1989). More specifically, a BCI is an interface that allows the user to communicate with or control his/her environment based on brain signals, without using body movements (such as the hands) (Wolpaw et al. 2002). However, BCIs are still in their infant years and the underlying perceptual and cognitive mechanisms are still poorly understood.

In this dissertation we investigate the underlying mechanisms of a promising category of BCIs that is based on responses of the brain to external events (Event Related Potentials), with the purpose of improving BCI performance. In this first chapter, we introduce the request for movement-independent control and set a scope for our research, review the state of the art of BCIs, and present relevant knowledge about the underlying perceptual and cognitive processes, all of which results in the research questions that we address.

This chapter is partly based on:

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1.1. A request for movement-independent control

Brain-Computer Interfaces aim to directly control the environment (e.g., a cursor on a display), so that the users' voluntary control of body parts becomes redundant (i.e., *movement-independent control*). Important purposes of voluntary body control are communication and navigation (Millan et al. 2004). In the following, we introduce when movement-independent control is needed or preferred.

1.1.1. When people need or prefer movement-independent control

BCI for people with disabilities

In the situation that people lose the ability to voluntarily control their muscles (e.g., as a consequence of a disease like ALS or brainstem stroke), it is clear that movement-independent control is needed to enable communication and navigation (Wolpaw et al. 2002). Hence, BCIs have its origin in the medical domain where the aim was to enable direct control and offer a last resort for people who lost (almost) all voluntary muscle control. The field of BCI is a relatively new research area and BCI was first introduced only four decades ago (Vidal 1973). The ground-breaking BCI of Farwell and Donchin (1988) serves to enable communication by selecting letter by letter from characters visually presented in a matrix. This system made the spelling of 2.3 characters per minute possible, and the concept is still the basis for many BCI studies. The majority of current BCI research is focussed at communication (e.g., Blankertz et al. 2007). However, in addition to being able to communicate, being able to navigate is important for the independency of people (Millan et al. 2004).

BCI for users of technological devices

In situations outside the medical domain, movement-independent control can be preferred. An important motivation for such a preference is when gaze and the hands are needed for more than one task. An example of when the eyes are required for two tasks is when people are gaming and need to look at their control device (e.g., a mouse or keyboard) to make the correct action while they need to view the game at the same time. Whereas alternative control devices can also be gaze- or hands-free (e.g., voice-based controllers), BCI additionally offers private control, as no external expression is required.

The growing interest in preferred direct brain control is illustrated by spin-offs from medical BCI research in the recent years. The developed knowledge and techniques from the original BCIs were explored by researchers in different fields. For example Trejo et al. (2006) studied the control of a cursor on a display for application in space shuttles, Middendorf et al. (2000) examined the selection of virtual buttons on a display for application in the air force, and Lalor et al. (2005) investigated the 1D control of balancing an animated character in a game. Especially in gaming, direct brain control is of interest because it could create an additional challenge, adding to the 'fun factor', and overall resulting in enhanced game experience (Gürkök et al. 2012; Plass-Oude Bos et al. 2010).

1.1.2. Scope of this dissertation

Brain controlled navigation

In this dissertation we focus on brain controlled navigation, as this could replace a key function of voluntary body control. Research on movement-independent navigation could both serve people with disabilities and potentially contribute to the development of a new generation of control devices for any user of technology. Navigation can occur in the real and virtual world, such as in (serious) gaming. The virtual world offers excellent possibilities for learning and training, and is pre-eminently a platform for new technology (Reuderink 2011). We aim at simple virtual navigation as a first step.

Key requirement for brain controlled navigation

Performance of brain controlled navigation (or BCI performance) depends on the accuracy with which a number of human intended control actions are correctly classified, i.e., *classification accuracy*, and the time required to determine the outcome. BCI performance is quantified as the amount of information transferred in time (bitrate; e.g., Serby et al. 2005). Classification accuracy depends on the sensitivity of the classifier and the signal-to-noise ratio from the recorded brain signals related to intended navigation. The latter is influenced by both the quality of the technological recording equipment and the quality of information in the brain signals. Before BCI-based navigation applications can become successful, BCI performance needs to be drastically improved, which is the general goal of BCI research.

Brain controlled navigation from a Human-Computer Interaction (HCI) perspective

Many BCI researchers focus on the sensitivity of the classifier to improve BCI performance, as illustrated by the BCI competitions (Blankertz et al. 2004; Blankertz et al. 2006; Tangermann et al. 2012). BCI research is pre-eminently a multidisciplinary field: neuroscience, medical disciplines, computer science, signal processing, machine-learning, engineering, and psychology are all involved. The field of Human-Computer Interaction (HCI) is concerned with the study, planning and design of interaction between humans and computers, with the aim to realize computers concurring with users' needs (Card et al. 1983). HCI researchers aim to optimize the relation between users' cognitive efforts to accomplish a certain goal and the computer's interpretation of the users' goal. While HCI knowledge has been proven useful to improve human task performance (e.g., Fitts and Seeger 1953). HCI research is slightly neglected within the field of BCI. Our approach on BCI is from a HCI perspective and we are interested in how interactions between humans and computers could be modified to possibly increase the signal-to-noise ratio from brain signals related to intended navigation.

1.2. State of the Art of BCIs suitable for navigation

In this section, we review appropriate techniques to record brain signals that can be employed in BCI, categorize BCIs for navigation, and evaluate BCIs suitable for navigation.

1.2.1. Appropriate recording techniques of brain signals

The first level at which we review the potential of BCIs for navigation is whether or not the recording technique of the brain signals occurs invasively or not. Invasive techniques record electrical potentials on or inside the cortex (for example electrocorticogram [ECoG]) (Nijholt and Tan 2008). Invasive compared to noninvasive recording does result in a higher signal-to-noise ratio of the recorded brain signal. However, because of the necessary operation and the risks involved, non-invasive techniques are preferred for people with disabilities (Birbaumer 2006), and clearly only a non-invasive brain signal recording technique is acceptable for healthy people.

At the second level, non-invasive BCIs can be distinguished based on the type of data that is used, such as Near Infrared Spectrometry (NIRS), electroencephalograms (EEG), magnetoencephalograms (MEG), and functional Magnetic Resonance Imaging (fMRI) data. These data reflect different features of brain activity: the oxygen level in blood flowing through the brains, the electrical signals, and magnetic field. The corresponding recording equipment varies on multiple aspects, such as costs and mobility of the equipment, and the quality of the recorded signals (Wolpaw et al. 2002). Because for navigation the delay between the user's intended navigation direction and the computer's execution should be minimal, the temporal resolution of the relevant brain signals should be high. This is the case for electrical signals (hence EEG), but not for the relatively slow response of oxygen levels in blood (Wolpaw et al. 2002).

For application in many technical devices it is important that the equipment is easily portable, because the user may change the location of use regularly. The need for portability is illustrated by the rapidly growing market of portable devices as laptops, tablets and smartphones. Furthermore, to interest a large target market costs should be low. EEG recording equipment is portable and costs are relatively small (Nijholt and Tan 2008). EEG therefore is an appropriate recording technique for a navigation BCI, and is used in many other BCI labs around the world (Wolpaw et al. 2003; Blankertz et al. 2007; Scherer et al. 2004). In the next section, we review EEG-based BCIs potentially suitable for navigation.

1.2.2. Categorization of EEG-based BCIs for navigation

EEG-based BCIs can be categorized based on the user's effort and task to control the BCI: active, reactive and passive BCIs (Zander et al. 2008; Zander et al. 2010). In the following, we present the state of the art of EEG-based BCI along those three categories. The focus is on BCIs used for direct control for navigation, but where relevant BCIs for communication are included.

Active BCIs

Active BCIs are based on users actively performing cognitive tasks, such as motor imagery (e.g. imagined movement of the left hand or the right foot), imagined word association and mental calculation. Usually participants have to train to be able to perform the mental tasks in such a way that the system can correctly classify the resulting brain signals (Pfurtscheller et al. 2006). To achieve optimal performance, this training period may take months. After the brain signals have been classified, they are translated into a system command, such as turn left or right, stop or continue. The match between mental task and resulting navigation action is

often arbitrary, which is in conflict with a HCI perspective because it may result in unnecessary additional users' cognitive effort, task errors, and decreased BCI performance.

Imagining motor movement is a mental task that has been intensively studied in the context of BCI. Both the Wadsworth BCI (Wolpaw et al. 2003) and the Graz BCI (Pfurtscheller et al. 2003) make use of mu and beta waves in the EEG. The maximum amplitude of these waves can be modified when well-trained participants are actively imagining motor movement. Imagined right and left limb movements can be distinguished, as can imagined foot and hand movements. The motor imagery principle has been used to control a cursor on a screen (usually 1D, but 2D is also possible) or a neuroprosthetic device. Well-trained participants can obtain information transfer rates of about 20-25 bits/minute. The examples mentioned so far use motor imagery to distinguish between different directions of movement, but it can also be used to start or stop an action (Leeb et al. 2006; Pfurtscheller et al. 2006). In these studies, foot movement imagery resulted in moving forward with constant speed in a projected virtual street. The motion was stopped when participants imagined moving their hands. The participants had at least four months experience in using the Graz BCI, preceding the experiment. Each of them went through a number of training sessions with the goal to set up a personal classifier able to discriminate online and in real-time between two mental states. Training required focussing attention to elicit specific brain patterns by means of motor imagery.

Besides moving one's own body within a real or virtual environment, moving a cursor is a widely investigated task within active navigation BCIs. An appealing example is Brain Pong, with which each user moves his or her own cursor 'bat' up and down using motor imagery in order to block an approaching ball (Mueller and Blankertz 2006). It has even been shown that all functions of a mouse can be replicated with an active BCI, using three sets of sensorimotor rhythm features (McFarland et al. 2008).

In most active BCI studies, participants are cued when to perform certain tasks. These BCIs are called synchronous. Asynchronous BCIs do not require allotted time intervals for performing mental tasks. Millán and colleagues have done many studies on asynchronous brain-controlled robots based on mental tasks. In one study they enabled a robot to execute six possible navigation tasks, based on a combination of one out of three user mental states together with one out of several robot's sensing's of the environment (e.g., obstacle in front) (Millán et al. 2004). In another study, they built an asynchronous active BCI to control a wheelchair. Participants were asked to drive a simulated wheelchair from a starting point to a goal following a prespecified path. They imagined left hand movement to turn left and relaxed to go forward and performed a word association task to turn right (Gálan et al. 2008).

One final example, though originally designed for communication rather than navigation, is the Hex-o-Spell from the Berlin BCI group (Blankertz et al. 2007). In the Hex-o-Spell application, users select letters by means of motor imagery. Interesting and relevant for navigation is the fact that the Hex-o-Spell paradigm is not based on Cartesian coordinates but on polar coordinates. This setup allows the selection of options in fewer steps: Six hexagons containing five letters (or symbols) are each positioned around a circle that contains an arrow. Two motor imagery states as classified by the system control the rotation and the length of the arrow. A hexagon is selected when an arrow of sufficient length points towards it. After the selection of a hexagon, the contained letters move individually to the different hexagons and offer a new choice to the user. A similar principle was applied to a navigation task in a virtual environment (Ron-Angevin et al. 2009). At each junction in a virtual labyrinth a circle was presented with a rotating bar in the middle. Instead of a hexagon with letters, directions were selected.

Reactive BCIs

Reactive BCIs are event driven and measure brain responses to visual, tactile or auditory (probe) stimuli. A reactive BCI depends on the presentation of external stimuli (and therefore also referred to as cue-based BCIs; Nijholt and Tan 2008). Each of the stimuli corresponds to a certain control option, the one corresponding to the intended control option is the *target* and the remaining stimuli are *nontargets*. When the user attends to the target, while ignoring the nontargets, distinguishable brain responses can be connected to attended or ignored stimuli. Consequently, the user is able to select one of several control options. The advantage of reactive BCIs is that they do not require user training as is the case for active BCIs (Pfurtscheller et al. 2006). Guger et al. (2009) showed that 89% of a large group of participants achieved effective control (80-100% classification accuracy) with a reactive BCI, while only 19% of participants achieved similar classification accuracies with an active BCI after a few minutes of training (Guger et al. 2003).

Reactive BCIs can be categorized into two groups, Event-Related Potential (ERP) and Steady-State-Evoked Potential (SSEP) based BCIs, which are respectively time-locked and frequency-locked to the (onset of) stimulus presentation. When stimuli are presented sequentially, and one stimulus is attended while the remaining stimuli are ignored, the ERP differs for the attended versus ignored stimuli. When stimuli are presented simultaneously, but at different presentation frequencies, the SSEP corresponding to the attended (versus ignored) stimulus is the largest. Next, we show how the ERP and SSEP are employed in BCI.

Reactive BCIs based on the ERP: The ERP usually contains several components. The P300 ERP component is of special interest to BCI-researchers, because of its sensitivity to *endogenous* (voluntary) attention: it is stronger for targets than nontargets and occurs after approximately 300 ms after stimulus onset (e.g., Farwell and Donchin 1988; Polich 2007). With the P300-matrix speller, Farwell and Donchin (1988) exploited the P300 in a BCI for communication. In this P300-matrix speller, letters and numbers are placed in a 6x6 matrix. Rows and columns flash after each other in random order. Every time a row or column flashes that contains the symbol the user is focusing on, a P300 is (potentially) elicited. In this way, users can spell words and communicate with their environment.

Besides using P300s for communication, several groups work on applications to control cursor movement with a P300-BCI. Ma et al. (2007) investigated the feasibility of a BCI that uses four sequentially flashing probe stimuli around a cursor. Participants had to focus on the stimulus that corresponded with the desired direction of motion of the cursor. Offline analyses resulted in an information transfer rate of 5.4 bit/min for high intensity stimuli and 4.6 bit/min for low intensity stimuli. The difference in information transfer between high and low intensity stimuli corresponded to a high respectively low P300 amplitude (Ma et al. 2007).

Another navigation application of a P300-BCI is the wheelchair reported by Pires et al. (2008). For this application, a screen is fixed on a wheelchair, showing eight arrows that present the possible directions the user can choose. A ninth stimulus in the middle of the arrows corresponded with 'no movement'. The authors mentioned the importance of evaluating such a BCI not just by error rate, but also by the amount of false positives and false negatives. A false positive would cause the wheelchair to move into the wrong direction, while a false negative only slows down the system. Obviously the first has much more impact and should be avoided. The performance was seven commands/min, although it was only tested with two persons.

Reactive BCIs based on the SSEP: The SSEP is a feature in the EEG that can be elicited by focusing on a stimulus that is presented at a certain constant frequency. The fundamental frequency of the initiating source can be found in the EEG (Regan 1989) as well as its

harmonics (Mueller-Putz et al. 2005). If multiple stimuli are provided simultaneously at different frequencies, the attended frequency will dominate the unattended frequency in the observer's EEG.

Cheng et al. (2002) demonstrated that the visual SSEP (SSVEP) may successfully be applied in a BCI, using twelve buttons flickering at different rates on a display. Trejo et al. (2006) demonstrated with the 'Think Pointer BCI System' the possibility of 2D cursor control, allowing navigation over a moving map. Participants selected a desired movement direction by focusing on one of four flickering checkerboards that corresponded with the commands up, down, left and right. Obtained accuracies were between 80 and 100%. Martinez et al. (2007) also showed the feasibility of an online SSVEP navigation BCI. In a game, four flickering checkerboards were located at each side of a car and moved along with it. The car was on a fixed path. A direction command could be given by focussing on one of the stimuli (left, right, up and down). An average of 96.5% success rate was achieved with a bitrate of 30 bits/min.

Passive BCIs

Cognitive processes related to high-level intent (such as navigation) should theoretically be present in EEG, but currently cannot be derived because of the complexity, distortion and variability of the recorded brain signals (Wolpaw et al. 2002). Thus passively navigating with a BCI, without the user having to perform a BCI-task to communicate the intended navigation direction is currently not possible. Passive BCIs are not used to interpret voluntary control intents, but are aiming at detecting changes in a cognitive or an affective user state that spontaneously occur, thus without specific user effort to communicate that state by performing a BCI-task (Muehl 2012; Van Erp et al. 2010; Zander et al. 2008). This type of BCI is mainly envisioned to enhance or facilitate other tasks or interactions. An example is when HCI is improved by the adaptation to the user's state, such as the level of workload (Brouwer et al. 2012).

Although passive BCIs cannot be used (yet) for direct control, passive brain signals may be used to improve EEG-based navigation. An example of employing a passive BCI for (subtasks of) navigation is a BCI that utilizes error potentials for correcting wrong selections. The work by Schalk et al. (2000) is a step towards such a BCI. They explored a BCI using motor imagery to move a cursor to a word (in this case, 'YES' or 'NO', but LEFT and RIGHT would be similar). This part of the BCI is active. As BCIs typically cannot obtain 100% classification accuracy, participants using this system did not always select the target they intended. Results showed that such a mistake was followed by an error potential. It was suggested that these error potentials could be used to improve the accuracy and communication speed of the system, which can be considered as (partly) passive BCI. Zander and colleagues used error potentials to enhance performance in a game where players had to rotate a letter presented on a monitor into a desired orientation using buttons on a keyboard (this part is not a BCI). In some cases, the button command was followed by an incorrect response of the computer, eliciting an error potential. When the error potential was used to correct the movement of the letter (even though the classifier detecting errors did not work 100% correct) total performance was better than when players had to correct for the errors manually (Zander et al. 2008). It was demonstrated in a similar task where participants had to steer a tactile cursor to a tactile target that tactile error potentials show up in the EEG as well, both for self-generated and computer-generated errors (Lehne et al. 2009). We consider BCIs based on the error potentials of the passive type, because the signal occurs automatically during interaction, and is not elicited voluntarily by performing a BCI-task to communicate a certain intent.

Evaluation of categories of EEG-based BCIs for navigation

Within the scope of this dissertation, a BCI usable for voluntary and explicitly controlled navigation is required. Active BCIs appear less appropriate because of the required intense user training and large cognitive resources involved. Passive BCIs are also not an option because high-level intent (such as navigation) is to date still too complex to derive robustly from recorded brain signals. The category of reactive BCIs seems most suitable for voluntary and explicitly controlled navigation, as user training is not required and brain responses to attended stimuli corresponding to intended control can be classified rather reliably.

1.2.3. Appropriate stimulus modality and paradigm in reactive BCI

Stimulus modality

Most reactive BCIs employ visual stimuli to present the user with options (e.g., Farwell and Donchin 1988). The drawback of visual ERP-BCIs is that the effectiveness of these systems depends to a large extent on the ability of users to gaze at the visual stimuli (Brunner et al. 2010; Thurlings et al. 2012; Treder and Blankertz 2010), which is not for all users (e.g., due to paralysis) or applications (e.g., gaze might be required elsewhere) appropriate. When a visual reactive BCI make use of people's ability to gaze at visual stimuli, this is considered a *gaze-dependent* BCI. *Gaze-independent* visual BCIs can be controlled by covert attention to visual stimuli, but performance is much lower compared to the gaze-dependent variant (Treder and Blankertz 2010).

To increase performance of gaze-independent BCIs, interest has grown in employing alternative sensory modalities like audition (Höhne et al. 2010; Nijboer et al. 2008; Schreuder et al. 2010). However, in addition to the visual modality, the auditory modality is also already heavily loaded in many situations (e.g. in gaming, driving and flying) (Van Erp and Van Veen 2004). To prevent sensory overload when using reactive BCI for navigation, the tactile modality should be considered. Recent research has shown that tactile stimuli may also be a viable alternative for application in gaze-independent BCI. Brouwer and Van Erp (2010) demonstrated the feasibility of employing tactile stimuli (tactors) around the waist in a tactile ERP-BCI (see also: Brouwer et al. 2010). Tactors around the waist correspond naturally with navigation directions around us (Van Erp 2005), which makes a tactile ERP-BCI especially interesting for navigation applications.

Paradigm for tactile reactive BCIs

In section 1.2.2, we reported on two types of reactive BCIs, based on the ERP and on the SSEP. Effects of attending tactile stimuli in SSEP-paradigms have also been shown (Giabbiconi et al. 2004), and attempts have been made to use the tactile SSEP in BCIs (Mueller-Putz et al. 2006; Severens et al. 2010; Zhang et al. 2007). However the requirements for tactile hardware for the SSEP paradigm are much more difficult to fulfil compared to the ERP paradigm. The appropriate hardware is expensive and not readily available, as a constant vibration at specific frequencies needs to be realized, which for the tactile SSEP is in the 20-30 Hz range (Giabbiconi et al. 2004). General requirements for tactile hardware in navigation applications are that it should be portable (similar to the requirements for the recording equipment), and should small and light such that it can be well integrated in for example clothing. Furthermore, the intensity of the tactile stimulation should be high enough to be perceived well at locations at the body that correspond logically with navigation directions, and are preferably not at the hands (to enable hands-free navigation). The electromotors used

in the ERP paradigm in (Brouwer and van Erp 2010) are integrated in a wearable vest and fulfil the general requirements. However, from our pilot studies it appeared that these electromotors are unsuitable for the SSEP-paradigm, as the required constant and specific frequencies could not be achieved, and no effects of attending stimuli could be observed. Therefore in this dissertation we focus on tactile ERP-BCIs for navigation.

1.3. Navigation with a tactile ERP-BCI

In this section, the working principle of a tactile ERP-BCI is discussed and its use for a visual navigation-task (in a gaming context) is demonstrated.

1.3.1. Working principle of a tactile ERP-BCI

Brouwer and Van Erp (2010) showed that attending to and ignoring of tactile stimuli (tactors) resulted in different ERPs that can be successfully classified to operate a BCI. A number of stimuli (two, four, or six) were located equally spaced around participants' waist at navel height. In that study, targets were indicated in the experimental design by a specific activation of the designated tactor. After the target designation the participant was presented with multiple (ten) repetitions of sequentially vibrating tactile stimuli, during which participants had to attend spatially to the target location. Each time the target stimulus vibrated, the participant had to recognize the stimulus being a target and count it mentally. Nontarget stimulus presentations had to be ignored. Meanwhile EEG was recorded and an algorithm classified the ERPs online in target or nontargets responses. After the tenth repetition, the classifier calculated which of the stimuli was most likely attended. This outcome was communicated back to the user by means of a vibration of the corresponding stimulus. Brouwer and Van Erp (2010) showed that participants obtained accuracies of ~70% using a four-class tactile BCI in a lab-setting for which participants did not perform a navigation task, but solely attended to prescribed target stimuli.

To use this tactile ERP-BCI for navigation, each of the stimuli needs to be connected to a navigation direction. Users should determine the desired target direction based on visual navigation information, and subsequently map the desired navigation direction onto the corresponding tactile stimulus.

1.3.2. Navigation with a tactile ERP-BCI

The feasibility of navigating in a game with a tactile ERP-BCI was shown with the demo 'Playing Pacman with a tactile ERP-BCI (see Figure 1.1) (Thurlings 2010; Veldt 2010). To this end, the user is wearing a tactile belt with four integrated tactile stimuli, each of which corresponds to a direction Pacman can move to: left, right, up (tactile stimulus on the front), down (tactile stimulus on the back). Users had to select directions for each intersection, after which Pacman automatically followed the path until the next intersection. In this game with four classes, the chance level of classification accuracy is 25%. Volunteers who tried this demo at conferences and the like obtained classification accuracies of ~60%, which is a satisfying result considering the noise of the environment and people that may distract the user, and the equipment around that causes artefacts in the EEG. Such problems are also of influence when using a BCI in a normal everyday setting, outside a lab.

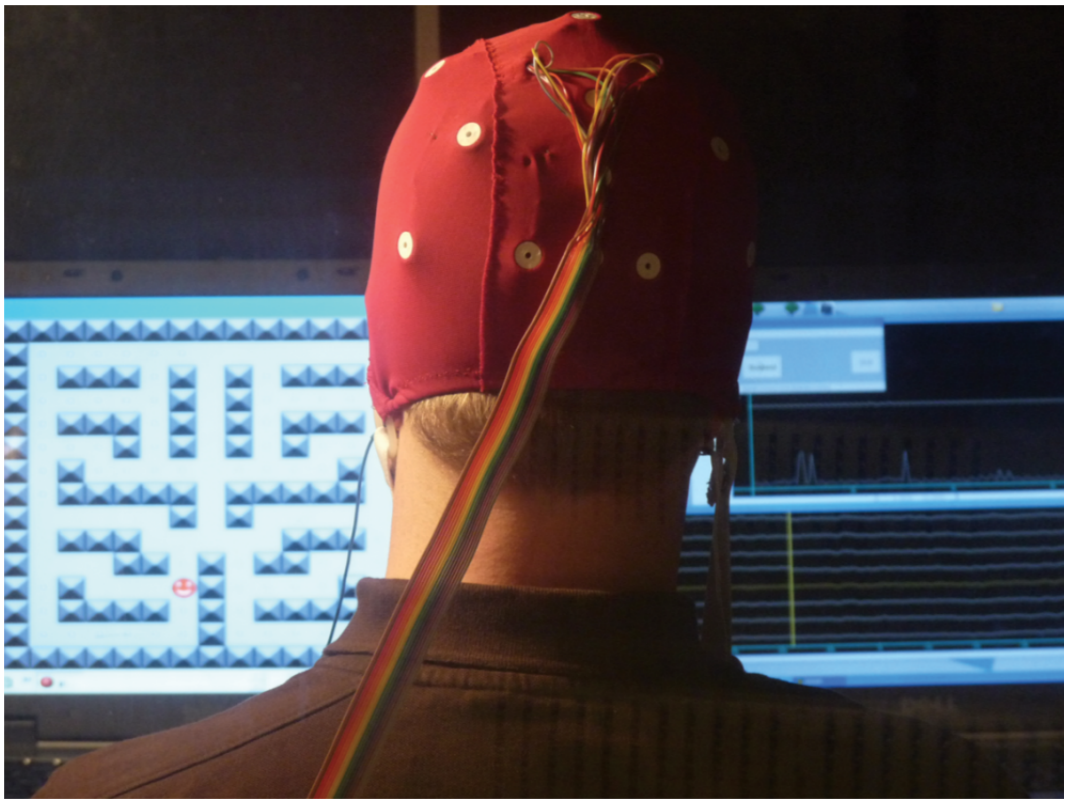

Figure 1.1: Demo 'Playing Pacman with a tactile ERP-BCI'.

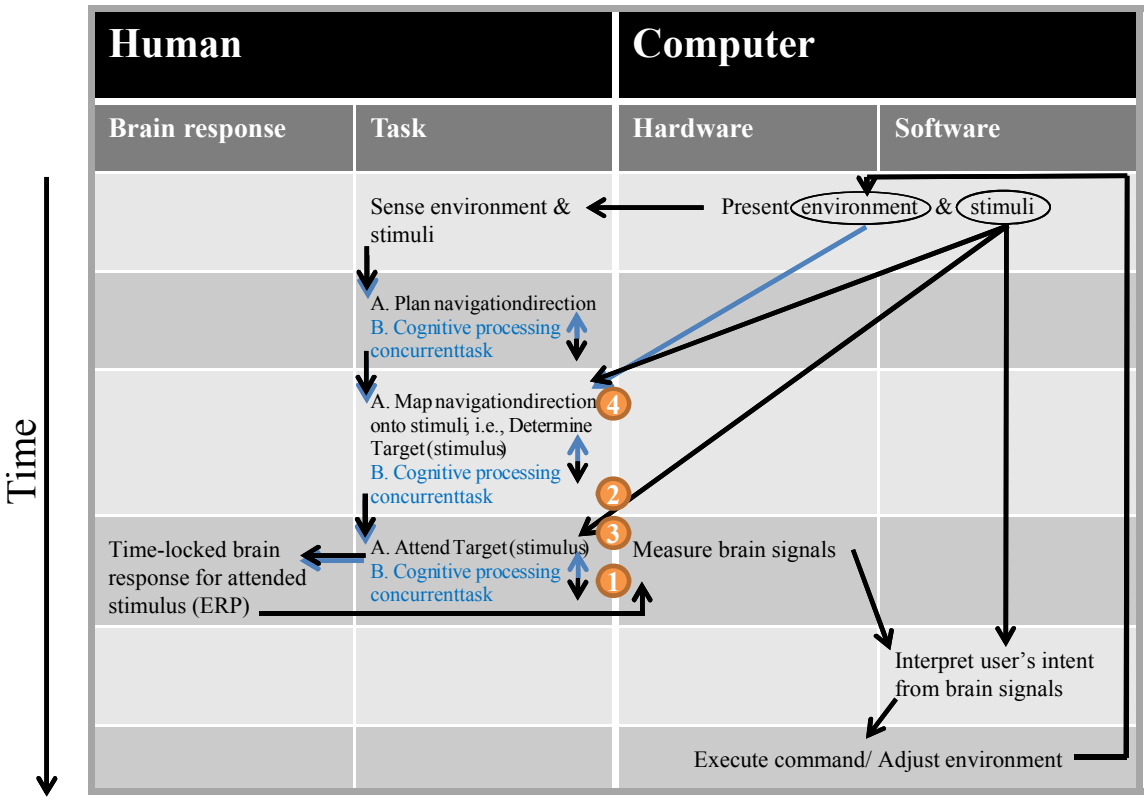

Figure 1.2: Interactions between a human and a computer in an ERP-BCI. The numbers indicate the target areas of the research questions as presented in section 1.5. The role of a (potential) concurrent task is indicated in blue. The black-blue paired arrows visualise the influence of the tasks on each other.

1.3.3. Interactions between human and computer in a tactile ERP-BCI

In Figure 1.2, the interactions between human and computer are visualised that occur when navigating with an ERP-BCI. We distinguish three high-level cognitive user tasks (all part of the BCI operation task) involved in navigating with ERP-BCIs: Planning Navigation Direction, Target Determination, and Target Attending.

The user is presented with an environment, and also with sequences of tactile stimuli that are each connected to a navigation direction. After sensing this information, the user has to plan his/her path of navigation and determine a direction (Planning Navigation Direction). This navigation direction has to be mapped onto the tactile stimuli, such that the target stimulus is determined (Target Determination). Subsequently, the user has to attend only to this target stimulus, while ignoring the remaining nontarget stimuli (Target Attending). Meanwhile the user's EEG is recorded, and the recorded brain responses to the stimuli (ERPs) are categorized into attended versus non-attended responses, such that the attended stimulus can be determined. The system can now use this information to execute the desired command; to navigate in a certain direction. The environment adjusts to the new position, and the process is repeated for the next navigational choice.

1.4. Challenges for navigating with a tactile ERP-BCI: A multisensory interface

When BCI is used for a navigation-task –as for most other tasks-, navigation information is typically sensed visually. Thus when navigating with a tactile ERP-BCI, both the visual and tactile modality are involved. Note that although the visual channel is involved for navigation, the resulting multisensory BCI may still be gaze-independent as navigation information does not necessarily require to be gazed at (unlike gaze-dependent visual ERP-BCIs). In this section, we determine the challenges that have to be tackled to navigate effectively with a tactile ERP-BCI.

1.4.1. Controlling a tactile ERP-BCI in a (multisensory) dual-task

Effective control of ERP-BCIs has been shown feasible in single-task situations (e.g., Brouwer and Van Erp 2010; Farwell and Donchin 1988). If the user would not only navigate with the BCI, but meanwhile also has to perform another task (or more) simultaneously, that concurrent task could potentially interfere with the BCI task. Interference of tasks may be expected as soon as they share the same (cognitive) resources such as attention and memory (also known as resource competition, see e.g., Wickens et al. 1983). Multi-task environments are present in everyday life, and appropriate integration of BCIs in multi-task situations is a prerequisite for successful BCI applications for healthy users (Van Erp et al. 2011). Acknowledging the importance of studying BCI in a complex environment (non-lab setting), recently researchers started to explore the effect of distraction on the use of an active BCI based on mental imagery (Friedrich et al. 2011). However, ERP-BCIs have not been studied in a multi-task environment yet and an important question is if, how and to what extent ERP-BCI performance is affected by concurrent tasks. The functional cost of controlling a tactile ERP-BCI in a multisensory dual-task needs to be investigated, which is the first challenge we tackle in this dissertation.

Many tasks –including navigation- are dependent on visual information. When operating a tactile BCI in a dual-task, the two tasks will likely be using information from different

sensory modalities: Visual and tactile. Therefore, the tasks are expected to overlap less than when both tasks would be based on information from the same sensory modality. Nevertheless, the task of attending tactile targets is still expected to overlap partly with a visual cognitive task. Because both tasks may (partly) use the same resources, it is likely that performance of these tasks will be lower when they are performed simultaneously compared to when they are performed individually. Also ERP components may be affected, as they reflect perceptual and cognitive processing (Kok 1997). Although task interference has not been studied with respect to ERP-BCI tasks and associated ERP components and BCI-performance, it has been extensively researched with respect to cognitive task performance. The P300 of a secondary task was shown to decrease when a primary visuomotor task required more mental effort (Isreal et al. 1980a; Isreal et al. 1980b; Kramer et al. 1983; Kramer and Strayer 1988), suggesting that the amplitude of the P300 ERP component is affected by allocated attentional resources. Therefore, we expect that the P300 in an ERP-BCI is reduced when operated simultaneously with a visual concurrent task compared to when operated without a concurrent task. Because the P300 is the most important ERP in gaze-independent ERP-BCIs (Brunner et al. 2010; Thurlings et al. 2012a; Treder and Blankertz 2010), we expect a corresponding drop in BCI performance.

1.4.2. Improving performance of navigation with a tactile ERP-BCI

As discussed in section 1.1.2., BCI performance needs to be drastically improved before BCI-based navigation applications can become successful and movement-free control can be realized. This is particularly true since we hypothesized in the preceding section that performance will even be decreased if a BCI is used in a dual-task situation.

We stated that we focus on how interactions between humans and computers could be modified to possibly increase the signal-to-noise ratio from brain signals related to intended navigation. In section 1.3.3., we distinguished three cognitive tasks involved when navigation with a tactile ERP-BCI (see Figure 1.2). The first task, Planning Navigation Direction, is a high level intent that cannot be interpreted from the brain-signals directly yet (see section 1.2.2.). Therefore we focus on the two other user tasks (Target Determination, and Target Attending), and how these are affected by the interface as reflected in the ERP.

More specifically, we address how multisensory stimuli could affect the users' cognitive processes related to the task of Target Attending, and how spatial relations within the multisensory interface could affect the users' cognitive processes related to the task of Target Determination.

Exploring bimodal stimulus presentation to increase ERP components usable in BCIs

ERP-BCIs typically rely on the sensory-specific (and higher-level) processing of one sensory modality only. Often, however, sensory inputs of more than one modality are integrated in the brain, causing additional neuronal activity. This phenomenon is called multisensory integration (for reviews, see: Driver and Noesselt 2008; Ernst and Bülthoff 2004; Stein and Stanford 2008) and may take place at perceptual stages (Molholm et al. 2002; Philippi et al. 2008), higher cognitive stages (Schröger and Widmann 1998), and/or during motor preparation and execution (Giray and Ulrich 1993). We are interested in whether or not and how effects of multisensory integration can be exploited in a BCI to increase the difference between target- and nontarget related ERPs and subsequently boost BCI performance.

Multisensory integration has been investigated in a number of behavioural and ERP studies. Task performance has repeatedly been shown to benefit from bimodal (compared to unimodal) stimulus presentation, exhibiting reduced reaction times (Gondan et al. 2005; Miller 1991; Molholm et al. 2002) and increased accuracy (Talsma and Woldorff 2005). Although previously multisensory integration was thought of as an exogenous process (automatic without voluntary control), recently—crucial to BCI—the role of endogenous attention was acknowledged (for a review, see: Talsma et al. 2010). Talsma and Woldorff (2005) found that multisensory integration of audiovisual stimuli is modulated by endogenous attention at different stages of processing: starting as early as 80 ms and peaking at approximately 100, 190 and 370 ms after stimulus onset. To date, only two studies have reported on the possible benefit of bimodal stimulus presentation in an ERP-BCI context. The first is from Brouwer et al. (2010), who investigated bimodal (covert) visual–tactile (compared to unimodal visual or tactile) stimulus presentation and found a slight local parietal enhancement of the P300 and an overall enhancement of offline classification accuracies. However, that study was not fully in line with BCI because endogenous attention and exogenous attention were confounded, as the targets were always physically different from the nontargets. The second study (Belitski et al. 2011) showed the positive effects of a bimodal audio-visual ERP-BCI paradigm (compared to both unimodal variants) on offline classification accuracies, but the underlying ERP components were not investigated.

We hypothesize that the task performance of participants is increased and early ERP components (<200 ms) and corresponding BCI performance are enhanced when attending to bimodal visual-tactile compared to unimodal stimuli.

Bimodal gaze-independent ERP-BCIs and the role of location-congruent bimodal stimuli

The (spatial) relation between the two unisensory parts of bimodal stimuli could possible play a role in bimodal stimulus processing, and thus in bimodal BCI performance. Literature on the effects of location-congruency is not equivocal. According to the *spatial rule* (Meredith and Stein 1986), stimuli from different modalities are only integrated when stimuli are spatially coincident (or proximate). Stein et al. (1989) showed for example that the performance of animals that were trained to approach visual stimuli is improved when matched with (unattended) auditory stimuli, but only if the visual-auditory stimulus pairs were spatially coincident (or proximate). Frassinetti et al. (2002) replicated these results in humans. Also when bimodal stimulus-pairs are not location-congruent, behaviour performance has been found to be enhanced compared to unimodal stimuli (Gondan et al. 2005; Philippi et al. 2008; Teder-Salejarvi et al. 2005). Nevertheless, also when bimodal benefits are found for incongruent bimodal stimuli, behavioural performance may be improved by location-congruency (Gondan et al. 2005). Teder-Salejarvi et al. (2005) did not observe such a behavioural benefit, but did report differences in the ERP for location-congruent and location-incongruent bimodal stimuli after 100 ms. We investigate bimodal ERP-BCI and the role of location-congruency, using a gaze-independent setup, and hypothesize a positive effect on the (late) ERP and BCI performance.

Congruency in multisensory interfaces

The final challenge we tackle also incorporates the effects of a congruent spatial relation, but now between the stimuli and the navigation information, and how this affects the users' task to map the navigation direction onto the stimuli to determine the target stimulus. For navigation in gaming, the display is the device that presents a visual environment from which

users extract navigation information. The control is the device that consists of tactors, each corresponding to possible navigation choices. A higher similarity between control and display, in terms of both spatial and non-spatial factors, results in a higher performance in time critical visuo-perceptual motor tasks: faster response times (Chan and Chan 2011; Zupanc et al. 2007), fewer errors (Zupanc et al. 2007) and more efficient task completion (Phillips et al. 2005). It might also lead to faster learning and a lower mental workload (Wickens 1987) and increased user satisfaction (Tlauka 2004). Basic spatial rules to optimize control-display mapping (CDM) state that control and display should be parallel and in the same direction in some inertial frame of reference (Worringham and Beringer 1998). CDM has not been investigated in ERP-BCIs yet, but is likely to affect performance and thus needs to be addressed. We hypothesize that incongruent CDM may negatively affect the initial determination of the corresponding tactor (Target Determination). This leads to attending to the wrong stimulus in the Target Attending Stage, and thus decreased endogenous ERP components, i.e. the P300, and corresponding BCI performance for incongruent compared to congruent CDM.

1.5. Research questions

Our research goal is to understand the underlying mechanisms of multisensory ERP based BCIs with the purpose of reducing the cognitive resources involved, and improving gaze-independent BCI performance.

The main questions of the dissertation are:

Does (multisensory) dual-tasking negatively affect ERP components, and consequently decrease BCI-performance of a tactile ERP-BCI?

Do (congruent) multisensory BCIs positively affect ERP components, and consequently increase BCI performance?

From the main questions we derive four specific research questions, each of which we address in a separate study and present in a chapter of this dissertation. The research questions are:

Research question 1: (How) does (multisensory) dual-tasking affect ERP components, and subsequently BCI performance?

Research question 2: Does attending to bimodal visual-tactile (compared to unimodal) stimuli positively affect ERP components, and subsequently BCI performance?

Research question 3: Does attending to bimodal visual-tactile gaze-independent and location-congruent (compared to unimodal or bimodal location-incongruent) stimuli positively affect ERP components, and subsequently BCI performance?

Research question 4: (How) does (multisensory) control-display mapping (CDM) affect ERP components, and subsequently BCI performance?

In Figure 1.2 the challenges at which the research questions are focussed are indicated with corresponding numbers.

1.6. Analysis methodology

In all studies we recorded EEG and analysed the ERP in detail, because attentional effects on the ERP not only serve as the basis to distinguish targets from nontargets, and are thus crucial for classification, they also help us to obtain insight in the cognitive processes involved in the interaction, which is useful to improve BCI design. Traditional methodology to investigate ERP (components) makes use of pre-knowledge, i.e., when and where certain activity may be expected (Luck 2005). When investigating new paradigms and exploring new directions such pre-knowledge is not available. This was also the case for our studies, and therefore we developed a method with which we detected and quantified endogenous ERP components.

Furthermore, BCI performance was investigated in all studies, in some the online performance was measured and in all studies performance was analysed offline. Offline analysis allowed us to estimate effects on performance in a realistic setting, using more suitable classifier choices for the specific (tactile) ERP-BCI.

1.7. Outline of the dissertation

This dissertation is organized along the four research questions in the form of scientific papers. We here give an overview of each chapter, their motivations, and the relation between them.

Chapter 2: Controlling a tactile ERP-BCI in a dual-task. In this chapter we present the evaluation of what the costs of mental resources are to control a tactile ERP-BCI while at the same time performing a concurrent task using visual information. This is the first step towards applying a tactile ERP-BCI for navigation. For tasks like (serious) gaming cognitive resources are required, but when operating an ERP-BCI attending to stimuli also demands (cognitive) resources. We investigate whether or not these two tasks can be performed simultaneously, and what the effects on brain signals (and subsequently BCI performance) and task performance are.

Chapter 3: Does bimodal stimulus presentation increase ERP components usable in BCIs? In this chapter we report the idea to increase ERP activity by means of bimodal (visual-tactile) stimulus presentation, with the goal to enhance BCI performance. Bimodal stimuli could evoke additional brain activity due to multisensory integration which may be of use in a BCI. We investigate effects of attending to bimodal visual-tactile (compared to unimodal) stimuli on the ERP. To this end we use stimulus pairs of tactile stimuli around the waist and visual stimuli embedded in a navigation environment presented on a display, corresponding in navigation direction.

Chapter 4: Bimodal location-congruent ERP-BCIs: Increasing gaze-independent performance. In this chapter we further investigate bimodal (visual-tactile) ERP-BCIs and the role of location-congruency of the bimodal stimulus. Research has shown that bimodal stimuli do not necessarily have to be location-congruent to observe positive bimodal effects on task performance and brain activity, yet location-congruent bimodal stimuli may (further) positively affect task performance and ERP components. Whereas in chapter 3 we use a gaze-dependent setup as a first step and to compare results to traditional BCIs, in chapter 4 we take the next step by using a gaze-independent setup. In the latter case, the potential benefits of bimodal stimuli are expected to be greater as gaze-independent BCI performance is typically relatively low. Additionally, we study the effect of selectively attending to a modality in bimodal BCIs.

Chapter 5: Control-display mapping in brain–computer interfaces. In this chapter we present our research on the effect of congruency regarding the relation between command options and stimuli in a BCI-context. When using a tactile ERP-BCI for navigation, mapping is required between navigation directions on a visual display and unambiguously corresponding tactile stimuli from a tactile control device: control-display mapping (CDM).

Chapter 6: Discussion and conclusions. We discuss the results of the separate studies and integrate the studies to answer the main research question. Furthermore, we discuss the implications of our results, reflect on the usefulness of ERP-BCI for direct control and for other purposes, and make recommendations for future research. We finalise with some concluding remarks.

2

Controlling a tactile ERP-BCI in a dual-task

***Abstract*—**When using Brain Computer Interfaces (BCIs) to control a game, the BCI may have to compete with gaming tasks for the same perceptual and cognitive resources. We investigated (1) if and to what extent Event-Related Potentials (ERPs) and ERP-BCI performance are affected in a dual-task situation, and (2) if these effects are a function of the level of difficulty of a concurrent task. Ten participants performed an ERP-BCI task that involved attending to a target location in sequences of tactile stimuli. The ERP-BCI task was performed either in isolation or secondary to a visual n-back task with two levels of difficulty. We observed (1) a decreased P300 and BCI bitrates, and an increased level of subjective mental effort for both dual-task conditions compared to the BCI-only condition. The decreased classification accuracies were still well above chance, but arguably too low for effective BCI control. Furthermore, (2) we did not find an effect of task difficulty on the P300, bitrates, and subjective mental effort. We discuss reallocation of attention caused by a concurrent task, but unaffected by task difficulty, and the role of task priority. Concluding, control of a tactile ERP-BCI in a dual-task situation is feasible, but performance is degraded.

Index Terms: BCI, ERP, dual-task, tactile, workload

This chapter is based on:

Thurlings, ME, Van Erp JBF, Brouwer A-M, Werkhoven P. 2013. Controlling a tactile ERP-BCI in a dual task. *IEEE Transactions on Computational Intelligence and AI in Games. (In press).*

2.1. Introduction

2.1.1. Applying ERP-BCIs to navigate in a game

Event-related potential (ERP) based Brain-Computer Interfaces (BCIs) can be used to actively and voluntarily control a system, e.g. for communication (Farwell and Donchin 1988) or navigation (Bell et al. 2008) (for an elaborate discussion on BCI for navigation, see: Thurlings et al. 2010). ERP-BCIs make use of stimuli which are corresponding to control options (e.g., 'left' or 'right'). The user can select an option by attending to the corresponding stimulus (target) while ignoring other stimuli (nontargets). Stimulus-locked brain responses (ERPs) differ between the attended targets and ignored nontargets.

Most ERP-BCIs employ visual stimuli. However, since the effectiveness of visual ERP-BCIs is mainly based on gaze (Brunner et al. 2010; Treder and Blankertz 2010), other modalities may be more appropriate under certain circumstances (e.g. when used by patients who cannot reliably focus their gaze). Additionally, in many potential application areas, such as driving or gaming, the visual (and auditory) channel is already heavily loaded (Van Erp and Van Veen 2004). The tactile channel has been suggested as a viable alternative, and in (Brouwer and van Erp 2010) the feasibility of employing tactile stimuli around the waist in a tactile ERP-BCI was demonstrated. The natural correspondence of tactile stimuli around the waist with navigation directions (Van Erp 2005) makes a tactile ERP-BCI especially interesting for navigation applications.

While BCIs based on brain patterns generated by mental imagery allow the user to select an option at any moment and are not dependent on externally presented stimuli (Nijholt and Tan 2008), ERP-BCIs may be more appropriate for application in games because user training is not required and the corresponding communication bandwidth is relatively high (Guger et al. 2009). Previous studies applied BCIs to control a game (Millan et al. 2008; Nijholt et al. 2009), but were usually based on mental task induced brain responses and not on ERPs (e.g., Scherer et al. 2008). These studies investigated BCIs in a single task situation (Millan et al. 2008; Pires et al. 2011; Van Erp et al. 2011), although gaming is typically a multi-task environment. Acknowledging the importance of studying BCI in a non-lab setting, recently researchers started to explore the effect of distraction on the use of mental imagery based BCI (Friedrich et al. 2011). ERP-BCIs have not been studied in a multi-task environment yet and an important question is if, how and to what extent ERP-BCI performance is affected by concurrent tasks.

2.1.2. Dual-tasking and resource competition

Gaming involves cognitive tasks that can potentially interfere with an ERP-BCI for navigation. Interference may be expected as soon as tasks share the same (cognitive) resources such as attention and memory (also known as resource competition, e.g. see: Wickens et al. 1983). Task interference has been extensively researched with respect to cognitive task performance but not with ERP-BCI tasks and associated ERP components and BCI-performance.

A thoroughly investigated and widely used cognitive task is the so-called 'n-back task' (Kirchner 1958). The n-back task requires participants to view sequences of letters, and compare each letter to the one presented 'n' letters before. This paradigm allows the controlled increase of required cognitive resources through increasing 'n' without changing visual and motor components. Both ERP-BCI and n-back tasks require perception of and

attention to sequentially presented stimuli, categorical decisions after each stimulus (target versus nontarget, and match versus nonmatch for the BCI- and n-back task respectively) and short term memory (current targets and current matches). This makes the n-back task well suited to investigate possible effects of performing a task besides controlling a BCI, as occurs during BCI controlled gaming.

In serious gaming, as for example for training or education, users are typically required to make long-term goals, which involves working memory and high cognitive load, while feedback on game performance is not directly available (Greitzer et al. 2007). If BCI is used to navigate in such a (serious) game, there will be continued feedback on BCI performance, but not on game performance. To resemble the practical situation of use, in this study only feedback will be provided on the BCI-task but not on the n-back task. Nevertheless, priority has to be given to the n-back task, as navigation is only a tool to play the serious game.

2.1.3. Possible effects of resource competition on ERPs

Because both tasks may (partly) use the same resources, it is likely that performance of these tasks will be lower when they are performed at the same time, compared to in isolation. Also the ERP components may be affected, as they reflect perceptual and cognitive processing (Kok 1997). The P300 of a secondary task was shown to decrease when a primary visuomotor task required more mental effort (Isreal et al. 1980a; Isreal et al. 1980b; Kramer et al. 1983; Kramer and Strayer 1988), suggesting that the amplitude of the P300 ERP component is affected by allocated attentional resources. Therefore, we expect that the P300 in an ERP-BCI is reduced when operated alongside the n-back task compared to standalone and is further reduced when the n-back task becomes harder. Because the P300 is the most important ERP component in gaze-independent ERP-BCIs (Brunner et al. 2010; Thurlings et al. 2012a; Treder and Blankertz 2010), we expect a corresponding drop in BCI performance.

Summarizing, the aim of this study was to investigate (1) if and to what extent ERP components and ERP-BCI control are affected in a dual-task situation and (2) if potential degradation of ERP components and ERP-BCI control are a function of the level of difficulty of a concurrent task. To answer these questions, we studied an ERP-BCI task in isolation (control condition), and with a concurrent 0-back and 1-back task. We analysed ERP components, online classification accuracy, more extensive offline classification accuracy and bitrates, all corresponding to the ERP-BCI task. Furthermore we examined participants' behavioural performance of the n-back task and participants' subjective levels of workload.

2.2. Method

2.2.1. Participants

Ten volunteers (students and young professionals) participated voluntarily in this study. Participants were aged between 20 and 33 years (mean age 24.7 years). Three were male and one was left-handed. All participants had normal or corrected-to-normal vision. The participants signed informed consent forms.

2.2.2. Design

See Figure 2.1 for a visualisation of the experimental design. The experiment involved three conditions, named after the type of tasks involved: BCI-only, BCI&0-back, and BCI&1-back. The order of the conditions was counterbalanced over the participants. Each condition consisted of two sets. The data of the first set (the training set) were used for the training of a classifier, which was applied to classify the data in the second set (the test set). Online BCI-feedback was given to participants in the test set about which tactor (tactile actuator) was classified as the target. The training set was also used for the analysis of participants' ERP components and behavioural performance of the n-back task. The test set was excluded for ERP-analysis, to prevent an influence of tactile target feedback on the ERPs and because the classifier is also only trained on the ERPs (and possibly other effects) of the training set.

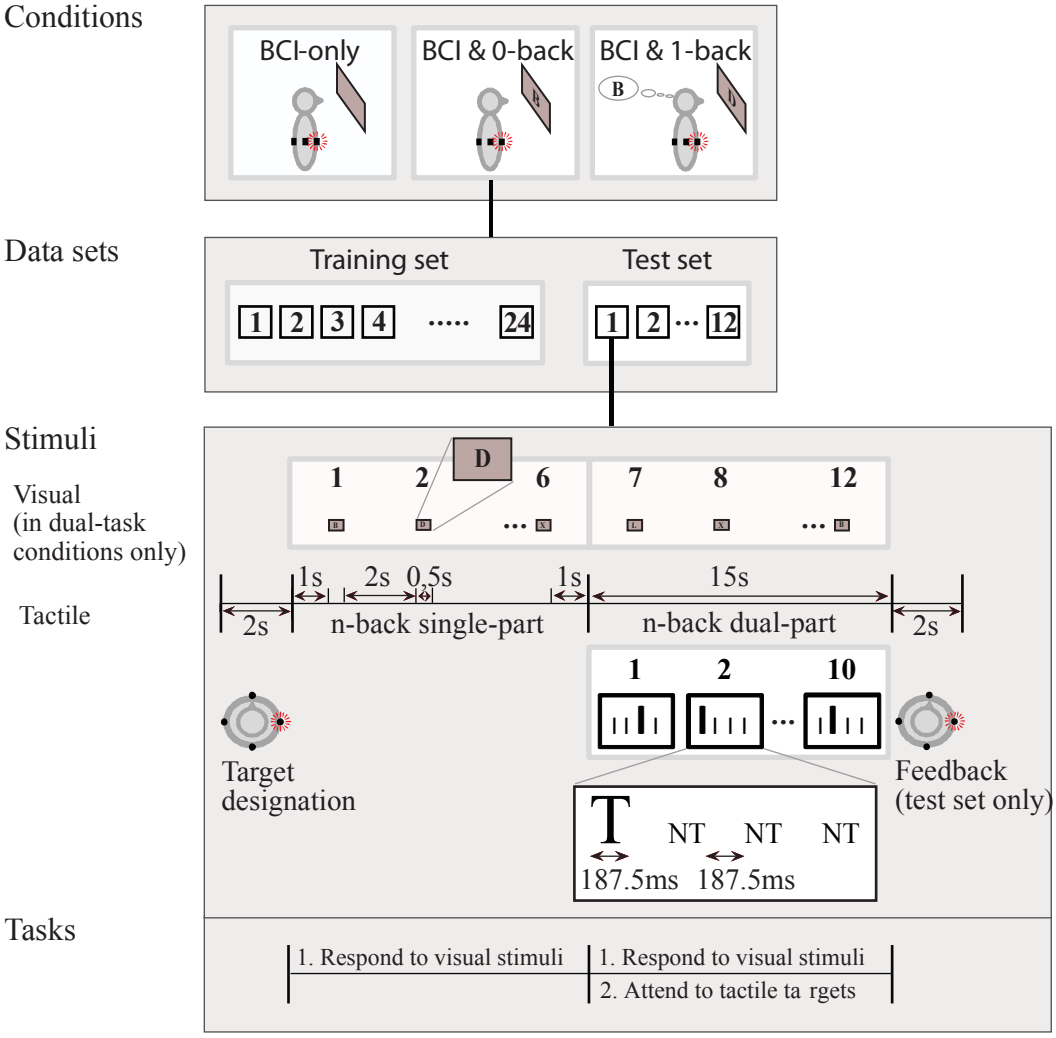

Figure 2.1: Overview of the experimental design. There were three conditions, each containing a training set (24 blocks) and a test set (12 blocks). Each block started with a tactile target designation, then for the dual-task conditions this was followed by the n-back single-task part (visual stimuli presentations, and the task to match and respond to visual stimuli). Subsequently, for all conditions the n-back dual-task part followed (visual and tactile stimuli presentations, and the task to match and respond to visual stimuli and attend to tactile targets). Next, in the test set only, tactile feedback was given.

The training and test set consisted of 24 and 12 blocks, respectively. The first half of each block consisted of the n-back task and stimuli solely (only in the dual-task conditions). The second half of each block consisted of both the n-back and ERP-BCI task and stimuli. In this way, participants would be fully engaged in the n-back task before the tactor vibrations for the ERP-BCI task were added, to support the priority they had to give to the n-back task. Thus, in the second half of each block, both tasks had to be carried out simultaneously.

For the n-back task participants looked at a visual display on which six visual letters were sequentially presented, once for the single- and once for the dual-task part of each block. On- and offtimes were 500 ms and 2 s respectively.

For the ERP-BCI task, participants were stimulated with four tactors around the waist (front, back, and one at each side), which vibrated sequentially in random order. Each of the four tactors was designated as the target six times in the training set and three times in the test set. The target was designated by means of a long vibration (2s) of a particular tactor, and in the dual-task part of blocks was followed by 10 consecutive repetitions of tactor sequences. In the test set, feedback was provided after the final repetition by means of a long vibration of the selected target (2s). In each repetition, each of the four tactors was presented once in random order, with the constraint that there was at least one nontarget in between two target tactors of consecutive repetitions. On- and offtimes were both 187,5ms. In our control condition (BCI-only) the visual letters of the n-back task were not shown at all.

2.2.3. Task

ERP-BCI task

Participants had to attend to a target tactor location and count the number of vibrations at that location. Participants were instructed that in the dual-task conditions, the n-back task was the primary task (i.e., participants were asked to give priority to this task), and the ERP-BCI task was the secondary task, which was supported by the design of the experiment (see section 2.2.2. Design).

N-back task

For each letter, participants had to indicate whether the letter was a match or not, by pressing the appropriate button as rapidly as possible. The numbers for ‘n’ were zero and one. The levels of ‘n’ for the n-back task used in single task studies are usually zero to two (e.g., (Brouwer et al. 2012)) but our pilot dual-task study indicated that for ‘n’ is two or higher, the task became too difficult resulting in participants quitting the experiment prematurely.

In the 0-back condition the letter ‘X’ was the target. This condition does not require an update of information within working memory with every letter that is presented (Owen et al. 2005). In the 1-back condition a letter was a match when it was the same as the previously presented letter. We used the percentages of correct responses (matching accuracy) and response times as a measure for task performance. Prior to the recording of each dual-task condition, the n-back task was practiced until a matching accuracy of above 80% was reached.

2.2.4. Materials

Tactile stimuli

Participants wore an adjustable belt with integrated tactors. The tactors were custom built and consisted of a plastic case with a contact area of 1x2 cm containing a 160 Hz electromotor (TNO, The Netherlands, model JHJ-3, see: Van Erp et al. 2007). To prevent participants from perceiving auditory information from the tactors, they listened to pink noise via in-ear headphones during the experiment.

For this study, the tactors consisted of two electromotors paired together, at each of the four locations around the torso at approximately navel height. The locations of the tactors corresponded to four basic navigation directions: front, back, left and right.

Visual display and n-back stimuli

Visual stimuli were presented at a central location of an LCD (Dell 20 inch flat panel, refresh rate 75 Hz). The stimuli (letters) were white consonants displayed on a black background. We did not use vowels in order to prevent participants from developing chunking strategies, which could result in reduced workload (Grimes et al. 2008). Since the letter 'X' was used as a visual target in the BCI&0-back condition, this letter was not used in the BCI&1-back condition.

EEG recording equipment

EEG was recorded from 8 linked-mastoids-referenced scalp electrodes (F_z, C_z, P_z, O_z, P_3, P_4, P_7, P_8) that used a common forehead ground (g.Tec medical engineering, GmbH). The impedance of each electrode was below 5 kΩ, as was confirmed prior to and during the measurements. EEG data were recorded with a hardware filter (bandpass 0.1-60 Hz, notch at 50 Hz) and sampled at a frequency of 256 Hz.

2.2.5. Procedure

After the participant read and signed the informed consent, we helped him or her into the tactile belt. The participant was seated in front of the visual display in a dimly lit, electromagnetically shielded room. We checked for tactor saliency by activating the tactors successively and asking the participant for the corresponding directions. If necessary, we tightened or relaxed the tactile belt and/or repositioned one or more of the tactors. During EEG preparation, we repeated the outline of the experiment and instructed the participant to move as little as possible during tactor presentations. This is an important instruction as (eye) movements, especially those time-locked to target presentations, could affect the ERP and correction remains difficult (Fatourechi et al. 2007).

Before each condition, we informed the participant about the oncoming condition, and the participant trained the n-back task when necessary. When the participant indicated to be ready to begin, we started the condition with the recording of the training set. Then the test set followed in which the trained classifier classified the data and online BCI feedback was given.

The BCI-only condition lasted approximately 7.6 min and the other two conditions 12.8 min. Conditions followed each other with 1 to 15 minutes breaks in between, depending on the participant's preferences.

2.2.6. Data analysis

EEG preprocessing and selection

To prepare the recorded EEG for offline processing, we followed similar procedures as taken in (Thurlings et al. 2012a; Thurlings et al. 2012b). The data were additionally low-pass filtered at 30 Hz; the resulting bandpass filter reduces influences from artefacts like eye blinks (Guger et al. 2009; Tereshchenko et al. 2009). For ERP-analysis only, responses to tactile (non)targets were selected if there were no (other) targets presented between -750 and 750 ms relative to (non)target onset, i.e. the two stimuli preceding and the one stimulus following were no target stimuli (see also: Treder and Blankertz 2010). For the selected (non)targets, epochs from all electrodes were extracted from -375 to 1000 ms relative to stimulus onset and baseline corrected relative to the average voltage during the 100 ms preceding the stimulus onset.

Additionally, to diminish influence from (eye) artefacts, we applied the EEG threshold rejection approach (Fatourechi et al. 2007). We discarded epochs from all electrodes belonging to a certain stimulus, if any epoch contained amplitude differences exceeding 125 μV. This left us with 54 to 174 target epochs and 58 to 158 nontarget epochs (ranges over participants and conditions). Subsequently, the selected target and nontarget epochs were averaged per participant, per condition and per electrode.

Finally, we subtracted the averaged clean nontarget epochs from the averaged clean target epochs for each participant, each condition and each electrode. With this step, we removed exogenous (involuntary or automatic) attention effects. Further analyses were performed regarding this difference ERP (or endogenous ERP).

Note that with the taken measures (eye) artefacts are not completely removed. However gaze-independent BCIs appear less sensitive to (eye) movement artefacts than gaze-dependent BCIs (Treder et al. 2011a; Treder and Blankertz 2010). Moreover, in this study we are interested in the differences in ERPs between the conditions. In all conditions the BCI-task and corresponding stimuli were the same, and therefore it is unlikely that time-locked (eye) artefacts influenced the conditions in different ways.

Identifying and quantifying ERP components

To identify and quantify ERP components triggered by endogenously attended tactors, we applied the same method as reported in (Thurlings et al. 2012a; Thurlings et al. 2012b) using the data of the training set. First, we identified significant endogenous effects by performing a sample-by-sample t-test (over participants) on the endogenous ERP (compared to zero) in the window 0-750ms after (non)target onset for each electrode and condition. When at least nine consecutive samples were significant, these samples indicated a stable segment in the difference ERP (see also: Guthrie and Buchwald 1991). Second, we clustered the stable segments over electrodes, taking the beginning and ending of their time periods and their averaged amplitudes into account. If segments of two or more electrodes were clustered together, the cluster was considered robust. These robust clusters defined the topographic distribution and the interval of the endogenous ERP components, taking the beginning of the earliest segment and the ending of the latest segment in the clusters as ERP component intervals.

After identifying ERP components based on the data of all participants, we used the ERP components' characteristics to quantify the endogenous ERP components per participant by

using the tAUC-value, as described in (Thurlings et al. 2012a; Thurlings et al. 2012b). To this end, for each ERP component and for each participant, first the AUC (area-under-the curve) in the difference ERP was calculated of each electrode-interval combination (i.e, stable segment) included in a detected ERP component. Thus in the difference ERP from the electrode for which a stable segment was detected, the segments' AUC was derived from the amplitudes within the segments' interval. Next, the AUCs of all stable segments included in an ERP component were summed (thus also over electrodes) to include the topographic distribution of ERP components in the tAUC measure. The tAUC reflects the magnitude of an ERP component not only by taking the averaged amplitude and duration of the component into account but also by considering the topographic distribution. This measure should correspond to perceptual and cognitive processes, and provide insight in the participants' mental states.

Online and offline BCI performance

Classification accuracies were calculated both online and offline. Online analysis was performed using the data from all eight recorded electrodes, with an epoch window from 0-797 ms after stimulus onset. This window differs from the one used in the ERP analysis (0-750 ms), because the ERP window was chosen to allow a selection of ERP responses without or with reduced target-evoked ERP overlap. The parameters for classification are similar to those in previous studies using the same classification method (Brouwer and van Erp 2010). We used SWLDA as implemented by BCI2000 (Schalk et al. 2004) for classification and its default parameter settings (decimation factor 4 (i.e., 64 Hz), maximum of 60 features, p-values included and excluded from the model <.1 and >.15, respectively). The classifier was trained using the training set for each participant and for each condition.

Additionally, we investigated classification accuracies more detailed offline, and calculated accuracies after each repetition rather than only after ten repetitions as done by BCI2000. To this end we used a similar classification method and parameters as for online classification, but to enhance the signal-to-noise ratio we used a decimation factor 10 (i.e. 25.6 Hz) and corresponding epoch length ~781 ms. Additionally, we calculated bitrates according to (Serby et al. 2005), based on each participant's classification probability for each repetition, and for each condition.

Finally, we investigated the effect of condition on BCI performance, by comparing bitrates after the most efficient number of repetitions for practical use (Thurlings et al. 2012a). We defined this most efficient number as the number of repetitions when the highest averaged bitrates were achieved while BCI control was successful. Successful BCI control was defined as a classification accuracy of 55% or higher (translating the criterion of 70% correct classifications in systems with 50% chance level (Birbaumer and Cohen 2007; Kubler et al. 2004; Pfurtscheller et al. 2010), to a criterion in systems with 25% chance level).

N-back task-performance

Similar as for the quantification of ERP components, we only used the data of the training set to analyse effects on the performance of the n-back task. We determined matching accuracies in the n-back task as the percentage of correct responses that were made within 1000 ms after visual stimulus onset during the first and second half of blocks (i.e., in the single- and in dual-task parts), for each participant and each condition. Response times of all responses were obtained and averaged for each participant and each condition.

RSME scales

Participants indicated their subjective level of workload after each condition (i.e., after recording the test set), using the RSME scale (Rating Scale Mental Effort, see: Zijlstra 1993). This scale runs from 0 to 150 with higher values reflecting higher mental effort. Nine categories are defined along the axis. For example the value 2 is 'not effortful' and value 58 is 'rather effortful'. In (Verwey and Veltman 1996) it was concluded that this simple one-dimensional scale is more sensitive than the often-used NASA-TLX (Hart and Staveland 1988).

Statistical analysis

ERP components, tAUC-values, bitrates, behavioural measures of the n-back task (matching accuracies and response times) and RSME-scores were tested for normality (Kolmogorov-Smirnov Test) and statistically analysed using Statistica 8.0 (StatSoft, Tulsa, USA). We used separate one-way repeated-measures ANOVAs for each dependent variable (tAUCs, classification accuracies and RSME-scores), with condition (3 levels: BCI-only, BCI&0-back, BCI&1-back) as the independent variable. For the behavioural measures of the n-back task, we used two-way repeated measures ANOVAs with n-back difficulty (2 levels: BCI&0-back, BCI&1-back) and number of tasks (2 levels: n-back single-task part, n-back dual-task part) as independent variables and response times and matching accuracies as dependent variables. Tukey post-hoc tests were applied when appropriate.

2.3. Results

2.3.1. Endogenous ERP components

Spatiotemporal representations of the amplitudes of the endogenous ERPs (see Figure 2.3b) are presented in Figure 2.2a. For all conditions, endogenous activity was observed during multiple periods within the analysed interval from 0 until 750 ms after stimulus onset. In Figure 2.2b, spatiotemporal plots show the significant stable segments. The red and blue areas indicate the polarities (positive and negative, respectively) of the clustered segments that were found to be robust and were thus identified as endogenous ERP components. In Figure 2.3a, these ERP components are visualised by means of scalp plots (averaged amplitudes of the endogenous ERP at all electrodes, within the ERP components' intervals).

Only one endogenous ERP component was identified in all three conditions: the P300. The area in which it was robustly detected was larger for the BCI-only condition than for the dual-task conditions. Its amplitude was largest in the central area. The P300 was detected in the windows 297-543 ms, 355-535 ms and 348-426 ms after stimulus onset, for the conditions BCI-only, BCI&0-back and BCI&1-back respectively.

Furthermore, for the BCI&1-back condition only, very early and late negative activity was detected and identified as N1 (35-78 ms) and N600 (570-637 ms) components respectively.

Other early negative significant activity, resembling an N2, was detected in both conditions containing the n-back task, but failed to reach the requirements to be labelled as an ERP component.

The effects of condition on the tAUC-values of the P300 only are reported next, as this was the only ERP component that was identified in more than one condition.

The effect of condition on the P300

In Table 2.1 the individual P300 tAUC-values are presented, and in Figure 2.5a the main effect of condition on the P300 tAUC-values is visualised. The P300 tAUC was significantly affected by condition ($F_{(2,18)}$=24.50 p<.001). The P300 was stronger for the BCI-only condition compared to both dual-task conditions (both p<.001). The P300 tAUC did not differ significantly between the two dual-task conditions.

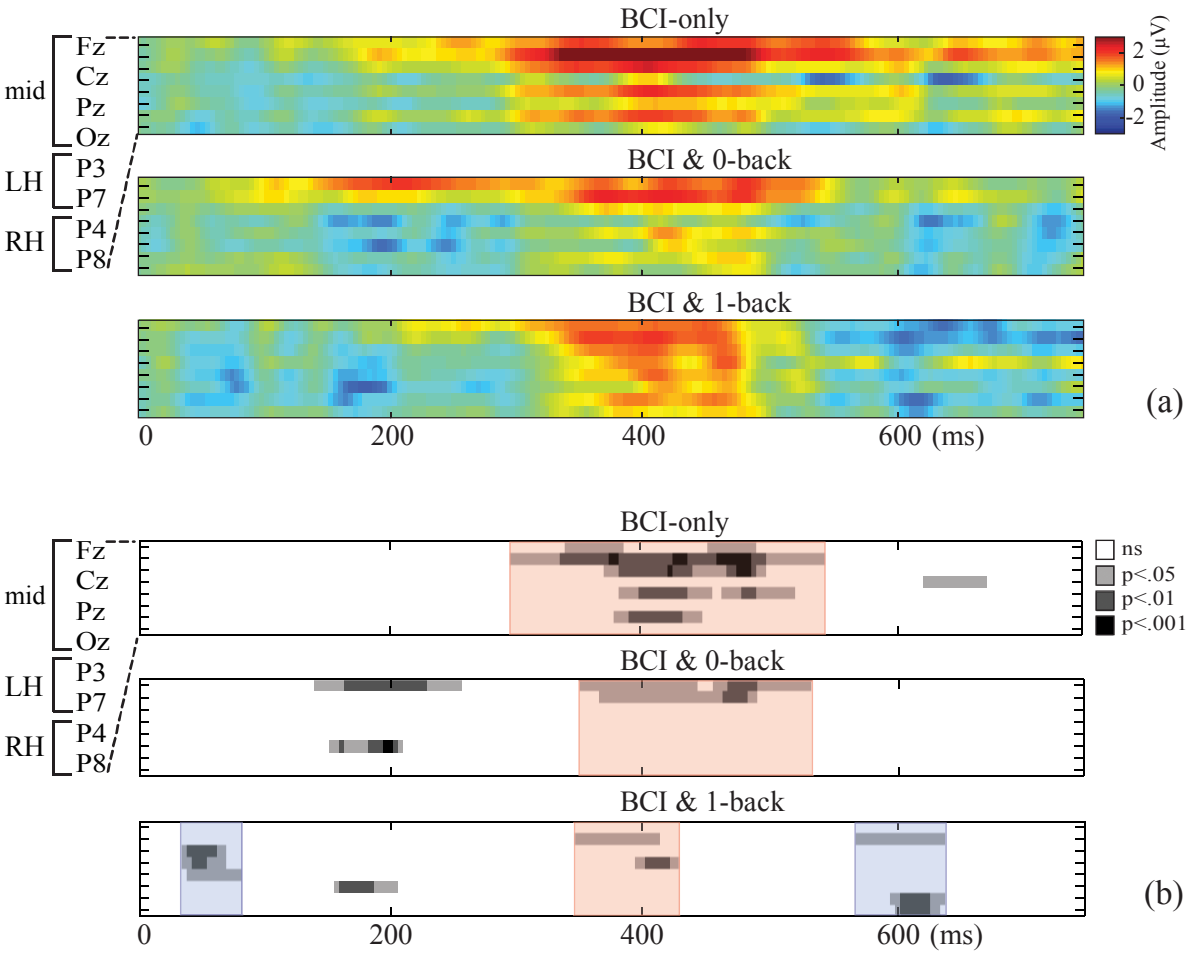

Figure 2.2: Spatiotemporal representations of the endogenous ERP for each condition, with time (ms) on the x-axis and electrodes on the y-axis. Electrodes from top to bottom: Fz, Cz, Pz, Oz, P3, P7, P4, P8. (a) The Grand Average of the amplitudes of the endogenous ERP (µV) for each condition. (b) The statistical significance of the endogenous ERP (p-values) resulting in stable segments, clustered in ERP components. ERP components are marked by coloured overlays in red and blue for positive and negative components, respectively.

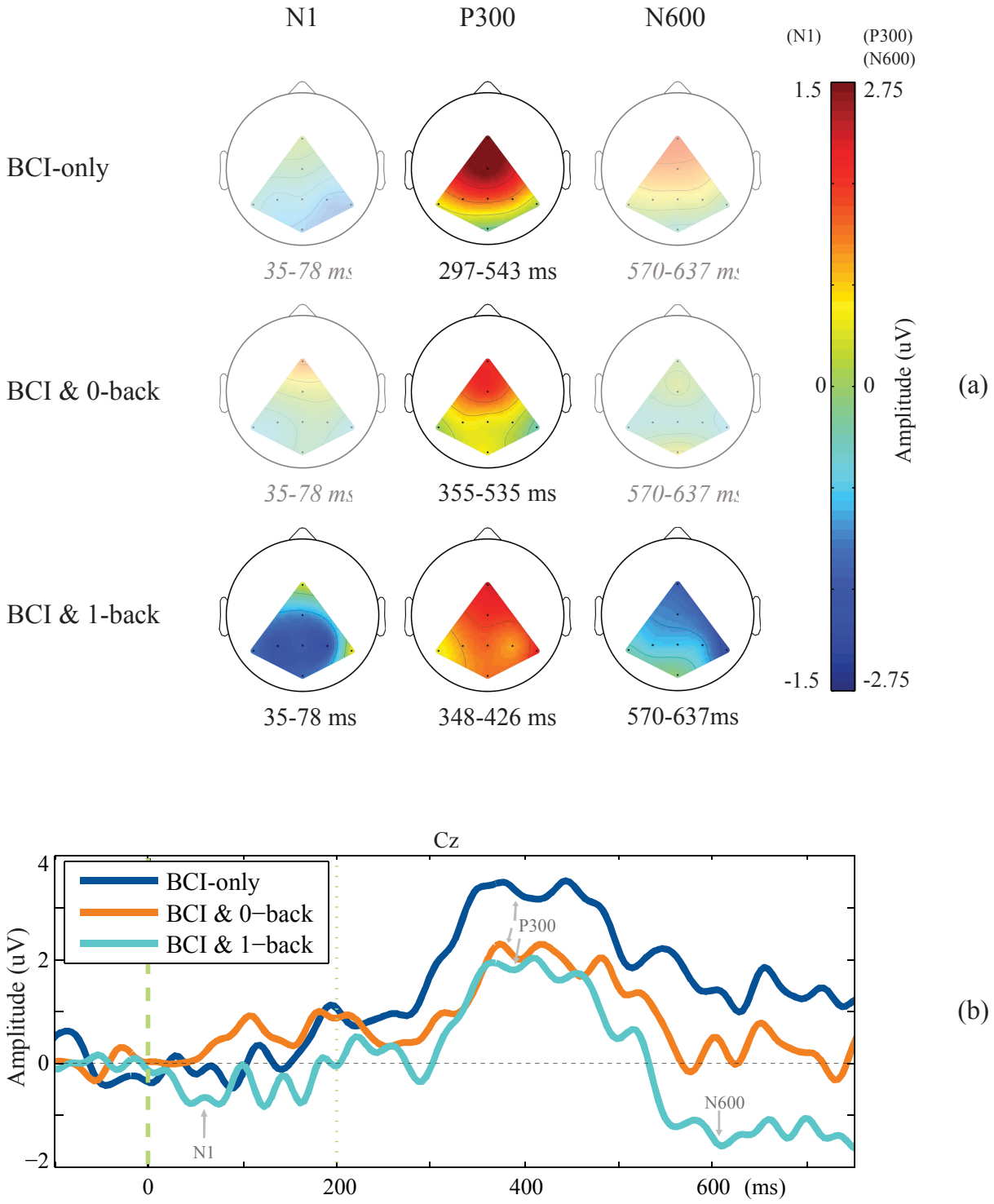

Figure 2.3: Endogenous ERPs and their components (reflecting endogenous attention) averaged over participants. (a) Scalp distributions of the endogenous ERP for the identified endogenous ERP components. Only that part of the scalp is visualised, in which electrode information could be interpolated. Amplitudes (µV) are averages calculated within each ERP component's interval. If no ERP component was identified, the corresponding interval was used to visualise that activity for comparison. In that case, the scalp plot is left semi-transparent, and the corresponding interval is shown in grey and italics. (b) Grand average of the endogenous ERP. The averaged endogenous ERP is visualised for electrode Cz.

2.3.2. BCI performance

Both online and offline classification accuracies are visualised in Figure 2.4a and Figure 2.4c respectively, and corresponding bitrates in Figure 2.4b and Figure 2.4d respectively. Overall classification accuracies (averaged over participants) are higher for the BCI-only condition compared to the dual-task conditions. Offline classification accuracies increase over the first repetitions and appear to reach a ceiling at the sixth repetition for the BCI-only condition, and at the fourth repetition for the dual-task conditions.

For the BCI-only condition, the highest averaged bitrates were achieved after six repetitions. Taking a threshold of 55% for classification accuracies (translating the 70% rule in binary systems, to a four-choice system like ours), nine out of the ten participants can be considered as having achieved effective BCI control after six repetitions. Therefore the sixth repetition is considered the most appropriate to assess effects in a practical setting, and was used to statistically analyse the effect of condition on bitrates. For the dual-task conditions only two participants achieved classification accuracies above 55% after six repetitions, but classification accuracies were significantly higher than chance level (25%) for all conditions ($t_{(9)}=8.16$, $p<.001$; $t_{(9)}=2.65$, $p<.05$; $t_{(9)}=2.50$, $p<.05$, respectively).

In Table 2.1 the individual offline bitrates are presented. For 9 out of the 10 participants a decreased P300 corresponded to a drop in BCI performance for the BCI&0-back compared to the BCI-only condition. A similar correspondence is visible for 8 participants for the BCI&1-back compared to the BCI-only condition.

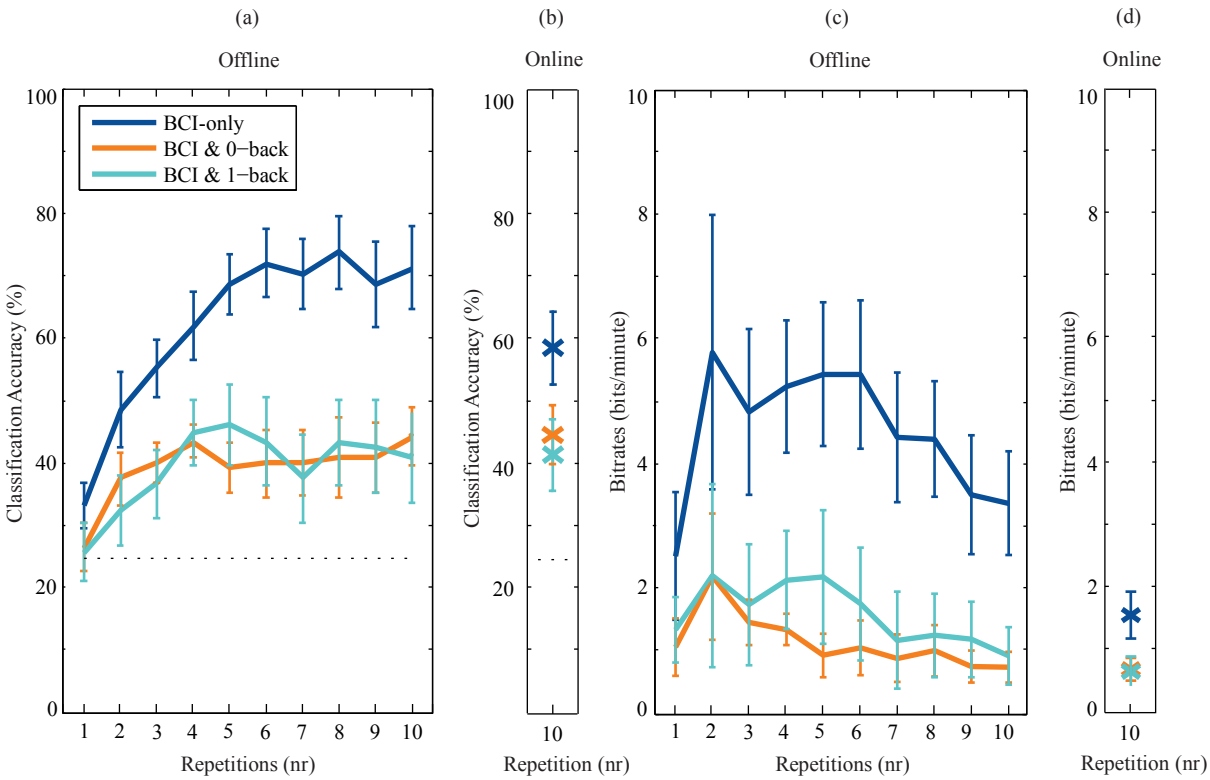

Figure 2.4: BCI performance. (a) Offline averaged classification accuracies and standard errors over participants, plotted at each repetition. Chance level is indicated with the dotted black line. (b) Online classification accuracies after the 10th repetition. (c) Offline averaged bitrates and standard errors over participants visualised for each repetition. (d) Online bitrates after the 10th repetition.

The effect of condition on bitrates

In Figure 2.5b the main effect of condition on bitrates is visualised. Bitrates were affected by condition ($F_{(2, 18)}=8.43$; $p<.01$). Like the P300, bitrates were higher for the BCI-only condition compared to both dual-task conditions ($p<.01$ and $p<.05$ for BCI&0-back and BCI&1-back, respectively), and did not differ between the dual-task conditions.

2.3.3. N-back task-performance

Both matching accuracies and response times on an individual subject level are presented in Table 2.1.

Matching accuracies

In Figure 2.5d, the percentage of valid correct responses for the n-back task is shown for the two dual-task conditions in both the single- (n-back task only) and dual-task part (n-back task and ERP-BCI task) of blocks. There was no main effect of the number of tasks, but there was a main effect of n-back difficulty ($F_{(1, 9)}=9.19$, $p<.05$) where matching accuracies were higher for the BCI&0-back compared to the BCI&1-back condition. Additionally, there was a significant interaction effect ($F_{(1, 9)}=9.90$, $p<.05$). Post-hoc analysis revealed that the main effect of n-back difficulty (BCI&0-back vs. BCI&1-back) was present in both the single- and dual-task parts of blocks (both $p<.01$).

Response times

Response times for the n-back task in both the single- and dual-task parts of blocks are visualised in Figure 2.5e for both dual-task conditions. We found main effects of the number of tasks ($F_{(1, 9)}=9.17$, $p<.05$) and of n-back difficulty ($F_{(1, 9)}=5.92$, $p<.05$). Response times were delayed for the dual-task part compared to the single-task part of blocks and for the BCI&1-back compared to the BCI&0-back condition. There was no interaction effect.

2.3.4. RSME-scores

The effect of condition on RSME-scores

An effect of condition on the RSME-scores was found ($F_{(2, 18)}=15.77$; $p<.001$), see Figure 2.5c. Posthoc analysis revealed that the RSME-scores were lower for the BCI-only condition compared to both dual-task conditions ($p<.05$ and $p<.01$ for BCI&0-back and BCI&1-back, respectively). Like the P300 and bitrates, RSME-scores did not differ significantly between the dual-task conditions.

Partici-pant	Conditions	P300 tAUC (µV*ms)	Bitrates (bits/min)	Matching accuracy (%) Dual-task	Matching accuracy (%) Single-task	Response times (ms) Dual-task	Response times (ms) Single-task
P1	BCI-only	130,2	2,40	-	-	-	-
	BCI&0-back	96,0	0,00	90,97	86,11	597	622
	BCI&1-back	75,7	1,38	38,89	37,50	1152	973
P2	BCI-only	609,6	13,33	-	-	-	-
	BCI&0-back	339,3	0,64	90,28	86,81	461	443
	BCI&1-back	53,9	0,00	95,83	94,17	466	444
P3	BCI-only	399,6	7,24	-	-	-	-
	BCI&0-back	185,4	3,69	79,86	96,53	746	578
	BCI&1-back	116,6	9,69	75,69	87,50	731	589
P4	BCI-only	683,6	5,28	-	-	-	-
	BCI&0-back	93,8	0,17	95,83	95,14	512	547
	BCI&1-back	50,2	0,00	90,97	87,50	576	577
P5	BCI-only	491,1	2,40	-	-	-	-
	BCI&0-back	171,3	0,17	77,78	91,67	804	755
	BCI&1-back	24,0	1,38	69,44	60,00	885	917
P6	BCI-only	347,5	2,40	-	-	-	-
	BCI&0-back	96,1	0,00	92,36	95,14	530	491
	BCI&1-back	24,6	0,64	87,50	75,83	654	570
P7	BCI-only	353,5	7,24	-	-	-	-
	BCI&0-back	145,1	3,69	81,25	90,97	611	549
	BCI&1-back	24,4	0,00	41,67	45,83	1070	971
P8	BCI-only	284,9	3,69	-	-	-	-
	BCI&0-back	78,9	0,64	88,19	96,53	577	536
	BCI&1-back	23,1	0,17	94,44	82,50	581	477
P9	BCI-only	420,1	0,64	-	-	-	-
	BCI&0-back	59,4	0,17	85,42	87,50	663	618
	BCI&1-back	59,0	0,64	74,31	67,50	793	711
P10	BCI-only	156,7	9,69	-	-	-	-
	BCI&0-back	240,1	1,38	95,14	98,61	534	529
	BCI&1-back	57,9	3,69	88,19	72,50	596	633
Avg *(std)*	BCI-only	**387,7** *(176,9)*	**5,43** *(3,96)*	**-**	**-**	**-**	**-**
	BCI&0-back	**150,5** *(86,9)*	**1,05** *(1,45)*	**87,71** *(6,39)*	**92,50** *(4,53)*	**603,6** *(107,2)*	**567** *(86,3)*
	BCI&1-back	**50,9** *(29,7)*	**1,76** *(3,01)*	**75,69** *(20,66)*	**71,08** *(18,64)*	**750,4** (225,5)	**686,3** *(199,3)*

Table 2.1: Results of the measures used to answer the research questions, on an individual subject level.

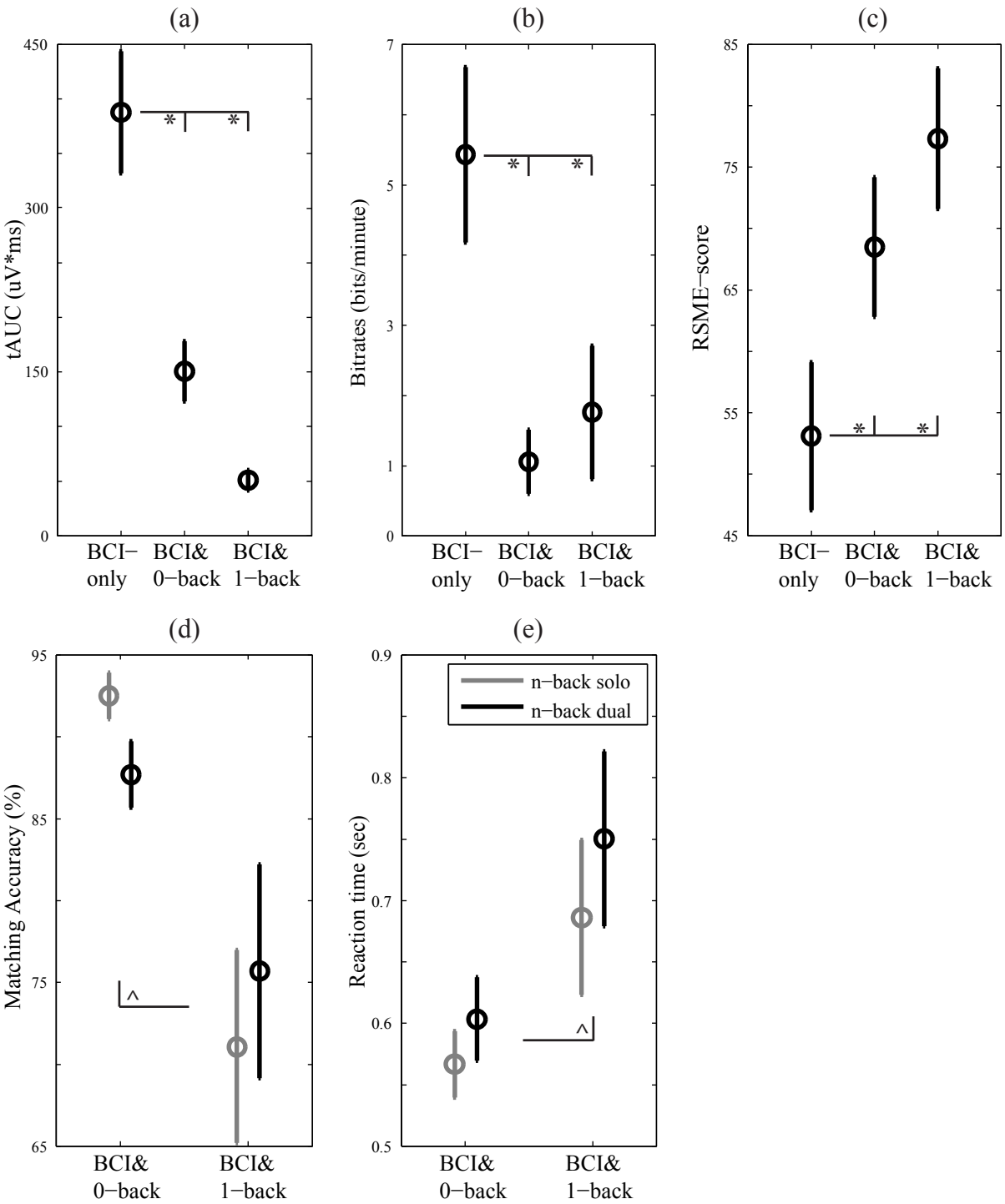

Figure 2.5: Means and standard errors of the dependent measures for each condition. Significant effects in a-c are indicated by an asterisk (*) symbol, referring to differences in condition pairs. Significant main effects of n-back difficulty in d-e are indicated by an accent circonflexe (^). (a) P300 tAUC. (b) Bitrate. (c) RSME-score. (d) Matching accuracy. (e) Response time.

2.4. Discussion

2.4.1. An ERP-BCI and dual-tasking

Our first research question was, if and to what extent ERP components and ERP-BCI performance are affected by a concurrent cognitive task. In accordance with our hypothesis, we showed that when a tactile ERP-BCI is operated alongside the n-back task rather than alone, an endogenous P300 is still robustly detected but significantly decreased. In divided attention studies using different perceptual or cognitive paradigms, a reduction of the P300 with increasing workload has been found as well. These studies showed that the amplitude of the P300 elicited by the rare stimuli of a secondary oddball task depends on the task difficulty of a primary task (for example a visuomotor tracking task) (Isreal et al. 1980a; Isreal et al. 1980b; Kramer et al. 1983; Kramer and Strayer 1988). The P300's amplitude as an index of workload was found for visual (Kramer and Strayer 1988), auditory (Isreal et al. 1980b), and tactile oddball tasks (Kida et al. 2004a; Kida et al. 2012; Kida et al. 2011).

Consistent with the effect on the P300, bitrates of the ERP-BCI are lower for the dual-task conditions compared to the BCI-only condition. Classification accuracies are still well above chance, but according to an accuracy criterion reflecting BCI usability (Birbaumer and Cohen 2007; Kubler et al. 2004; Pfurtscheller et al. 2010), only two out of ten participants achieve successful BCI control after six stimulus repetitions in the dual-task conditions while for the BCI-only condition, this was the case for nine participants. Previous studies on tactile ERP-BCIs report on classification accuracies of 60-70% (chance level being ~16-25%) (Brouwer and van Erp 2010; Thurlings et al. 2012b), which is in line with the offline results of the BCI-only condition in this study. Tactile ERP-BCI performance can possibly be improved by a classifier that is optimized for tactile ERP components and when more training data is used.

In contrast to our study, in (Friedrich et al. 2011) a secondary task (or distraction) did not affect performance of a BCI based on mental imagery. One explanation for the different results found in this study and (Friedrich et al. 2011) is that, whereas in our study every single stimulus of both tasks needed to be categorized, a mental imagery task may easier allow switching attention between tasks. More importantly, in (Friedrich et al. 2011) participants had to focus on the BCI-task while in our study participants were explicitly instructed to give priority to the non-BCI task. Therefore relatively few attentional resources may have been allocated to the BCI-task in this study, explaining a higher sensitivity to effects of dual-tasking on BCI performance.

The results from participants' subjective levels of mental effort are also in line with the effect on the P300. The participants indicated that the dual-task conditions required more mental effort than the BCI-only condition. The decreased P300 for the ERP-BCI task in the dual-task conditions compared to the BCI-only condition indicates the reallocation of attentional resources. Evidently, participants did not have sufficient resources for both the BCI and the n-back tasks.

Assuming that participants followed task priority, it may be expected that when participants would give no priority or priority to the ERP-BCI task, the effects of a concurrent task on BCI performance would be less severe, but performance of the concurrent task may be more negatively affected. After all, both tasks require (at least partly) the same (cognitive) resources. Thus, when the ERP-BCI task would be given priority, relatively more resources would be allocated to attending stimuli (compared to when the concurrent task is prioritized), and the P300 would be relatively higher (Kok 1997), which is also expected to correspond to higher BCI performance (Brunner et al. 2010; Thurlings et al. 2012a; Treder and Blankertz 2010). Whether or not participants followed task instructions concerning task priority cannot

be inferred from the results, and could have been influenced by the opposite order for feedback. Nonetheless, this setup corresponds to the context of use when BCI is used as a control in a (serious) game.

As discussed in the introduction, an important motivation to use tactile stimuli to navigate a game using an ERP-BCI, is that the visual (and auditory) channel are already heavily loaded (Van Erp and Van Veen 2004). In this dual-task study using one task with tactile and one task with visual stimuli, we already found affected performances of both tasks. Such competition for resources may be expected even larger when both tasks use stimuli in the same modality (e.g., a visual ERP-BCI for gaming).

2.4.2. Effect of concurrent task difficulty on operating an ERP-BCI

Our second research question concerned the effect of increasing task difficulty of the secondary task (as operationalized by an n-back task level of 0 and 1) on ERP components and BCI performance. In contrast to our expectations, we found no significant difference between the P300 in the BCI&0-back compared to the P300 in the BCI&1-back condition. We also did not find an effect of task difficulty on BCI performance (bitrates). Although effects on the P300 and bitrates do not necessarily have to correspond, as classification algorithms use other information to discriminate targets from nontargets than just the P300, the P300 is the most important component in gaze-independent BCIs (Brunner et al. 2010; Thurlings et al. 2012a; Treder and Blankertz 2010), and thus often correlates with bitrate. Finally, task difficulty, as manipulated in this study, did not significantly affect participants' subjective level of mental effort.

The lack of an effect of task difficulty on the P300, bitrates, and participants' subjective mental effort indicates that the amount of resources used for the ERP-BCI task did not differ between the two dual-task conditions. Yet, the behavioural performance of the n-back task did differ between the dual-task conditions. Both matching accuracies and response times were negatively affected for n=1 compared to n=0. These effects (that have been found before when the n-back task was the only task (Brouwer et al. 2012; Grimes et al. 2008; Watter et al. 2001), and were also found in the single-task part of the dual-task conditions in this study) may indicate that participants did not allocate (a large amount of) additionally required resources to the 1-back task. For a dual-task performance, it seems that participants reallocate resources to the n-back task and away from the BCI task, but not fully to keep a specific minimum available to remain able to do the BCI task. When task difficulty of the primary task was increased, it appears that resources were not further reallocated, resulting in a similar performance for the ERP-BCI task and a degradation of performance of the n-back task.

However, other ERP components did differ between the dual-task conditions. Besides the P300, we robustly detected two other ERP components in the BCI&1-back condition, which were not detected in the other conditions: an N1 and an N600. N600-like activity has been related to memory (Ohara et al. 2006; Salmon and Pratt 2002), and may well reflect memory load in this study since memory load involved in the n-back task was highest for n=1, as working memory had to be updated after each presented letter, which was not the case for n=0.

In contrast to the P300 and the N600, the N1 has a more bottom-up origin and is linked to perceptual processes. We suggest that the N1 reflects crossmodal interaction (Thurlings et al. 2012a). Although the visual and tactile stimuli were neither time-locked to each other nor were they spatially or semantically linked, the presence of visual stimuli can still influence the perception of tactile stimuli: Attended tactile stimuli are processed earlier and differently

when the visual system is engaged compared to when it is not (Forster et al. 2009). In both the BCI&0-back and the BCI&1-back conditions the visual system was involved and visual stimuli were attended, yet only in the BCI&1-back condition the N1 was detected. The visual system includes not only visual sensory processing, but also visual memory. Visual stimulus processing, and target retrieval from memory should be similar in both conditions. However, encoding of new targets in memory was only required for the 1-back task. Therefore the visual system was more involved in the BCI&1-back condition, which may have influenced the processing of tactile stimuli and explain the occurrence of the N1.

Note that the ERPs in this study were analysed for the BCI-task, and thus are time-locked events to the tactile stimuli. The ERPs analysed in single-task studies using the n-back task are not directly comparable to our results, as the perceptual and cognitive processes involved in the processing of stimuli are time-locked. However, in general such studies indicate that more resources are allocated to memory related processes for a higher level of 'n'. For example, in (Watter et al. 2001) it was shown that the P300's amplitude is decreased for a higher level of difficulty of the n-back task, which was related to a reallocation of attention to working memory activity. In this study, the N1 and N600 differed for the two levels of dual-task conditions, and we have suggested that the cause for both components could be explained in terms of memory.

As no effect of task difficulty of the primary task on the P300 of the secondary (BCI) task was found, the amount of resources allocated to the secondary task seems to be unaffected by task difficulty in this study. However the stimuli of that secondary task were processed differently, as indicated by the other ERP components. It appears that a shift in resources allocated to the primary task results in different perceptual and cognitive processes which interact with the processes involved for the secondary task.

2.4.3. An ERP-BCI for practical use

When evaluating an ERP-BCI for practical use, it is important to investigate the effect of controlling the BCI in a multi-task environment, as this is imposed by everyday life. For a BCI that is used to control certain aspects in a game, concurrent tasks could be related to the content of the game, or for an in-car BCI, they could be related to attending traffic. Therefore, in this study we investigated the effect of performing a concurrent cognitive task alongside the task to control the BCI. Our results show that these tasks interfere and that BCI-control is degraded, but still feasible. However, for more difficult concurrent cognitive tasks (e.g., n-back task with 'n' being 2) than used in this study, BCI-control may not be achieved anymore. We did not find an additional decrease of the P300 and BCI performance for an increased task difficulty. Therefore, it remains unclear whether the negative effects of performing the dual-task are due to resource competition at a cognitive level, or have a more perceptual basis. The dual-task did not only involve an additional cognitive task, but also the perception of additional stimuli. Stimuli in any sensory modality occur continuously in daily life, and even if no real 'task' is required, they form a distraction that may interfere with any task (including, but surely not restricted to BCI-tasks), which may result in performance degradation.

2.5. Conclusion

In this study we showed that a tactile ERP-BCI can be operated while users are primarily involved in a concurrent cognitive task. The P300 and BCI-performance are severely degraded when dual- compared to single-tasking, but the endogenous P300 can still robustly

be detected, and classification accuracies are still well above chance. Operation of a tactile ERP-BCI while dual-tasking may still be considered feasible (i.e., classification accuracies above chance, here 25%), although effective control (i.e., in this study classification accuracies above 55%) was achieved by a minority of users. We also showed that increasing the level of difficulty of the cognitive task, did not further degrade the P300 or BCI performance. This suggests that the presence of a concurrent task has more effect than the level of difficulty of that task. The underlying causes for the effects of the concurrent task, may involve both perceptual and cognitive processes.

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3

Does bimodal stimulus presentation increase ERP components usable in BCIs?

Abstract**—**Event-related potential (ERP)-based Brain-Computer Interfaces (BCIs) employ differences in brain responses to attended and ignored stimuli. Typically, visual stimuli are used. Tactile stimuli have recently been suggested as a gaze-independent alternative. Bimodal stimuli could evoke additional brain activity due to multisensory integration which may be of use in BCIs. We investigated the effect of visual-tactile stimulus presentation on the chain of ERP components, BCI performance (classification accuracies and bitrates) and participants' task performance (counting of targets). Ten participants were instructed to navigate a visual display by attending (spatially) to targets in sequences of either visual, tactile, or visual-tactile stimuli. We observe that attending to visual-tactile (compared to either visual or tactile) stimuli results in an enhanced early ERP component (N1). This bimodal N1 may enhance BCI performance, as suggested by a nonsignificant positive trend in offline classification accuracies. A late ERP component (P300) is reduced when attending to visual-tactile compared to visual stimuli, which is consistent with the nonsignificant negative trend of participants' task performance. We discuss these findings in the light of affected spatial attention at high-level compared to low-level stimulus processing. Furthermore, we evaluate bimodal BCIs from a practical perspective and for future applications.

Index Terms: BCI, ERP, P300, N2, N1, tactile, bimodal, multisensory, visual-tactile, gaze-independent, attention, navigation

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3.1. Introduction

3.1.1. Event-related potential based Brain-Computer Interfaces

Event-related potentials differ for attended and ignored stimuli. This makes them suitable for use in Brain-Computer Interfaces (BCIs) where users can select options (e.g., the commands 'left' or 'right') by attending to the corresponding stimulus (target) while ignoring other stimuli (nontargets). The successive components in an ERP are related to different levels of stimulus processing, starting from low-level sensing up to high-level cognition. ERP-BCIs have focussed on the high-level P300 ERP component which is stronger for targets than for nontargets (Farwell and Donchin 1988). It occurs rather late because a perceived stimulus first needs to be *endogenously* (with voluntary control) recognized and categorized as the target. Spatial attention can also modulate earlier ERP components, such as the N1 (low-level) and N2 (intermediate-level), which are enhanced if stimuli occur within the focus of attention (Mangun and Hillyard 1991; Wang et al. 2010). This effect is useful for ERP-BCIs employing spatially distributed stimuli because targets and nontargets can be endogenously discriminated based on their location. Attention can be focused and sustained at the target location even before the target is presented, allowing endogenous modulation of high- and low-level ERP components. Although given much less attention in BCI research, early ERP components are indeed different for targets and nontargets (Shishkin et al. 2009) and may influence BCI performance because the EEG of the corresponding intervals is usually included during classification (e.g., Krusienski et al. 2008).

Most ERP-BCIs use visual stimuli to present the user with options (e.g., Farwell and Donchin 1988). The drawback of visual ERP-BCIs is that the effectiveness of these systems depends to a large extent on the ability of users to gaze at the visual stimuli (Brunner et al. 2010; Treder and Blankertz 2010), which is not possible for either all users (e.g., due to paralysis), or in applications that require users to look elsewhere, such as during driving (Thurlings et al. 2010). Therefore, novel approaches employ brain signals related to covert visual spatial attention in various types of BCIs (Allison et al. 2008, Bahramisharif et al. 2010) and gaze-independent visual-based ERP-BCIs are being developed (Acqualagna and Blankertz 2011; Liu et al. 2011; Treder et al. 2011a). In addition, interest has grown in employing alternative sensory modalities such as audition (Höhne et al. 2011; Nijboer et al. 2008; Schreuder et al. 2011). However, in many situations (e.g., in gaming or driving), both the visual and auditory sensory channels are already heavily loaded (Van Erp and Van Veen 2004). Recent research has shown that tactile stimuli may be a viable alternative. Brouwer and Van Erp (2010) demonstrated the feasibility of employing tactile stimuli (tactors) around the waist in a tactile ERP-BCI (see also Brouwer et al. 2010). Tactors around the waist correspond naturally to navigation directions (Van Erp 2005), which makes a tactile ERP-BCI especially interesting for navigation applications.

3.1.2. Effects of Multisensory Integration on task performance and the ERP

The ERP-BCIs described above all rely on the sensory-specific (and higher-level) processing of one modality only. Often, however, sensory inputs of more than one modality are integrated in the brain, causing additional neuronal activity. This phenomenon is called *multisensory integration* (for reviews, see: Driver and Noesselt 2008; Ernst and Bülthoff 2004; Stein and Stanford 2008) and may take place at perceptual stages (Molholm et al. 2002; Philippi et al. 2008), higher cognitive stages (Schröger and Widmann 1998), and/or during motor preparation and execution (Giray and Ulrich 1993). We are interested in if and how

effects of multisensory integration can be exploited in a BCI to boost BCI performance. To investigate this, we created a bimodal ERP-BCI by the simultaneous presentation of gaze-dependent visual stimuli and gaze-independent tactile stimuli.

Multisensory integration has been investigated in a number of behavioural and ERP studies. Task performance has repeatedly been shown to benefit from bimodal (compared to unimodal) stimulus presentation, exhibiting reduced reaction times (e.g., Gondan et al. 2005a; Miller 1991; Molholm et al. 2002) and increased accuracy (Talsma and Woldorff 2005). Associated results from ERP studies revealed that multisensory integration starts as early as 50 ms after stimulus onset for audio-tactile stimuli in central/postcentral areas (Foxe et al. 2000), 46 ms after stimulus onset for audio-(covert) visual stimuli (Molholm et al. 2002), and between 80 and 125 for visual-tactile stimuli (Sambo and Forster 2009). These studies focused on the start of the integration and therefore only investigated the EEG until approximately 200 ms after stimulus onset. Although previously multisensory integration was thought of as an *exogenous* process (automatic without voluntary control), recently – crucial to BCI – the role of endogenous attention was acknowledged (for a review, see: Talsma et al. 2010). Talsma and Woldorff (2005) found that multisensory integration of audiovisual stimuli is modulated by endogenous attention at different stages of processing: starting as early as 80 ms and peaking at approximately 100 ms, 190 ms, and 370 ms after stimulus onset.

Note that the multisensory integration studies mentioned above differ from those performed in a BCI context with respect to the participants' task and attention involved and the characteristics of targets and nontargets. In a BCI paradigm, observers are presented with rapid sequences of stimuli that are physically similar. Only the observers' endogenously focused attention distinguishes between targets and nontargets. To date, only two studies have reported on the possible benefit of bimodal stimulus presentation in an ERP-BCI context. The first is from Brouwer et al. (2010), who investigated bimodal (covert) visual-tactile (compared to unimodal visual or tactile) stimulus presentation and found a slight local parietal enhancement of the P300 and an overall enhancement of offline classification accuracies. However, that study was not fully in line with BCI because endogenous and exogenous attention were confounded, as the targets were always physically different from the nontargets. The second study (Belitski et al. 2011) showed the positive effects of a bimodal audio-visual ERP-BCI paradigm (compared to both unimodal variants) on offline classification accuracies, but the underlying ERP components were not investigated.

3.1.3. Research questions and hypotheses

In the current study, our research questions are as follows:

1. To what extent does (spatially) attending to visual-tactile stimuli enhance ERP components compared with unimodal stimuli in an ERP-BCI paradigm?
2. If enhanced bimodal ERP components are found, can BCI performance benefit from them?
3. How is participants' task performance affected by attending to visual-tactile (compared to unimodal) stimuli?

Our hypotheses are that participants, who are asked to count the number of targets, perform better and that early ERP components (< 200 ms) are enhanced when attending to visual-tactile targets compared to unimodal ones. Finally, we expect that related features of the EEG enhance offline classification accuracies. We investigated these questions and hypotheses in a

navigation ERP-BCI context. First we determined the endogenous ERP components for attending targets in a visual, tactile, and visual-tactile ERP-BCI context, and compared the ERP components to investigate the effect of stimulus modality. Subsequently, we explored how these endogenous ERP components can be employed in BCI and how stimulus modality affects BCI performance.

3.2. Method

3.2.1. Participants

Ten volunteers (seven men and three women with a mean age of 29.1 years and age range of 23-39 years) participated in this study. Prior to the experiment, two of them had participated in a tactile ERP-BCI experiment, and three had participated in a visual ERP-BCI experiment. All participants had normal or corrected-to-normal vision.

3.2.2. Task

The participants looked at a visual display (see Figure 3.1a) that was divided into hexagons. The participants navigated a blue disc (representing the participant's position) along a route, visualised by hexagons coloured a lighter shade of grey than the environment. The direction from the blue disc to the next hexagon on the route was the target direction (forward-right in Figure 3.1a). The other directions were the five nontarget directions. Each direction corresponded to a unique stimulus; depending on the condition, this was an arrow on the visual display, a tactor in the tactile display (Figure 3.1a) or both simultaneously. The six stimuli were presented sequentially in random order. The participants' tasks were to pay attention to the tactile, visual, or visual-tactile stimulus corresponding to the desired navigation direction and to count the number of times it was presented. The participants reported the counted number at the end of each step by means of a keyboard. We used the reported numbers as a measure for task performance.

3.2.3. Design

The experiment involved three conditions, named after the modality that the stimuli were presented in: Visual, Tactile and Visual-Tactile. Each condition was presented in each of two sessions. Within each session, one route for each condition was completed. The conditions were offered in random order during a session.

A route consisted of 18 navigation steps, back and forth over a path of 10 hexagons. We designed routes such that all directions were balanced, and these were randomly linked to conditions for each participant. Each of the 18 steps in a route consisted of 10 consecutive sequences of stimuli, i.e., 10 repetitions. In each repetition, each of the six stimuli was presented once in random order, with the constraint that there was at least one nontarget in between two targets of consecutive repetitions (see Figure 3.1c-e). To prevent the number of targets in each step from always being equal to ten, we varied the number of presented targets for each step by adding one dummy sequence of six stimuli before and one after the 10 actual repetitions. In a dummy sequence, zero to three targets could occur, also with at least one nontarget in between two targets (see Figure 3.1d). Thus, the number of targets within

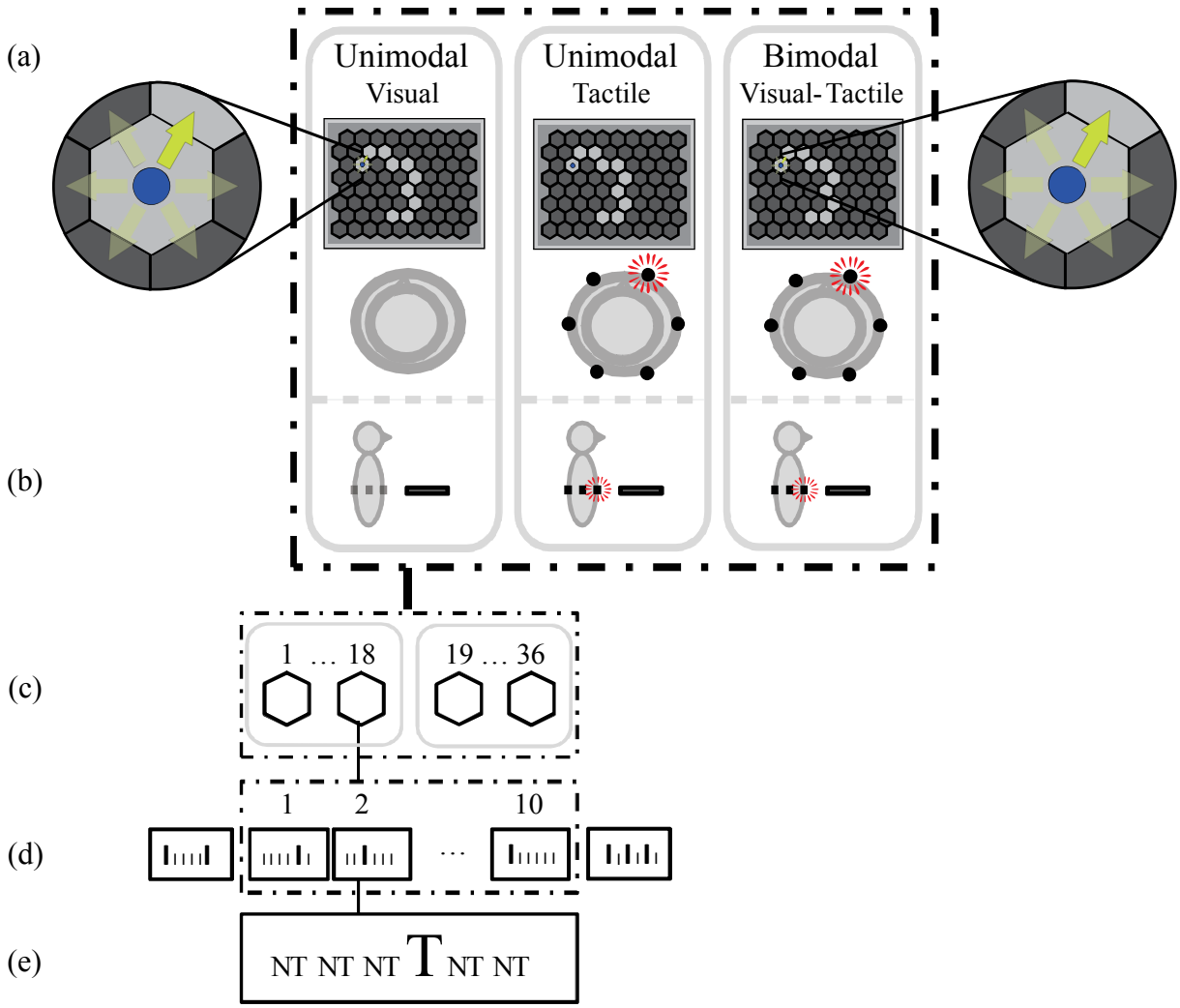

Figure 3.1: Overview of the experimental setup. (a) Top view: For each condition, the locations of the stimuli corresponding to all possible directions. Current targets are highlighted, and visual nontargets are here visualised semi-transparently for demonstration purposes only. (b) Side view. (c) Eighteen steps in each of two routes in one condition. (d) Ten repetitions of targets and nontargets in a step. (e) One target and five nontargets in each repetition.

one step varied between 10 (from the 10 repetitions) and 16. The EEG data recorded during the dummy sequences were not used in the analysis.

Each participant's position was represented by a blue disc in the centre of a hexagon. At the end of each step, after the participant reported the counted number of targets, the blue disc automatically went to the next hexagon on the route as long as the final hexagon had not yet been reached. Then, 2.5 seconds after the number was reported, the next step began. One step took 25.54 sec - (6 stimuli *(10 actual +2 dummy repetitions) * (200 on + 120 ms off time)) + 2.5 sec reporting time.

3.2.4. Materials

Visual Stimuli and Display

Visual stimuli were presented on a Samsung 19" TFT monitor (1280 × 1024, 60 Hz) and consisted of yellow-green arrows starting from the blue disc in the current hexagon and

pointing to a neighbouring hexagon (see Figure 3.1a). These stimuli were sequentially presented for 200 ms (on time) and not visible in the following 120 ms (off time). Participants were allowed to gaze directly at the visual stimuli. The visual display was positioned horizontally (flat on a table) such that the visual and tactile stimuli were congruent in direction and corresponded with natural 2D navigation directions (for the importance of directional congruence in ERP-BCIs, see: Thurlings et al. 2012b). The viewing distance was approximately 50 cm from the eyes to the centre of the visual display, and each hexagon was approximately 3.5 degrees of visual angle.

Tactile Stimuli

Participants wore a vest (which could be adjusted to body dimensions) with integrated tactors. The tactors were custom built and consisted of a plastic case with a contact area of 1x2 cm containing a 160 Hz electromotor (TNO, The Netherlands, model JHJ-3, Van Erp et al. 2007). To prevent participants from perceiving auditory information from the tactors, they listened to pink noise via in-ear headphones during the experiment.

For this study, the tactors were arranged in groups of two at six locations in a circular layout on a horizontal plane (around the torso at approximately navel height). The locations of the tactors corresponded to the navigation directions of the task: left, right, and two directions in between along both the frontal and back side (see Figure 3.1a, 3.1b). The on and off times of the tactors were the same as those for the visual stimuli (200 ms on and 120 ms off).

Visual-tactile stimuli

Bimodal visual-tactile stimuli were created by triggering corresponding visual and tactile stimuli simultaneously. Because the visual and tactile stimuli have varying technical properties, the corresponding intensity-time functions are different. This maximum intensity of the tactile stimulus is reached within 50 ms after the visual stimulus has reached its maximum intensity.

EEG recording equipment

EEG was recorded from 60 nose-referenced scalp electrodes that used a common forehead ground (Brain Products GmbH, Germany). The impedance of each electrode was below 20 kΩ, as was confirmed prior to and during the measurements. EEG data were recorded with a hardware filter (0.05-200 Hz) and sampled at a frequency of 1000 Hz.

3.2.5. Data analysis

EEG, BCI and task performance analyses were performed using Matlab 2007b (The Mathworks, Natick, USA).

EEG preprocessing and selection

To prepare the recorded EEG for further processing, the data were once again bandpass filtered (0.5-30 Hz) and sampled with a sampling frequency of 100 Hz. Such a bandpass filter reduces influences from artefacts such as eye blinks (e.g., Guger et al. 2009; Tereshchenko et al. 2009). We are interested in the clean effects of endogenous attention on the ERP and

attempted to isolate such effects in the ERP. To this end, we used two strict rejection criteria, which were only applied to select data for ERP analysis and not for classification analysis. Finally, a difference measure was computed to isolate endogenous effects. The rejection criteria will be described next, followed by the difference measure

The first rejection criterion was that EEG was not used for ERP analysis if it was expected to be contaminated by previous or following target responses relative to the stimulus response of current interest using an approach similar to that of Treder and Blankertz (2010). To this end, we only selected EEG data associated with (non)targets when the three preceding and the three following presented stimuli were nontargets, i.e., when there were no (other) target responses between -960 and 1280 ms relative to (non)target onset. For the selected (non)targets, epochs from all electrodes were extracted from -320 to 750 ms relative to stimulus onset. This resulted in an average number of 246 target epochs (range 230-262) and 189 nontarget epochs (range 167-214) per participant. Similar numbers of epochs were selected per condition. The epochs were baseline corrected relative to the average voltage during the 320 ms preceding the stimulus onset.

As a second rejection criterion, we discarded all epochs within one repetition if epochs recorded at both frontal electrodes (Fp_1 and Fp_2) contained amplitude differences exceeding 100 µV, indicating eye-movements. This was the case for 5.6% of the measurements. For all conditions, this left us with averages of 227 target epochs (range 107-262) and 183 nontarget epochs (range 130-209) per participant. Subsequently, the selected target and nontarget epochs were averaged per participant, per condition and per electrode.

Finally, we subtracted the averaged clean nontarget epochs from the averaged clean target epochs for each participant, each condition and each electrode. In this step, we removed exogenous (involuntary or automatic) attention effects. Further analyses were performed regarding this difference ERP (or endogenous ERP).

Identifying ERP components triggered by endogenously attended stimuli

We aimed to identify and quantify all ERP components triggered by endogenously attended stimuli occurring during the interval until 750 ms after stimulus onset. First, we identified significant endogenous effects by performing a sample-by-sample t-test on the difference ERP for each electrode and condition. To correct for multiple testing, the method of Guthrie and Buchwald (1991) was applied (Molholm et al. 2002; Rugg et al. 1995; Vidal et al. 2008). In our case, this implied that (at least) four consecutive samples (equivalent to 40 ms) had to be significantly different from zero to consider the corresponding samples as a stable segment. Second, we clustered these segments over electrodes (hierarchical clustering of pairwise objects) to label the elicited endogenous ERP components using the cluster's time interval, topography and polarity. The clustering of segments was based on the beginning and end of their time periods and their averaged amplitudes (using the following standard parameters: Euclidean distance in feature space, single linkage, and maximum 15 clusters; Webb 2002). We also applied the method of Guthrie and Buchwald (1991) to correct for multiple testing with respect to the electrode dimension. Clusters were considered robust if they contained segments of at least four electrodes. Robust clusters that had overlapping intervals and comparable averaged amplitudes were assumed to be subcomponents of the same ERP component and were combined. These combined robust clusters defined the topographic distribution and the interval of the endogenous ERP components, taking the beginning of the earliest segment and the end of the latest segment in the clusters as ERP component intervals.

Quantifying and comparing endogenous ERP components

After identifying the elicited endogenous ERP components, we quantified these to compare them between conditions. To capture the strength of a local (at a certain electrode site) ERP component, regardless of its shape, we used the area-under-the-curve values (AUC; Allison et al. 1999; Luck 2005; Puce et al. 2007). To also allow for topographic distributions of an ERP component as a measure of the component's magnitude, we determined the sum of AUCs from the electrodes included in a defined ERP component to quantify endogenous ERP components in each condition and for each participant, i.e., AUCs from stable segments included in an ERP component were calculated and summed. We refer to the sum of topographic distributed AUCs from an ERP component as the *tAUC*. With the tAUC, we can describe the magnitude of an ERP component not only by taking the averaged amplitude and duration of the component into account but also by considering the topographic distribution. Endogenous ERP components with overlapping intervals and equal polarities between conditions were considered to reflect the same ERP component. Associated tAUCs were statistically compared. Note that this measure corresponds to perceptual and cognitive processes but not necessarily to discrimination, as in BCI classification, because the information of neighbouring electrodes in broadly distributed components can be redundant.

Additionally, we compared ERP components over conditions using the more traditional peak-picking (Luck 2005) to validate the tAUC value and to allow for a comparison of ERP components to be made between conditions when these were absent in one or more conditions. We looked for peaks in condition-specific intervals as defined in the previous step. If an ERP component was only detected in one or two but not in all three conditions, the (overlapping) interval of the detected ERP component was used to determine peaks in all conditions. Six electrodes were chosen for the determination of peak amplitudes for each ERP component based on the topographic distribution of that component.

Offline analysis of BCI performance

Classification accuracies were analysed offline by linear discriminate analysis (LDA) because previous BCI research showed good results using this relatively simple method (Blankertz et al. 2011; Krusienski et al. 2008; Zander et al. 2011). We applied a stepwise LDA (SWLDA) with similar parameter settings as Krusienski et al. (2008): a maximum of 60 features employed in the model, a p-value of <.1 for features included in the model initially, and a p-value of >.15 for features removed from the model backwards. Features were extracted from each electrode, and voltages were averaged within a subwindow of a specific ERP interval, which was determined according to the method previously described in this section. For each condition, we divided each specific ERP interval into four subsequent subwindows of similar lengths. In total, the number of features prior to selection corresponded to: the number of subwindows (4) * the number of ERP components involved (1, 2 or 3) * the number of electrodes (60). The training set was based on the first half and the test set on the second half of the recorded data from each participant and each condition and followed pre-processing steps similar to those described for the ERP analysis; however, no data were rejected to realistically assess potential online classification performance. To investigate how conditions interacted with the amount of data necessary to improve the signal-to-noise ratio, we investigated the effect of the number of repetitions for averaging over test repetitions (1-10).

A goal of this study was to determine whether increased bimodal (compared to unimodal) ERP components are usable in BCI, which we have approached both theoretically and practically. For the theoretical approach we focussed on the effect of bimodally increased

ERP components on BCI performance only. In contrast, for the practical approach we included all ERP components that could boost BCI performance, to evaluate the effect of stimulus modality. The theoretical approach may produce relevant information for further development of bimodal BCIs, whereas the practical approach directly evaluates the visual-tactile BCI in a practical sense.

For the theoretical approach, we compared classification accuracies from all conditions based on the same ERP components, which were enhanced for bimodal, and based on the same number of repetitions. The number of repetitions included in this analysis was established according to a criterion by which successful BCI control could be expected. Successful BCI control was considered when a threshold for classification accuracies of 70% or higher were obtained (e.g., Schreuder et al. 2010) by at least 80% of the participants.

For the practical approach, for each condition separately, we determined the most optimal classifier choices, i.e., on which ERP components (separately or combined) the classifier should be based and the number of repetitions that are required to result in the highest bitrates, while successful BCI control could be achieved. We calculated bitrates (Serby et al. 2005), based on each participant's classification probability for each repetition. Using the most appropriate classifier and number of repetitions for each condition, bitrates were calculated and statistically compared.

Counting accuracy

As a measure of task performance, we determined the counting accuracies as the percentage of steps in which the number of targets was counted correctly for each participant and each condition.

Statistical analysis

ERP components' tAUC values and peak amplitudes, classification and counting accuracies were statistically analysed using Statistica 8.0 (StatSoft, Tulsa, USA). We used one-way repeated-measures ANOVA with Modality (3 levels) as the independent variable to test for effects of stimulus modality on tAUCs, on classification accuracies and on counting accuracies (or paired t-tests if suitable). Two-way repeated-measures ANOVAs were applied to analyse peak amplitude (with the electrode as the second independent variable). We report the main effects of Modality and interaction effects if these revealed local effects of Modality. Tukey post-hoc tests were applied when appropriate.

3.2.6. Procedure

We helped participants into the tactile vest and seated them in front of the visual display. We checked for tactor saliency by activating the tactors successively and asking the participants for the corresponding directions. If necessary, we tightened or relaxed the tactile vest and/or repositioned one or more of the tactors. During EEG preparation, we explained the outline of the experiment and instructed participants to move as little as possible during tactor presentations. Before each recording, we informed the participants about the sensory modality of the stimuli employed in the current recording. Then, participants accustomed themselves to the current modality by activating the six stimuli by pushing keys 1-6 for a maximum period of two minutes. When the participants indicated they were ready to begin, we started the recording. Each route recording lasted approximately 10 minutes, and

recordings followed each other with 1 to 15 minutes breaks in between, depending on the participants' preferences.

3.3. Results

3.3.1. Endogenous ERP components

Spatiotemporal presentations of the amplitudes of the endogenous ERPs are presented in Figure 3.2a. For all conditions, endogenous activity was observed during multiple periods within the analysed interval from 0 until 750 ms after stimulus onset. In Figure 3.2b, spatiotemporal plots show the significant stable segments. The red and blue areas indicate the polarities (positive and negative, respectively) of the clustered segments that were found to be robust and were thus identified as endogenous ERP components. In Figure 3.3a, these ERP components are visualised by means of scalp plots (averaged amplitudes of the endogenous ERP at all electrodes, within the interval as defined in section 3.2.5: "Identifying ERP components triggered by endogenously attended stimuli"). In Figure 3.4, the main effects of Modality on tAUC values and peak amplitudes are visualised for each condition and each identified ERP component.

An endogenous ERP component reflecting an N1 was identified in the bimodal visual-tactile condition between 70-130 ms after stimulus onset, but not in the unimodal conditions (Figure 3.2, Figure 3.3b). This ERP component had maximum amplitudes in the parietal area and was also present at the temporal area in the right hemisphere (Figure 3.3a). An endogenous N2 was found for all conditions (Figure 3.2, Figure 3.3b). Significant attention effects were associated with maximum amplitudes at the lateral-temporal and central-parietal sides between 110-260 ms after stimulus onset in the visual, between 210-350 ms in the tactile and between 140-270 ms in the visual-tactile condition (Figure 3.3a). Besides the N2, an endogenous ERP component reflecting a P300 was also identified in all three conditions (Figure 3.2, Figure 3.3b). It had a central-parietal distribution for all conditions and was significant between 280-510 ms after stimulus onset in the visual condition, between 330-690 ms in the tactile condition and between 280-490 ms in the visual-tactile condition (Figure 3.3a). The intervals of both the N2 and P300 resembled one another in the visual-tactile and visual conditions (Figure 3.3b). Finally, one ERP component was detected in the visual condition only, an N400 (Figure 3.2), with a frontal distribution between 570-650 ms after stimulus onset (Figure 3.3a). Similar but reduced activity appeared to be present in the visual-tactile condition (Figure 3.2a); however, that activity was not robustly detected as an ERP component (Figure 3.2b). The effects of Modality on the tAUC values and peak amplitudes of ERP components are reported next.

Effect of modality on the N1

The N1 was only identified for the visual-tactile condition, with its tAUC values (Figure 3.4f) differing significantly from zero ($t_{(9)}=5.18$; $p<.001$). Additionally, a comparison of peak amplitudes (Figure 3.4a; determined at electrodes: CP_z, P_z, PO_z, O_z, FT_8, Fp_8) between all conditions, using the interval values of the visual-tactile condition, reveals an effect of Modality ($F_{(2,18)}=4.77$; $p<.05$) caused by higher peak amplitudes for visual-tactile than for both unimodal conditions (both $p<.05$).

Effect of modality on the N2

The shape, latency and distribution of the N2 were remarkably similar for the visual and visual-tactile conditions. Indeed, statistical analyses of tAUC values (Figure 3.4g) and peak amplitudes (Figure 3.4b; determined at electrodes: T_7, TP_7, CP_5, T_8, TP_8, CP_6) revealed an effect of Modality on the N2 ($F_{(2,18)}$=24.86; p<.001 and $F_{(2,18)}$=5.39; p<.05, respectively), which was caused by a stronger N2 for visual and visual-tactile compared to tactile conditions (for respective analyses, both p<.001 and both p<.05). The significant interaction effect of Modality × Electrode ($F_{(10,90)}$=2.6; p<.01) on the N2 peak amplitude showed that the main effect is caused by higher amplitudes at electrodes $TP_{7/8}$ and $CP_{5/6}$ (all p<.05) and not $T_{7/8}$.

Effect of modality on the P300

A main effect of Modality was found on the tAUCs (Figure 3.4h) of the P300 ($F_{(2,18)}$=16.35; p<.001). Post-hoc analysis showed that the P300 was stronger in the visual compared to visual-tactile and tactile conditions (both p<.01). The main effect of Modality on the P300's tAUC was confirmed by an effect of Modality on the P300 peak amplitudes (Figure 3.4c; determined at electrodes C_z, CP_z, P_z, PO_z, CP_1, CP_2; $F_{(2,18)}$=15.15; p<.001). Similar to the tAUC value, post-hoc analysis showed a stronger P300 for the visual compared to the tactile condition (p<.01), but also revealed higher P300 peak amplitudes for the visual-tactile compared to the tactile condition (p<.01). This highlights the different characteristics of the P300 with respect to modalities; the tactile P300 has lower amplitudes but lasts longer compared to the visual and visual-tactile P300. Such information is important for feature selection in classification analysis. Additionally, an interaction effect of Modality × Electrode on the P300 peak amplitudes was found ($F_{(10,90)}$=3.49; p<.001). The post-hoc analysis revealed the same main effects of Modality, indicating that the visual and visual-tactile P300 amplitudes were higher than the tactile amplitudes (reproducing the main effect of Modality presented above) and that the visual P300 amplitudes were higher than visual-tactile amplitudes (p<.05 for all). The latter effect (indicating that adding a tactile stimulus to the visual stimulus did not enhance but reduced the P300) confirmed the results of the former analysis.

Effect of modality on the N400

The N400 was only detected to be robust in the visual condition, with a tAUC value (Figure 3.4i) differing significantly from zero ($t_{(9)}$=3.71; p<.01). Additionally, we compared the N400 peak amplitudes (Figure 3.4d; determined at electrodes: F_z, F_3, F_4, FC_z, FC_3, FC_4) with respect to the conditions using the interval detected for the visual N400 and found an effect of Modality ($F_{(2,18)}$=13.63; p<.001). However, post-hoc analysis indicated enhanced visual and visual-tactile amplitudes relative to the tactile amplitudes (both p<.001).

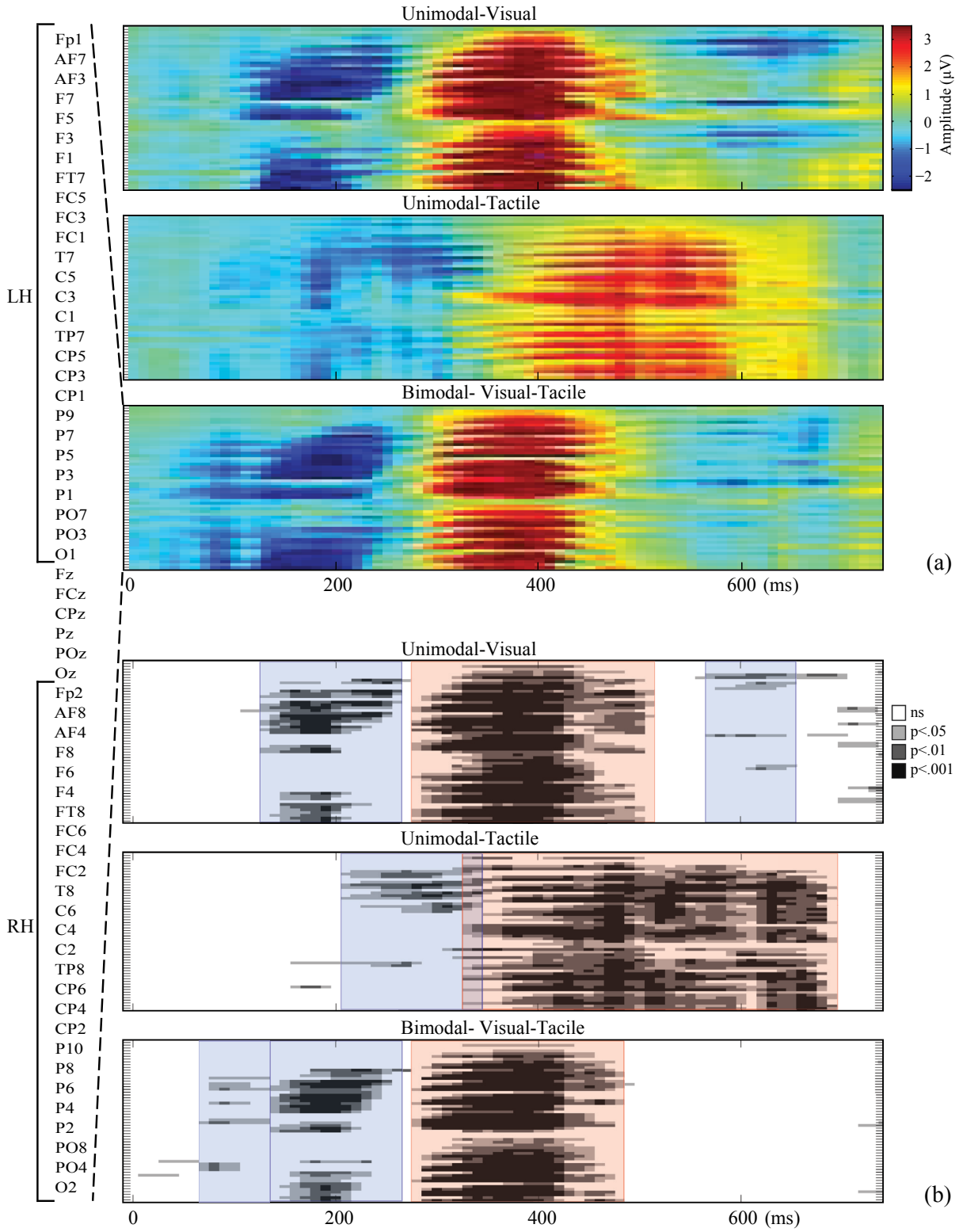

Figure 3.2: Spatiotemporal representations of the difference ERP for each condition, with time (ms) on the x-axis and electrodes on the y-axis. Electrodes are structured as follows: left hemisphere (LH), midline electrodes, right hemisphere (RH), and substructured with the most frontal electrodes on top and occipital electrodes at the bottom. (a) The Grand Average of the amplitudes of the difference ERP (µV) for each condition. (b) The statistical significance of the difference ERP (p-values), clustered in ERP components, which are marked by coloured overlays in red and blue for positive and negative components, respectively.

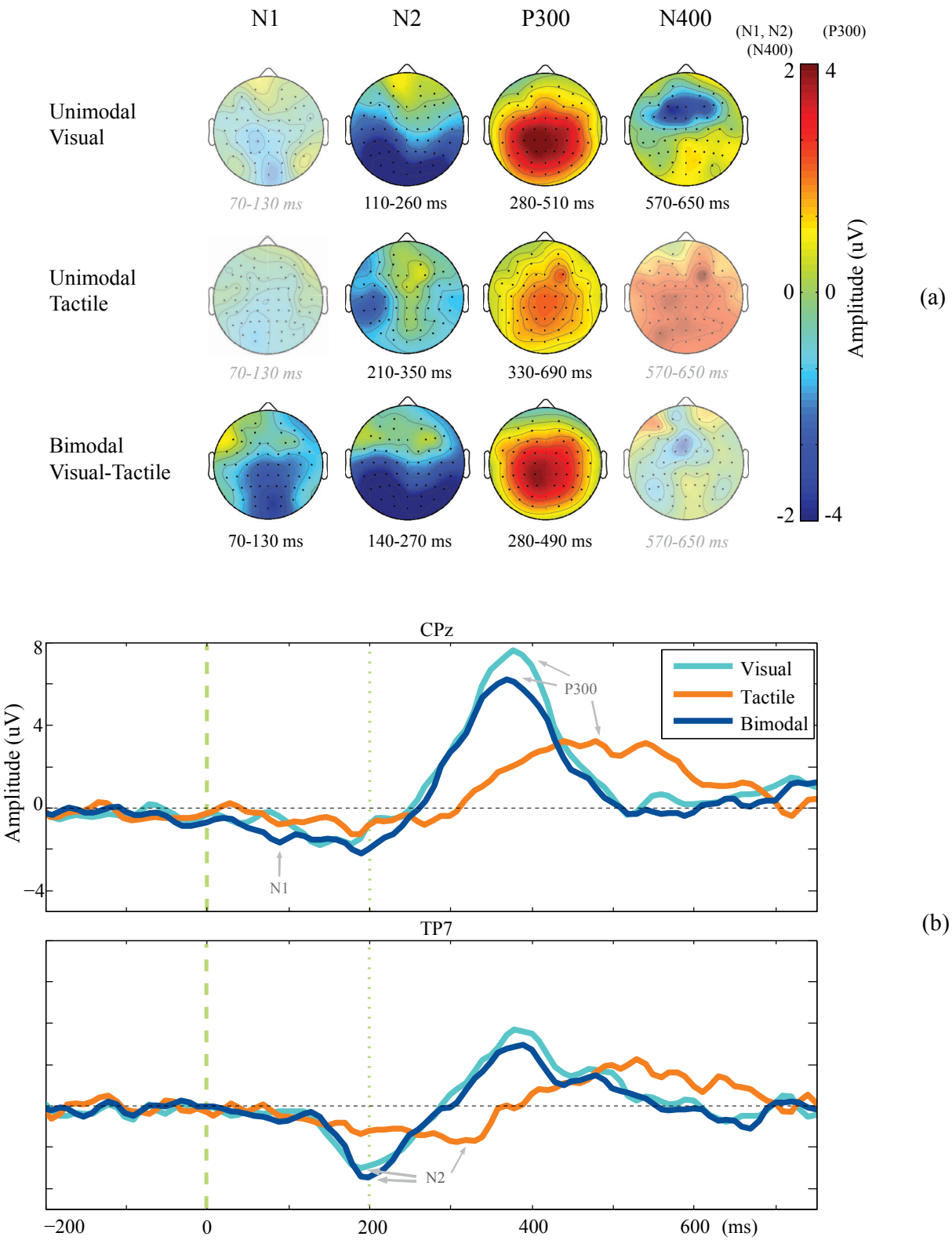

Figure 3.3: Difference ERPs and their components (reflecting endogenous attention) averaged over participants. (a) Scalp distributions of the difference ERP for the identified endogenous ERP components. Amplitudes (µV) are averages calculated within each ERP interval, as defined in section 3.2.5. If no ERP component was identified, the corresponding interval was used to visualise that activity for comparison. In that case, the scalp plot is left semi-transparent, and the corresponding interval is shown in grey and italics. (b) Grand average of the difference ERP. The averaged difference ERP is visualised for electrode CPz (standard, and N1 and P300 were present) and for electrode TP7 (N2 was present).

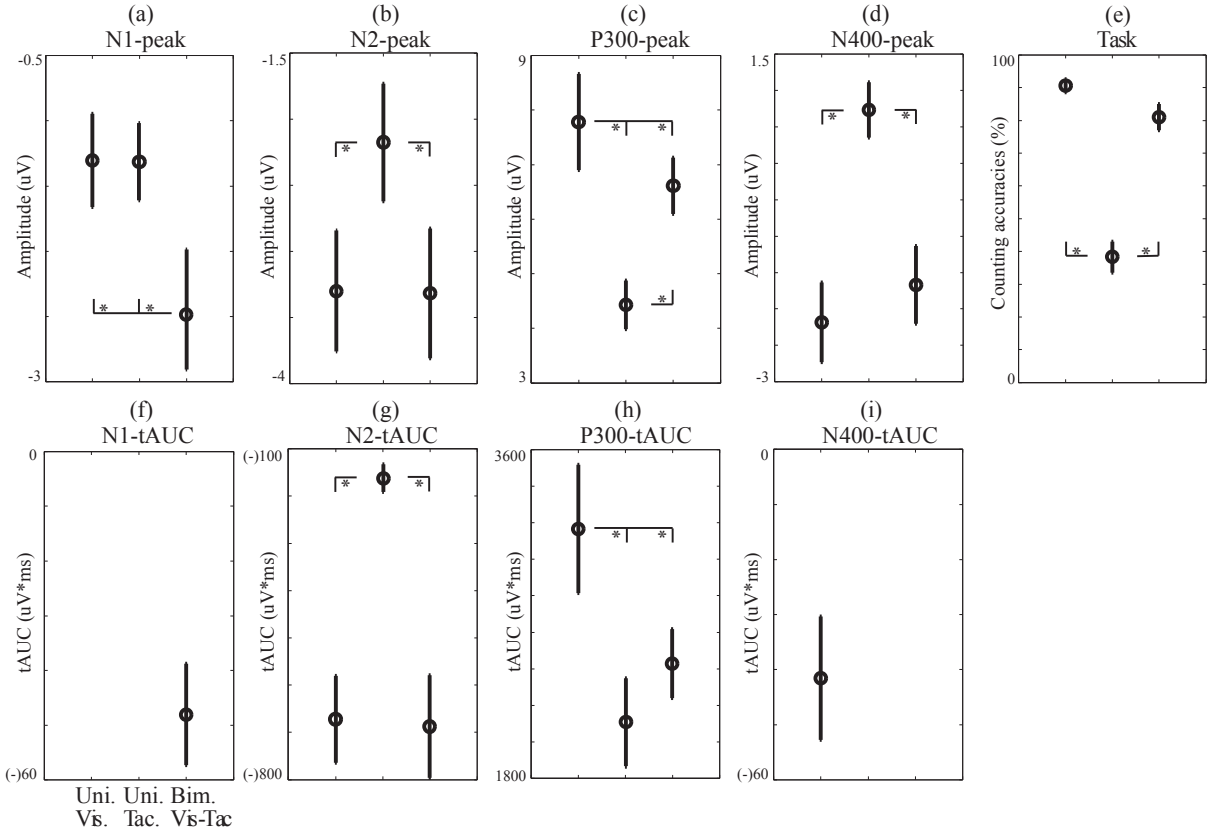

Figure 3.4: Means and standard errors averaged over participants of task performance and ERP components, separately for each condition. Condition pairs that significantly differed from each other are indicated by an asterisk (*) symbol. (a-d) Peak amplitudes (peaks averaged over the ERP-specific set of six electrodes used for statistical analysis). (e) Counting accuracies. (f-i) tAUC values.

3.3.2. Offline BCI performance

The effect of increased bimodal ERP components: a theoretical approach

Offline classification analyses were based on the N1, and on a combination of the N1 and N2. These ERP components were selected, because the visual-tactile N1 was increased with respect to the unimodal conditions, and although the visual-tactile and the visual N2 did not significantly differ, the N2 should provide a neutral basis to increase classification accuracies. Figure 3.5a and 3.5b show the classification results for N1-based and N1&N2-based respectively. All participants scored 100% classification accuracy in the visual-tactile condition when data from sufficient repetitions were used (6 or more) using the N1&N2-based classifier. Such homogeneous top performance was not reached in either of the unimodal conditions. To investigate the effect of stimulus modality, classification accuracies for the N1-based classifier were compared when successful BCI control is expected (80% of the participants achieved accuracies of 70% or higher). This criterion was met at the eighth repetition for the visual-tactile condition, and not met at all for the visual or tactile condition (Figure 3.5a). A comparison of N1-based classification accuracies at the eighth repetition, reveals a significant effect of Modality ($F_{(2, 18)}$=32.73, $p<.001$), and posthoc analysis showed that tactile classification accuracies were lower than for visual and tactile (both $p<.001$). For the N1&N2-based classifier, the criterion was already met at the first repetition for both visual-tactile and visual (Figure 3.5b). Statistical analysis showed a significant effect of Modality ($F_{(2, 18)}$=63,76 $p<.001$), and posthoc analysis also indicated that tactile classification

accuracies were lower than for visual and tactile (both p<.001). However, the enhanced trend in visual-tactile compared to visual classification accuracies was not significant.

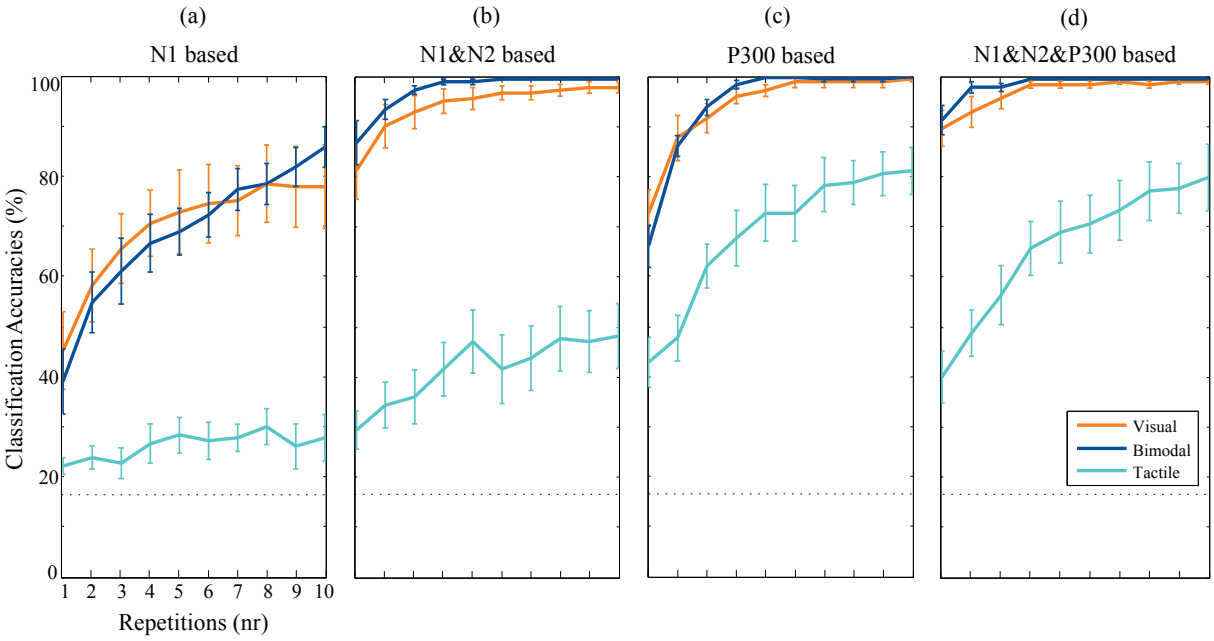

Figure 3.5: Mean classification accuracies and standard errors of participants for all conditions, based on SWLDA. Features prior to automatic feature selection were averaged amplitudes for each of the 60 electrodes within each of four subwindows per ERP component. Chance level is visualized by the black dotted line. Classification accuracies are based on the (a) N1 only, (b) N1& N2 only, (c) P300 only, (d) N1& N2& P300.

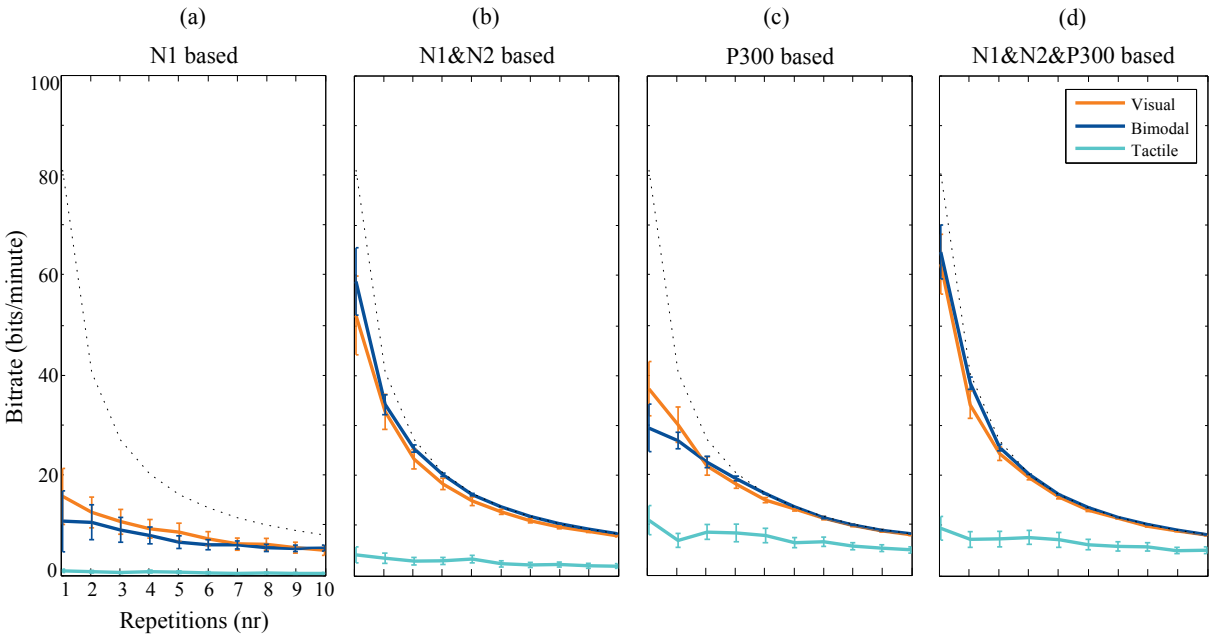

Figure 3.6: Mean bitrates (bits/minute) and standard errors of participants for all conditions, based on the classification probability (0-1), the number of possible selections, and the time necessary to communicate a decision as determined by the stimulus presentation of the experimental setup. The maximum bitrate (classification probability is 1) is visualised by the black dotted line. Bitrates are calculated for classification accuracies based on the (a) N1only, (b) the N1 and N2 only (c) P300 only, (d) N1, N2, and P300.

Evaluation of visual-tactile BCI performance: a practical approach

In addition to the N1-based and N1&N2-based classification, classification accuracies were also calculated with a P300-based (Figure 3.5c) and N1&N2&P300-based classifier (Figure 3.5d). Based on all classification results, bitrates were calculated as a function of the number of repetitions. In general, for all three conditions averaged bitrates (see Figure 3.6) were highest at the first repetitions and decreased when multiple repetitions were used. However BCI operation at the first trial was not considered successful in all cases, because the corresponding criterion was not met. We determined the highest bitrates achieved for each condition when at least 80% of the participants had classification accuracies of 70% or higher. For visual 90% and for visual-tactile 100% of the participants exceeded the threshold using the N1&N2&P300-based classifier at the first repetition resulting in bitrates of 62.45 (*SD 20.05*) and 64.93 (*SD 18.18*) bits/ minute respectively. The best performance and successful BCI control may be expected for tactile at the seventh repetition: 6.52 (*SD 3.18*) bits/ minute since then 80% of the participants exceeded the threshold when the P300-based classifier was used. To statistically analyse the effect of Modality on BCI performance for practical use, these condition-specific classifiers were used and the corresponding bitrates were compared. The effect of Modality on bitrates was significant ($F_{(2, 18)}$=91.37, p<.001), and posthoc analyses confirmed that bitrates for visual and visual-tactile were higher than for tactile (both p<.001), but did not differ from each other. However, similar to the theoretical approach using the N1&N2-based classifier, also with the practical approach using the N1&N2&P300-based classifier, only for the visual-tactile condition a 100% classification accuracy was achieved by all participants (for repetitions 4 and higher).

3.3.3. Task performance

In Figure 3.4e, the percentage of steps over which the number of presented targets was counted correctly is shown for each condition. Counting accuracy was significantly affected by Modality ($F_{(2, 18)}$=57.3, p<.001). Post-hoc analysis showed that the percentages of correctly counted targets in the visual and visual-tactile conditions were significantly higher than those in the tactile condition (both p<.001). Thus, the conditions that contained visual stimuli differed from the conditions that did not. The lower counting accuracy for the visual-tactile compared to that of the visual condition was a non-significant trend (p=.17).

3.4. Discussion

3.4.1. General

In this study, we investigated the possible enhancement of ERP components for attending to bimodal visual-tactile stimuli compared to unimodal visual or tactile stimuli and explored if such an effect can be employed to increase BCI performance. Confirming our first hypothesis, we showed that an early (<200 ms) ERP component, the N1 (70-130 ms), was elicited for attending to visual-tactile stimuli and was enhanced relative to either visual or tactile activity. A consecutive ERP component, the N2, was remarkably similar for attending to visual and visual-tactile stimuli and was stronger in both conditions compared to attending to tactile stimuli. Such early ERP components may be usable in BCIs and increase performance, for example by: increasing overall classification accuracies, reducing the time required to communicate a command, and by diminishing the delay in the control loop in

(future) applications. We will discuss the potential benefits of bimodal BCIs in the light of these advantages.

Although the effects related to the early stage of multisensory processing tended to be in favour of the visual-tactile condition, the results for participants' task performance were not. The non-significant trend was opposite to our expectations formulated in the third hypothesis, with task performance almost being lower for the visual-tactile compared to the visual condition rather than being higher (both were higher than for the tactile condition). A similar pattern was present for the P300, and the P300 was even significantly reduced with respect to the visual-tactile compared to the visual condition. The pattern of effects in the chain of ERP components suggests that multisensory information was processed differently over time than unimodal information, which may be explained by a difference in directing endogenous attention in early and late stages of processing multisensory information.

Below, we will first discuss the early stage of multisensory processing, including the effect of endogenous attention and how BCI performance may benefit from it, followed by a discussion of the later stages, which are associated with task performance. We conclude with a discussion of potential advantages of multisensory ERP-BCIs and evaluate them from a practical point of view.

3.4.2. Early multisensory effects: an enhanced bimodal N1 and its usefulness for BCIs

The endogenous visual-tactile N1 and its relation to early multisensory integration

Early processing of attended visual-tactile stimuli resulted in the elicitation of the N1. This bimodal N1 cannot be explained by either of the unimodal stimuli alone because the activity in the corresponding interval is significantly higher for attending to visual-tactile stimuli compared to either of the unimodal stimuli. The input from both sensory modalities contributed to the bimodal N1 through the (sum of the) two separate processes and possibly by additional integration activity due to crossmodal links in sensory processing at that early stage (Foxe et al. 2000). The latency of our bimodal N1 is well in line with previously reported multisensory integration effects modulated by spatial (selective) attention: Talsma and Woldorff (2005) reported the first effect to peak at approximately 100 ms, and ours was present between 70-130 ms after stimulus onset. Furthermore, Talsma et al. (2007) showed that it is required that both modalities of bimodal stimuli are attended for early ERP multisensory integration effects to occur and are not present if one modality is explicitly ignored. This suggests that the participants in our study correctly followed the instructions to attend to both modalities and did not ignore one modality in the bimodal condition.

Implications of the visual-tactile N1 for (real-time) applications

The effect of endogenous attention on the visual-tactile N1 in this study was already clearly present 70 ms after stimulus onset, which is earlier than what was observed for the unimodal stimuli, for which the earliest attentional effects were only locally present at 110 ms for visual stimuli and at 210 ms for tactile stimuli. This finding is in line with that of Forster et al. (2009), who reported that attended unimodal stimuli are processed faster when the input of more than one modality is processed and crossmodal links are involved.

To investigate the theoretical advantage of visual-tactile stimulus presentation on classification accuracies, we analysed offline classification accuracies that were only based on the features related to early ERP components. Our results showed a nonsignificant positive

trend for bimodal compared to unimodal stimuli. If ERP components are enhanced, we also expect higher classification accuracies, when the classifier is sensitive enough and the data has not reached a ceiling yet. Therefore, the absence of a significant effect of visual-tactile compared to visual classification accuracies may indicate that the classifier was not sensitive enough to fully employ the visual-tactile ERP component.

If we would hypothesize that in the future, technology and knowledge will develop such that with a combination of appropriate electrodes and classifier the difference between targets and nontargets could be detected almost immediately after the brain response, then the bottleneck for a fast response would be biologically determined. The small latency of the visual-tactile N1 is in that case especially interesting for applications for which (near) real-time interaction is desired, such as in gaming or steering and control tasks that are hampered by delays in the control loop. Using the N1-based classifier, only the visual-tactile BCI could be considered to be successfully operated, although bitrates were considerably higher when the classifier was also based on other ERP components.

Early ERP components may also be relevant for gaze-independent ERP-BCIs

Recent studies using a visual ERP-BCI showed that when participants gazed at a central point of fixation compared with gazing at targets directly, BCI performance dropped tremendously (Brunner et al. 2010; Treder and Blankertz 2010). This result suggests that gaze-dependent BCIs are not (solely) based on the P300 and make use of low-level visually evoked potentials that are elicited by foveating targets, which is confirmed in the present study. Moreover, it appeared from the investigated relation between time and classification error by Treder and Blankertz (2010) that for gaze-dependent BCIs, the classification error was minimal at approximately 200-250 ms, an interval during which both early and late ERP components were present. A comparison of classification accuracies based on the early (including an early negative ERP component comparable to our N2) versus the late (including the P300) part of the ERP was made for a non-representative participant with a strong early negative ERP component, for whom the early part of the ERP appeared to be more influential (Bianchi et al. 2010). We observed a similar dominance of the early ERP components for visual and visual-tactile ERP-BCI performance (compare visual and visual-tactile traces in Figure 3.5d to those in 3.5b and 3.5c).

Besides gaze-dependent BCIs, also gaze-independent BCIs may benefit from the early ERP components. In our study the visual ERP-BCI was gaze-dependent, and only elicited a N2, while the visual-tactile ERP-BCI elicited a N1 and a N2. Thus by adding a tactile, gaze-independent stimulus, more early ERP activity was enhanced. Whether this N1 depends on gaze or not, is not clear and we are currently investigating this. The tactile N2, however, is by definition gaze-independent. Interestingly, we detected this tactile N2 in our previous studies only when vision was involved for determining the target direction (Thurlings et al. 2012b), but not when the target direction was presented in the tactile modality (Brouwer and Van Erp 2010). Therefore it seems plausible that the tactile N2 in this study also has some type of multisensory nature. In line with our observations are the results of Forster et al. (2009), who found earlier effects of spatial attention on the tactile ERP when vision was involved, compared to when it was not. Our tactile N2 may contribute to the effectiveness of a tactile BCI, if the classifier is only based on the N2 and the P300, and cannot make use of earlier information. Thus we hypothesize that the application of a tactile BCI when using a visual task, such as navigation, could result in enhanced BCI performance compared to if the visual modality is not involved at all.

3.4.3. Late multisensory effects: a reduced visual-tactile compared to visual P300 and corresponding task performance

The endogenous P300 was reduced for attending to visual-tactile compared to visual stimuli. This result is in line with the non-significant trend observed in task performance, with more accurate results for visual compared to visual-tactile stimuli. For tactile stimuli, the results of both the P300 and task performance were the lowest. These results indicate a reduction in allocated attention on visual-tactile compared to visual targets, contradicting our hypothesis. In general, it is recommended that signals are semantically, temporally and spatially congruent in order to optimize the integration of multisensory input (Driver and Noesselt 2008). Next, we will discuss the late multisensory effects in light of the congruency relations within the bimodal stimuli of our study and propose a possible explanation.

Semantic and temporal congruence within the bimodal stimuli

In our study, the bimodal stimuli were semantically congruent because the indicated directions of the visual and tactile stimuli were the same. Temporally, the visual and tactile stimuli within a bimodal stimulus were triggered congruently and may be considered temporally congruent. However, the course of stimulus intensity slightly differed between visual and tactile stimuli because of technical properties with a difference of less than 50 ms between the latencies of maximum stimulus intensity. Because previous research showed that multisensory signals are perceived as emanating from the same source if presented within a delay of approximately 100 ms (Vroomen et al. 2004), we believe that this temporal difference is unlikely to be the cause of the degraded late multisensory effects.

Spatial incongruence within the bimodal stimuli

The semantic and temporal relations within the bimodal stimuli are unlikely to explain the absence of an advantage of bimodal stimuli on task performance, but the spatial relation may do so. The locations of the stimuli indicated directions, which referred to the participants' bodily anteroposterior axes for the tactile stimuli and to the participants' displayed current position on the route for the visual stimuli. Therefore, the indicated directions of the stimuli were congruent, but the stimuli had different locations and thus were location incongruent (for the effect of directional congruency in ERP-BCIs, see: Thurlings et al. 2012b).

Previous research has reported contradicting results regarding the necessity of spatial congruency for multisensory integration. While some researchers have reported enhanced task performance for spatially incongruent bimodal stimuli compared to unimodal stimuli (Gondan et al. 2005b; Philippi et al. 2008; Teder-Salejarvi et al. 2005), others have reported the opposite (Ho et al. 2009). We believe that the spatial incongruence of bimodal stimuli only hampers multisensory integration if the task involves spatial selective attention, which is the case in both our study and that of Ho et al. (2009).

A spread of attention possibly caused by a distracting modality

The location-incongruence within the visual-tactile stimuli may have degraded task performance because participants had to divide their attention between two locations (and modalities). The bimodal P300 in our study does not reflect a tactile P300 (which occurred relatively late and lasted long), suggesting that tactile targets were not specifically endogenously selected and attended in the visual-tactile condition. Though the bimodal N1

indicated that both modalities were attended in the early stage, endogenous selection occurs only after the first multisensory processing effects that occur within the (pre-located) focus of attention. Thus, spatial attention could have shifted between those two processes around the intermediate stage. One reason for such a shift may be that the tactile stimuli were distracting rather than cooperative and attracted attention away from the visual stimuli so that attention became more dispersed instead of focused on the target location(s). The effects of spatial congruency under various circumstances were previously related to higher perceptual-cognitive processes well after our N1 but around the latency of our N2 in the intermediate stage (Gondan et al. 2005b; Teder-Salejarvi et al. 2005; Zimmer et al. 2010).

3.4.4. Possible advantages of bimodal ERP-BCIs

The potential added value of bimodal stimulus presentation on the effectiveness of BCIs

In section 3.4.2., we discussed the potential added value of the bimodal N1 to decrease the response times in future BCIs. In this study we could not show significant improvement of performance for the visual-tactile compared to the visual condition, neither from a theoretical approach (on classification accuracies when only analyse early ERP components were used, which were increased for bimodal compared to unimodal), nor from a practical approach (on bitrates when using the most appropriate ERP-based classifier and number of repetitions for each modality separately). Nevertheless, in both cases we did find some indications that bimodal BCIs could help the effectiveness of a BCI, as for example only for bimodal 100% top performance was reached for all participants. Future research should point out whether significant improvement can be reached when: other classification techniques are used, when bimodal and visual BCIs are not gaze-dependent (and overall performance will be lower), and when bimodal stimulus presentation is offered location congruently. We are currently investigating both latter factors.

Other possible advantages of bimodal ERP-BCIs

A visual-tactile ERP-BCI as outlined in this study makes use of additional ERP components that are elicited or enhanced due to multisensory integration. In addition to the potential added value of bimodal stimulus presentation on the effectiveness of a BCI, bimodal ERP-BCIs possess other potentially interesting properties. As discussed previously, gaze-dependence is a problem for users with impaired vision or eye muscles and in situations in which gaze is needed elsewhere (e.g., while driving or gaming). However, the advantage of gaze-dependent visual ERP-BCIs is that these are associated with high BCI performance while performance of gaze-independent ERP-BCIs (visual, tactile or auditory) is relatively low. In a bimodal ERP-BCI, participants do not necessarily have to attend to both stimulus modalities, but they may decide to attend only one modality, thus alternating between the two ERP-BCIs. In that way, the advantages of both modalities may be exploited alternately, as appropriate for a specific situation. This flexibility during usage could be of interest to both able-bodied and disabled users and fits with the growing interest in flexibility by combining different BCIs, also referred to as hybrid-BCIs (e.g., Allison et al. 2010). To realize such an alternating bimodal BCI, an additional classifier may be needed to detect the currently attended modality if the ERPs would differ when one or the other modality is attended, so that the appropriate classifier for the currently attended modality can be applied to distinguish targets from nontargets. Furthermore, for less able-bodied users with, for instance, a neuromuscular disorder, it might be helpful to use a bimodal ERP-BCI during the period

when their ability to use their muscles is degrading so that a smooth transition from a visual gaze-dependent to a tactile BCI can be realized (Klobassa et al. 2009).

The usability of bimodal ERP-BCIs

In this study we investigated one aspect which is of importance to the evaluation of any system; effectiveness of the BCI. However, other aspects such as usability are relevant as well. Usability may be influenced by the limitations induced by the hardware required. For the use of the tactile or bimodal BCI, tactors have to be attached to the body. In this study we used a vest in which tactors are integrated, but are connected with cables and other equipment. The limitations of this hardware seem less restricted though than the hardware necessary to record EEG. Also, recently a tactile wireless belt was developed (Eaglescience[1] and TNO), which is as easy to wear as a regular belt.

3.5. Conclusion

We are interested in the possible facilitation of bimodal stimulus presentation for ERP-BCIs. In this study, we investigated the effect of visual-tactile stimulus presentation on the chain of ERP components, BCI performance (classification accuracies and bitrates), and task performance (counting targets). Visual-tactile stimulus presentation had positive effects at an early stage of attended stimulus processing (N1) compared to only visual or tactile stimulus presentation, but negative effects at a late stage (P300) compared to visual stimulus presentation. We discussed that early bimodal ERP effects (enhanced compared to unimodal) may be the result of (the sum of) two separate sensory-specific processes for visual and tactile stimulus processing and possibly also of a multisensory integration effect. Late bimodal ERP effects (reduced compared to visual) may be explained by affected spatial attention, caused by a (partly) spatially incongruent relation within the visual-tactile stimulus. Additionally, we evaluated the potential advantages of a bimodal BCI on effectiveness. Although bimodal (compared to visual) performance was not significantly enhanced, we did find indications that bimodal BCIs could be more effective than unimodal BCIs: Only for the bimodal condition 100% top performance was reached for all participants. Future research should point out whether the gain of bimodal BCIs may be greater for bimodal gaze-independent and location congruent BCIs. Furthermore, the small latency of the bimodal N1 might become relevant in future applications when the delay of the feedback is directly determined by the biological response.

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4

Bimodal location-congruent ERP-BCIs: Increasing gaze-independent performance

***Abstract*—**Event-related potential (ERP) based Brain-Computer Interfaces (BCIs) that are independent of gaze yield relatively low BCI performance. Bimodal ERP-BCIs may increase BCI performance due to multisensory integration or summation activities in the brain. An additional advantage is that they may let users free to attend one of two modalities. We studied bimodal visual-tactile gaze-independent BCIs and investigated whether or not ERP components and subsequent classification accuracies are increased for (1) bimodal versus unimodal stimuli, (2) location-congruent versus location-incongruent bimodal stimuli, and (3) attending both modalities versus either one modality. Compared to unimodal stimuli, we observed an enhanced bimodal P300, which appeared to be positively affected by location-congruency (p=.056), and resulted in higher classification accuracies. Attending to either one or both modalities of the bimodal location-congruent stimuli resulted in differences between ERP components, but BCI performance was equally good. We conclude that location-congruent bimodal stimuli improve ERP-BCIs, and offer the possibility to switch the attended modality.

Index Terms: BCI, ERP, gaze-independent, bimodal, tactile, multisensory, location-congruency, selective attention, multimodal.

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4.1. Introduction

4.1.1. Gaze-independent ERP-BCIs

Event-related potential (ERP) based Brain-Computer Interfaces (BCIs) can be used to actively and voluntarily control a system, e.g. for communication (Farwell et al. 1988) or navigation (Bell et al. 2008; Thurlings et al. 2010). ERP-BCIs make use of stimuli that correspond to control options (e.g., 'left' or 'right'). The user can select an option by attending to the corresponding stimulus (target) while ignoring other stimuli (nontargets). Stimulus-locked brain responses (ERPs) differ between the attended targets and ignored nontargets.

Most ERP-BCIs employ visual stimuli and allow the user to gaze at the attended stimulus, i.e. such a BCI is *gaze-dependent*. When the user does not directly gaze at the visual stimuli, but covertly attends to targets, BCI performance is much lower (Brunner et al. 2010; Treder et al. 2010). Such a BCI is considered *gaze-independent*. When users cannot reliably focus their gaze, or when other tasks interfere with gaze, stimuli can also be presented in other modalities like auditory modality (Höhne et al. 2011; Schreuder et al. 2010; Schreuder et al. 2011). In application domains such as driving and gaming, BCIs must be gaze-independent as gaze is required for control and navigation tasks and the visual (and auditory) channel is already heavily loaded (Van Erp et al. 2004). The tactile channel has been suggested as a viable alternative for these situations, and Brouwer and Van Erp (2010) demonstrated the feasibility of employing tactile stimuli around the waist in a tactile ERP-BCI. The natural correspondence of tactile stimuli around the waist with navigation directions (Van Erp 2005) makes a tactile ERP-BCI especially interesting for navigation applications.

BCI performance of tactile ERP-BCIs (Brouwer et al. 2010; Thurlings et al. 2012a; Thurlings et al. 2012b) is, however, relatively low compared to the traditional visual gaze-dependent BCIs (Thurlings et al. 2012a). In addition, when a BCI is used as a control device in the context of a dual-task, for example to navigate in a game, BCI performance is even lower than in BCI-only tasks (Thurlings et al. 2013).

Generally, the performance of ERP based BCIs depends on the characteristics of the brain activity in response to attending of presented stimuli, on the quantity of the responses, on the quality of information on brain responses that can be extracted using EEG recording equipment, and on the accuracy of software to discriminate between target and nontargets responses (i.e., classification). This study focusses on potential benefits regarding brain activity of stimulus presentation in multiple sensory modalities, using a gaze-independent setup.

4.1.2. The bimodal ERP-BCI

The processing and integration of multisensory stimuli is likely to cause additional neuronal activity (Driver et al. 2008; Ernst et al. 2004; Stein et al. 2008). Integration may take place at perceptual stages (Molholm et al. 2002; Philippi et al. 2008), higher cognitive stages (Schröger et al. 1998), and/or during motor preparation and execution (Giray et al. 1993). Bimodal stimuli generally yield faster responses and more accurate discrimination (Gondan et al. 2005; Philippi et al. 2008; Teder-Salejarvi et al. 2005).

Multisensory integration has extensively been investigated in cognitive science, but has barely received attention in the field of BCI. In a recent BCI-study, we showed that an additional (early) ERP component was present when participants were presented with and attended to stimuli in two modalities rather than one, due to multisensory interaction (Thurlings et al.

2012a). To the best of our knowledge, only two other BCI-related studies investigated bimodal stimuli: visual-tactile stimuli (Brouwer et al. 2010), and audio-visual stimuli (Belitski et al. 2011). In both studies the authors reported increased classification accuracies (i.e., the percentage of correctly classified target responses) for bimodal compared to unimodal conditions, which is in line with the trend we reported in (Thurlings et al. 2012a).

As motivated in the previous section, we are interested in multisensory BCIs, as a way to potentially increase BCI performance of traditional unimodal ERP-BCIs, in particularly the gaze-independent variants. From the three above mentioned bimodal studies, only Brouwer and Van Erp (2010) used a gaze-independent setup with visual-tactile stimuli. However in that study the effects on target and non-target responses of *endogenous* attention (driven by 'will') and *exogenous* attention (driven by stimuli) were confound. Both endogenous and exogenous attention can affect ERP components (Woldorff et al. 1991), but only endogenous attention is relevant for BCI operation. Thus, the question whether or not gaze-independent ERP-BCIs benefit from bimodal stimulus presentation remains unanswered.

As discussed in our previous bimodal BCI-study (Thurlings et al. 2012a), we expect enhanced early ERP components for bimodal compared to unimodal conditions. Multisensory integration has been shown to start as early as 80-120 ms after stimulus onset for visual-tactile stimuli (Sambo et al. 2009), but is modulated by endogenous attention at different stages of processing (Talsma et al. 2005). As reported in (Thurlings et al. 2012a), positive effects of bimodal stimulus attending have been shown on an early stage of processing, i.e., early negative activity (N1) in the difference ERP (target minus nontarget ERP) was stronger for the bimodal compared to the unimodal conditions. However, we observed negative effects of bimodal stimulus attending on a late stage of the ERP, i.e., positive late activity (P300) in the difference ERP was stronger for one of the unimodal conditions (visual) compared to the bimodal condition. We hypothesized that the latter effect was caused by the spatial relation of the two unimodal stimuli that formed a bimodal stimulus pair. More specifically, while the spatial relation unambiguously indicated which unimodal stimuli formed a pair, those stimuli were not co-located. Possibly, this affected spatial attention and top-down stimulus processing. Therefore in the present study we focus on co-located (i.e., *location-congruent*) bimodal stimuli.

Thus, our first research question is: Are ERP components and corresponding classification accuracies of a bimodal visual-tactile ERP-BCI enhanced compared to its unimodal counterparts? We hypothesize enhanced bimodal ERPs both on early and late stages of processing when employing location-congruent bimodal stimuli in a gaze-independent setup, which should result in enhanced BCI performance.

4.1.3. Effects of location-congruency on the bimodal ERP-BCI

In case we find a benefit of bimodal compared to unimodal stimulus presentation and attending, as hypothesized in the previous section, it is relevant to know whether or not that effect depends (partly) on the spatial relation within the bimodal stimulus pairs. This is important for the designing of bimodal ERP-BCIs, especially since the most straightforward design might employ incongruent bimodal stimulus pairs as in (Thurlings et al. 2012a). In that study, a display presented visual navigation information and included visual stimuli located at the possible navigation directions. Tactile stimuli were presented around the waist, corresponding with navigation directions around us. To make the spatial relation as congruent as possible in that setup, the display was oriented in the horizontal plane, to match the horizontal lay-out of the tactile stimuli (Thurlings et al. 2012b). Therefore the bimodal

stimulus pairs were directional-congruent, but not location-congruent. We hypothesized in (Thurlings et al. 2012a) that location-incongruency resulted in negative effects of bimodal (compared to unimodal) stimulus attending on a late stage, while effects on the early stage were positive (see previous section).

Literature on the effects of location-congruency is not equivocal. According to the *spatial rule* (Meredith et al. 1986), stimuli from different modalities are only integrated when stimuli are spatially coincident (or proximate). Stein et al. (1989) showed for example that the performance of animals that were trained to approach visual stimuli is improved when matched with (unattended) auditory stimuli, but only if the visual-auditory stimulus pairs were spatially coincident (or proximate). Frassinetti et al. (2002) replicated these results in humans. Also when bimodal stimulus-pairs are not location-congruent, behaviour performance has been found to be enhanced (Gondan et al. 2005; Philippi et al. 2008; Teder-Salejarvi et al. 2005). These studies differ in tasks, but have in common that the task does not enforce selective attention to one modality (as in the studies of Meredith and Stein), but rather both modalities need to be attended. Apparently the role of the spatial relation within multisensory information and if and how it affects multisensory integration depends on the specific circumstances. (We address the role of selective attention to modality in the next section). Nevertheless, also when bimodal benefits are found for incongruent bimodal stimuli, behavioural performance may be improved by location-congruency (Gondan et al. 2005). Teder-Salejarvi et al. (2005) did not observe such a behavioural benefit, but did report differences in the ERP for location-congruent and location-incongruent bimodal stimuli after 100ms. They concluded that there are overlapping and distinct processes involved in processing of location-congruent and incongruent stimuli.

Multisensory studies typically involve a task that requires participants to distinguish targets from nontargets based on physical stimulus characteristics, instead of on (only) spatial differences such as is the case in a BCI-setup (which uses spatial selective attention). Possibly, the role of the spatial relation is larger when the task is only based on spatial discrimination. Therefore it is important to study the role of the spatial relation of bimodal stimuli in ERP-BCIs.

Our second research question is: What is the effect of location-congruent compared to location-incongruent bimodal stimuli on the ERP and corresponding classification accuracies in an ERP-BCI? We hypothesize positive effects for location congruent bimodal stimuli at late stages (e.g., P300) of stimulus processing, which should correspond to enhanced classification accuracies.

4.1.4. Effects of selective attention to modality on the bimodal ERP-BCI

Both exogenous and endogenous attention affect the ERP (Eimer et al. 2001). When participants are presented with bimodal stimuli, but they endogenously attend to either one or both modalities, exogenous attention involved in both cases is the same (as the physical characteristics have not changed). However, the amount of attentional resources allocated endogenously for processing the stimulus information of the two modalities involved differs between these cases (Macaluso 2010). For example, when participants are precued and (pre)attending to the visual rather than the auditory modality, audio-visual stimuli are processed differently, resulting in enhanced early activity starting around 110 ms and peaking around 150ms (Foxe et al. 2005). Talsma et al. (2007) showed that for the earliest multisensory integration effect (a superadditive effect) of audiovisual stimuli to occur, both modalities need to be attended. Nevertheless, if only a single modality was attended

integration still occurred but the process appeared to start later (after 250 ms after stimulus onset) and was dependent on which modality was attended.

Users of a bimodal ERP-BCI could choose to attend to either one or both modalities, which could affect the resulting ERP and may require individually trained classifiers for optimal performance. In this study, we investigated the trade-off between possibly affected classification accuracies and the advantage of the flexibility offered to the user to choose the modality to attend to.

Our third research question is: Does, and if so how does, attending to the visual or tactile modality, or both modalities affect ERP components and corresponding classification accuracies in a bimodal ERP-BCI? We hypothesize that when both modalities (as opposed to either one alone) of bimodal (location-congruent) stimuli are attended, the early stage of the bimodal ERP is enhanced. Such an enhancement of the ERP could also result in enhanced classification accuracies.

Additionally, we investigated how these classification accuracies depend on the degree of overlap in the attended modalities of the datasets during training and classification. Would it be possible to switch the attended modality during use, or does the classifier then need to be retrained? We hypothesize that classification accuracies are negatively affected if the applied classifier is trained on data with a different attended modality than the data that are being classified. When attended modalities during training and classifying partly overlap (i.e., visual and bimodal, or tactile and bimodal) higher classification accuracies are expected than when they do not overlap (i.e., visual and tactile).

4.2. Method

4.2.1. Participants

Ten students voluntarily participated in this study. Participants were aged between 22 and 26 years (mean age 23.5 years). All participants were male and had normal or corrected-to-normal vision. None had previously participated in a BCI-experiment and one was left-handed. The participants signed informed consent forms.

4.2.2. Task

The task was to select one of two possible control options: left or right. In contrast to our previous tactile BCI studies (Brouwer et al. 2010; Thurlings et al. 2012a; Thurlings et al. 2012b; Thurlings et al. 2013) in which tactor locations were around the waist to correspond to navigation directions around us, in this study we use the index fingers. The reason is that we here focus on a gaze-independent and location-congruent setup of bimodal stimuli. To comfortably perceive visual and tactile information a setup was chosen in which the index fingers are stimulated.

The two control options were presented sequentially in random order, at the left and right index finger through a tactile actuator, an LED, or both. To select an option, participants had to attend to a target stimulus location and modality, and count the number of tactile, visual or visual–tactile activations at that location. At the beginning of each trial the current target (i.e. a combination of finger and modality) was indicated by means of a short activation of the particular target stimulus. Within one trial, each control option (target and nontarget) was activated ten times.

Note that although ERP-BCIs typically make use of more than two control options (i.e, more than one nontarget), Brouwer and Van Erp (2010) have shown that the P300 is also elicited in a 2-class tactile BCI and operation is not significantly reduced compared to a 4- or 6-class BCI

4.2.3. Design

The experiment involved six conditions, named after the type of stimuli and attended modality involved. In four conditions targets had to be attended in the modalities that the stimuli of that condition were presented in (no selective attention to modality): Visual, Tactile, Bimodal, Bimodal-Incongr. In the Bimodal condition a control option consisted of the simultaneous activation of a visual and tactile actuator at the same finger, while for Bimodal-Incongr a visual and tactile actuator of opposite fingers were matched. In the two other conditions, only one modality had to be attended, while bimodal (location-congruent) stimuli were presented. For attending the visual or tactile modality, the conditions were named: Bimodal-Att-V and Bimodal-Att-T, respectively. The order of the conditions was counterbalanced over participants.

Each condition consisted of three sets. The data of the first two sets (the training sets) were used for the training of a classifier, which was applied to classify the data in the third set (the test set). Online BCI-feedback was given to participants in the test set about which stimulus was classified as the target. The training (but not the test) set was also used for the analysis of participants' ERP components.

Each of the two control options was designated as the target three times in each set, i.e., there were six trials. Each trial consisted of 10 consecutive repetitions of the control options in random order, i.e. in each set there were 60 target and 60 nontarget activations.

4.2.4. Materials

General

An actuator pair, consisting of a tactile vibrator and a visual LED, was attached with Velcro to each index finger (22 degrees from the fixation cross). The target and nontarget stimuli consisted of a single pulse with a pulse duration of 187.5 ms. The interval between pulses was 437.5 ms. To indicate the designated target control option at the beginning of a trial and the classified control option for BCI-feedback at the end of a trial, a 2s and a 1s single pulse were presented respectively.

Stimuli

Tactile stimuli: The tactile stimuli were presented through a vibrating element called a tactor. The tactors were custom built and consisted of a plastic case with a contact area of 1x2 cm containing a 160 Hz electromotor (TNO, The Netherlands, model JHJ-3, see: Van Erp et al. 2007). To prevent participants from perceiving auditory information from the tactors, they listened to pink noise via speakers during the experiment in all conditions.

Visual stimuli: Visual stimuli were presented through two white LEDs of 5 mm, 3.2V.

Bimodal stimuli: For all bimodal conditions, except for Bimodal-Incongr, bimodal stimuli consisted of the simultaneous activation of the visual and tactile stimulus on the same index

finger (location-congruent). For the Bimodal-Incongr condition, the visual stimulus of one index finger and the tactile stimulus of the other index finger were activated simultaneously.

EEG recording equipment

EEG was recorded from eight linked-mastoids-referenced scalp electrodes (F_z, C_z, P_z, O_z, P_3, P_4, PO_7, PO_8) that used a common forehead ground (g.Tec medical engineering, GmbH). The impedance of each electrode was below 5 kΩ, as was confirmed prior to and during the measurements. EEG data were recorded with a hardware filter (bandpass 0.1-60 Hz, notch at 50 Hz) and sampled at a frequency of 256 Hz.

4.2.5. Data analysis

EEG preprocessing and selection

To prepare the recorded EEG for ERP-analysis, we followed similar procedures as taken in (Thurlings et al. 2012a; Thurlings et al. 2012b): Selecting (non)target responses, baseline correction, threshold rejection of responses, and computation of a difference ERP. However, the data were not additionally low-pass filtered (the relatively large band was chosen because of potential multisensory effects in the 30-60 Hz band).

Selecting (non)target responses: For ERP-analysis, both target and nontarget responses were used when preceded by a nontarget. Responses preceded by a target were discarded (i.e., there were no (other) targets presented between -625 and 625 ms relative to (non)target onset) (see also (Treder et al. 2010).

Baseline correction: For the selected targets and nontargets, epochs from all electrodes were extracted from -100 to 625 ms relative to stimulus onset and baseline corrected relative to the average voltage during the 100 ms preceding the stimulus onset.

Threshold rejection of responses: We discarded epochs from all electrodes belonging to a certain stimulus, if any epoch contained amplitude differences exceeding 100 µV, indicating movement artefacts. On average, the previous steps left us with 58.8 target epochs (with a range over participants and conditions from 35 to 70) and 54.0 nontarget epochs (with a range over participants and conditions from 32 to 67). Subsequently, the selected target and nontarget epochs were averaged per participant, per condition and per electrode.

Difference ERP: We subtracted the averaged clean nontarget epochs from the averaged clean target epochs for each participant, each condition and each electrode. With this step, we removed exogenous (involuntary or automatic) attention effects. Further analyses were performed regarding this difference ERP (or endogenous ERP).

Identifying and quantifying ERP components

To identify and quantify ERP components triggered by endogenously attended stimuli, we applied the detection method as reported in (Thurlings et al. 2012a; Thurlings et al. 2012b). Only data of the training set was used, to prevent influence of BCI feedback. We identified significant effects of attending stimuli by performing a sample-by-sample t-test on the difference ERP (between 0 and 625 ms relative to (non)target onset) for each electrode and condition and clustered the stable segments (i.e., in this case at least seven consecutive significant samples; see also: Guthrie et al. 1991). Clusters were considered robust if they contained segments of at least two electrodes. These robust clusters defined the topographic

distribution and the interval of the endogenous ERP components, taking the beginning of the earliest segment and the ending of the latest segment in the clusters as ERP component intervals.

We quantified the endogenous ERP components by using the tAUC-value (topographic Area Under the Curve), as described in (Thurlings et al. 2012a; Thurlings et al. 2012b). The tAUC reflects the magnitude of an ERP component not only by taking the averaged amplitude and duration of the component into account but also by considering the topographic distribution.

Online and offline BCI performance

Classification accuracies were calculated both online and offline. Online analysis was performed using BCI2000 (Schalk et al. 2004), which made use of SLWDA on epochs from 0-797 ms after stimulus onset, decimation factor 4 (i.e., 64 Hz), and other standard parameters (maximum of 60 features, p-values included and excluded from the model <.1 and >.15 respectively). The classifier was trained using the training set for each participant and for each condition.

We investigated classification accuracies more detailed offline, to establish possibly more appropriate parameters for bimodal BCI, and using those parameters to assess the effects of conditions for BCI in practical use. To this end we executed a parameter sweep with all combinations of decimation factors (between 4 and 26) and the length of the part of the epoch used, divided into blocks of downsampled windows (between 1 block and the maximum number of blocks approaching a correspondence of 800 ms). The parameter-pair resulting in the highest overall classification accuracies (averaged over all six conditions) after ten repetitions was selected for further analyses. Then we calculated accuracies after each repetition and established the number of repetitions which is expected most appropriate in practical use. We considered the number of repetitions the most appropriate, when classification accuracies of 70% or higher were achieved using a minimal number of repetitions (Birbaumer et al. 2007; Kubler et al. 2004; Pfurtscheller et al. 2010).

For all conditions, classification accuracies were determined by classifying the test set using a classifier trained on the training set. Additionally, to assess what the costs on BCI performance are of switching attended modality during BCI operation, analysis was done cross-conditionally: That is, for each of the conditions Bimodal, Bimodal-Att-V, and Bimodal-Att-T, the test set was classified using a classifier trained on the test set of each of the other two conditions. From the nine resulting classes of responses, we clustered three categories: 1. Trained and tested on data of the same condition (‘Equal’). 2. Trained and tested on data of two different conditions, but with an overlap in the attended modality (e.g. trained on Bimodal, tested on Bimodal-Att-V; attending of the visual modality is overlapping) (‘Overlap’). 3. Trained and tested on data of two different conditions, but without an overlap in the attended modality (e.g. trained on Bimodal-Att-V, tested on Bimodal-Att-T (‘No Overlap’). Within each category the included classes were averaged per participant.

Statistical analysis

ERP components’, tAUC-values and classification accuracies were statistically analysed using Statistica 8.0 (StatSoft, Tulsa, USA). We used separate one-way repeated-measures ANOVAs (or paired *t*-tests if suitable) to examine different subsets of data appropriate to answer each of the three research questions. tAUCs and classification accuracies were the dependent variables. For the three research questions, the independent variables were: (1)

Bimodality (three levels: Visual, Tactile, Bimodal), (2) Location-Congruency (two levels: Bimodal, Bimodal-Incongr), (3A) Attending Modality (three levels: Bimodal, Bimodal-Att-V, Bimodal-Att-T), and (3B) Cross-training (three levels: Equal, Overlap, No Overlap). Tukey post-hoc tests were applied when appropriate.

4.2.6. Procedure

After the participant was verbally instructed and had read and signed the informed consent form, we attached the visual-tactile actuator pairs on his index-fingers using Velcro. The participant was seated in a dimly lit, electromagnetically shielded room and positioned his arms on the desk in front of him. We allowed the participant to become accustomed to the stimuli, by activating them for several minutes. The participant was asked to gaze at the fixation cross in front of him on the table.

During EEG preparation, we repeated the outline of the experiment and instructed the participant to move as little as possible during stimulus presentations. Before each condition, we informed the participant about the oncoming condition. When the participant indicated to be ready to begin, we started the condition. In the test sets, online BCI feedback was given after each trial (i.e., the 10th repetition). Each condition (including two training and one test recording) took approximately 3.8 min recording time. Conditions followed each other with 1 to 15 minutes breaks in between, depending on the participant's preferences.

4.3. Results

First we describe the general observed results considering ERP components and BCI performance for each condition. Subsequently, the effects for each of the three research questions are reported both with respect to ERP components and classification accuracy.

4.3.1. General

Endogenous ERP components

Spatiotemporal presentations of the amplitudes of the endogenous ERPs are presented in Figure 4.1a. For all conditions, endogenous activity was observed during one or two periods within the analysed interval from 0 until 625 ms after stimulus onset. In Figure 4.1b, spatiotemporal plots show the significant stable segments. The red and blue areas indicate the polarities (positive and negative, respectively) of the clustered segments that were found to be robust and were thus identified as endogenous ERP components. In Figure 4.2, these ERP components are visualised by means of scalp plots (averaged amplitudes of the endogenous ERP at all electrodes, within the ERP components' intervals). The complete ERPs are visualized for each condition for electrode Pz in Figure 4.3 (grouped per research question). The main effect of conditions on the ERP components' tAUC-values are visualised in Figure 4.5a-c.

As apparent from Figure 4.1b, only one endogenous ERP component was identified in all six conditions: the P300. Its amplitudes were largest in the central-parietal area. The P300 appeared to be the strongest in the Bimodal and Bimodal-Att-V conditions, and the weakest for the Visual condition. The windows in which the P300 was detected were: 203-367 ms (Visual), 230-441 ms (Tactile), 188-402 ms (Bimodal-Incongr), 203-348 ms (Bimodal), 230-442 ms (Bimodal-Att-V), and 297-439 ms (Bimodal-Att-T) after stimulus onset.

Furthermore, early positive activity was detected and identified as P1 for the Visual, Bimodal-Att-V and Bimodal-Incongr conditions, in the windows 86-137 ms, 59-105 ms, and 66-164 ms respectively, after stimulus onset. For the Tactile and Bimodal-Att-T conditions a different early component was detected. Early negative activity was identified as an N2 in the windows 184-230 ms, and 180-223 ms respectively after stimulus onset.

BCI performance

A parameter-sweep was performed for combinations of decimation factors and the length of the epoch used (divided into blocks of downsampled windows). The parameter-pair of decimation factor 5 (i.e., 51,2 Hz) and epoch length of 625 ms resulted in the highest overall classification accuracies of 82,2% (*SD: 11,1*) over conditions. Thus, these parameters were further used for offline analysis.

Both online and offline classification accuracies are visualised in Figure 4.4. Overall classification accuracies (averaged over participants) are highest for all bimodal conditions employing location-congruent stimuli (i.e., Bimodal, Bimodal-Att-V, and Bimodal-Att-T). For all conditions offline classification accuracies increase with each repetition, except for the Bimodal-Incongr condition. After six repetitions, the averaged classification accuracies for five out of the six conditions exceeded the threshold of 70% necessary for effective control. For the Bimodal-Incongr condition this threshold was not reached at all. Therefore the sixth repetition is considered the most appropriate to assess effects of all research questions in a practical setting, and was used for statistical analysis.

4.3.2. The effect of Bimodality

ERP components

The P300 tAUC was significantly affected by Bimodality ($F_{(2,18)}=23.93$, $p<.001$). The P300 was stronger for the Bimodal condition compared to both unimodal conditions (both $p<.001$). The P300 tAUC (Table 4.1) did not differ significantly between the unimodal conditions (Figure 4.5a).

The P1 was only identified for the Visual condition (neither for Tactile nor for Bimodal) and the P1's tAUC (Table 4.1) differed significantly from zero ($t_{(9)}=6.69$, $p<.001$).

The N2 was only identified for the Tactile condition (neither for Visual nor for Bimodal) and the N2's tAUC (Table 4.1) differed significantly from zero ($t_{(9)}=6.41$, $p<.001$).

Classification accuracies

The effect of Bimodality on classification accuracies was significant ($F_{(2,18)}=7.30$, $p<.01$), with higher accuracies for Bimodal compared to Visual ($p<.05$) and Tactile ($p<.01$) (Figure 4.5d).

4.3.3. The effect of Location-Congruency

ERP components

An enhanced P300 tAUC (Table 4.1) for Bimodal compared to Bimodal-Incongr approached significance ($t_{(9)}=2.19$, $p=.056$) (Figure 4.5b).

The P1 was only identified for the Bimodal-Incongr condition (not for Bimodal) and the P1's tAUC (Table 4.1) differed significantly from zero ($t_{(9)}=5.91$, $p<.001$).

Classification accuracies

An effect of Location-Congruency on classification accuracies was found, with higher accuracies for Bimodal compared to Bimodal-Incongr ($t_{(9)}=3.88$, $p<.01$) (Figure 4.5e).

4.3.4. The effect of Selective Attention to Modality

ERP components

The P300 tAUC (Table 4.1) was significantly affected by Attending Modality ($F_{(2,18)}=7.50$, $p<.01$). The P300 was stronger for the Bimodal and Bimodal-Att-V conditions compared to the Bimodal-Att-T condition ($p<.05$ and $p<.01$, respectively) (Figure 4.5c).

The P1 was only identified for the Bimodal-Att-V condition (neither for Bimodal-Att-T nor for Bimodal) and the P1's tAUC (Table 4.1) differed significantly from zero ($t_{(9)}=8.19$, $p<.001$).

The N2 was only identified for the Bimodal-Att-T condition (neither for Bimodal-Att-V nor for Bimodal) and the N2's tAUC (Table 4.1) differed significantly from zero ($t_{(9)}=6.20$, $p<.001$).

Classification accuracies (attended modality specific classifier)

For the attended modality specific classifier, the data used for training of the classifier and for the actual classification are recorded under the same attending-modality conditions (using bimodal location-congruent stimuli only).

No effect of Attending Modality on classification accuracies was found (Figure 4.5f).

Classification accuracies (attended modality cross classifier)

For the attended modality cross classifier, training of the classifier occurred for each of the attending-modality conditions, and the resulting classifier was used to cross-classify the data of each of the attending-modality conditions.

Table 4.2 shows the results of the cross-condition classification analyses. In Figure 4.5g the effect of Cross-training on the clustered categories is visualised. Cross-training affected classification accuracies ($F_{(2,18)}=4.86$, $p<.05$), with higher accuracies for Equal compared to No Overlap ($p<.05$).

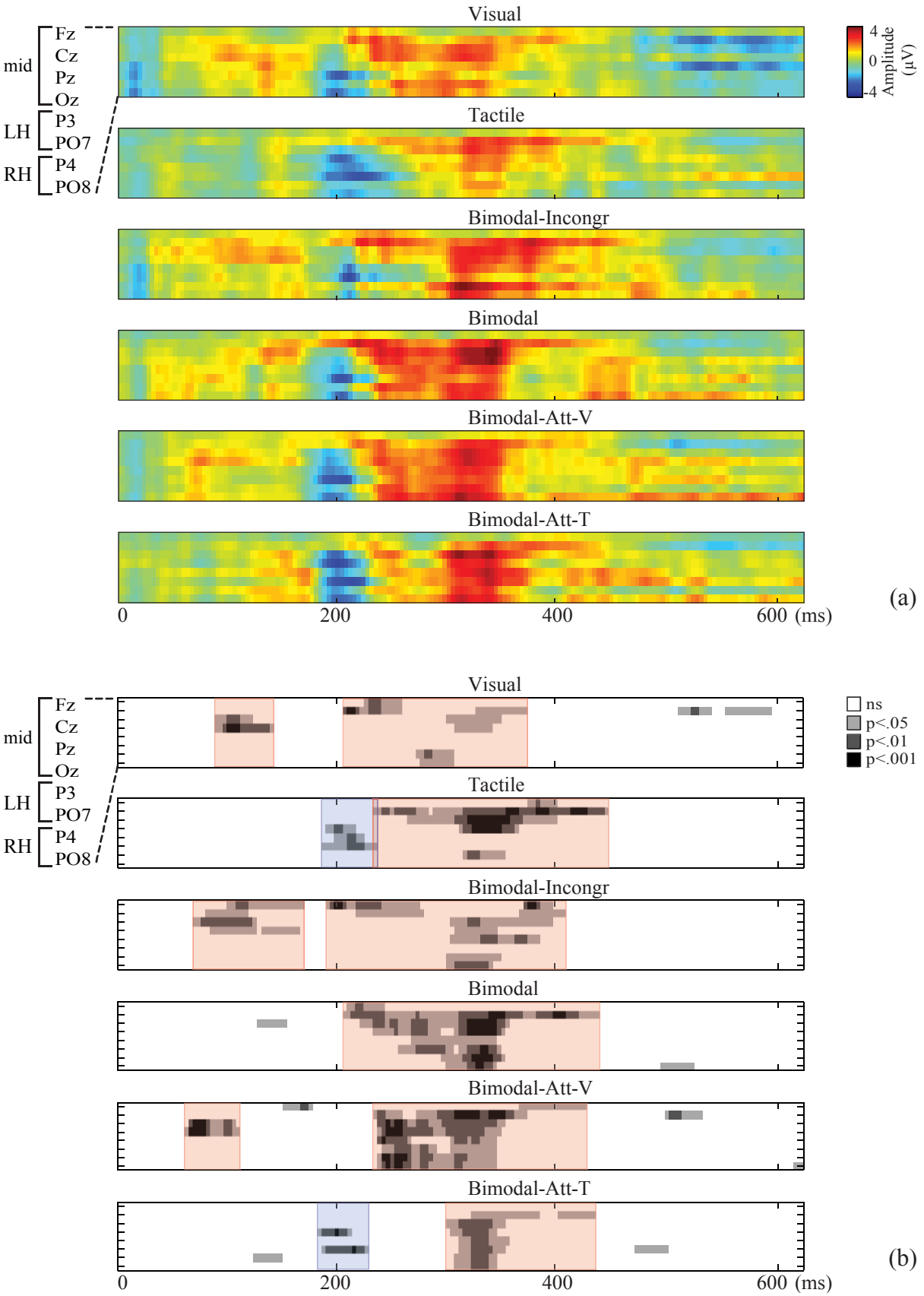

Figure 4.1: Spatiotemporal representations of the endogenous ERP for each condition, with time (ms) on the x-axis and electrodes on the y-axis. Electrodes from top to bottom: Fz, Cz, Pz, Oz, P3, P4, PO7, PO8. (a) The Grand Average of the amplitudes of the endogenous ERP (µV) for each condition. (b) The statistical significance of the endogenous ERP (p-values) resulting in stable segments, clustered in ERP components. ERP components are marked by coloured overlays in red and blue for positive and negative components, respectively.

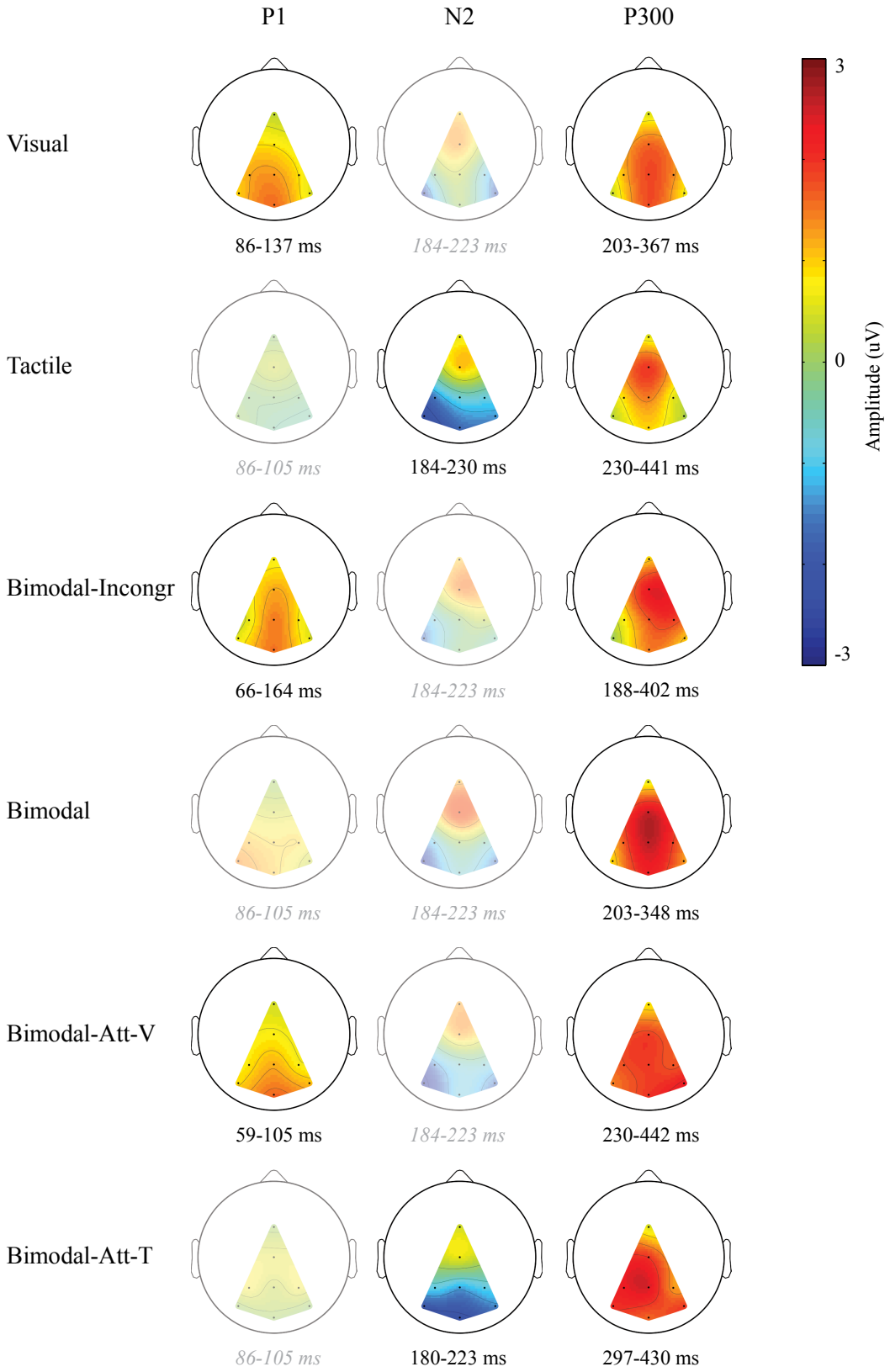

Figure 4.2: Scalp distributions of the endogenous ERP for the identified endogenous ERP components. Only that part of the scalp is visualised, in which electrode information could be interpolated. Amplitudes (µV) are averages calculated within each ERP component's interval, averaged over participants. If no ERP component was identified, the overlapping interval (of the windows of the ERP component for conditions in which it was identified) was used to visualise that activity for comparison. In that case, the scalp plot is left semitransparent, and the corresponding interval is shown in grey and italics.

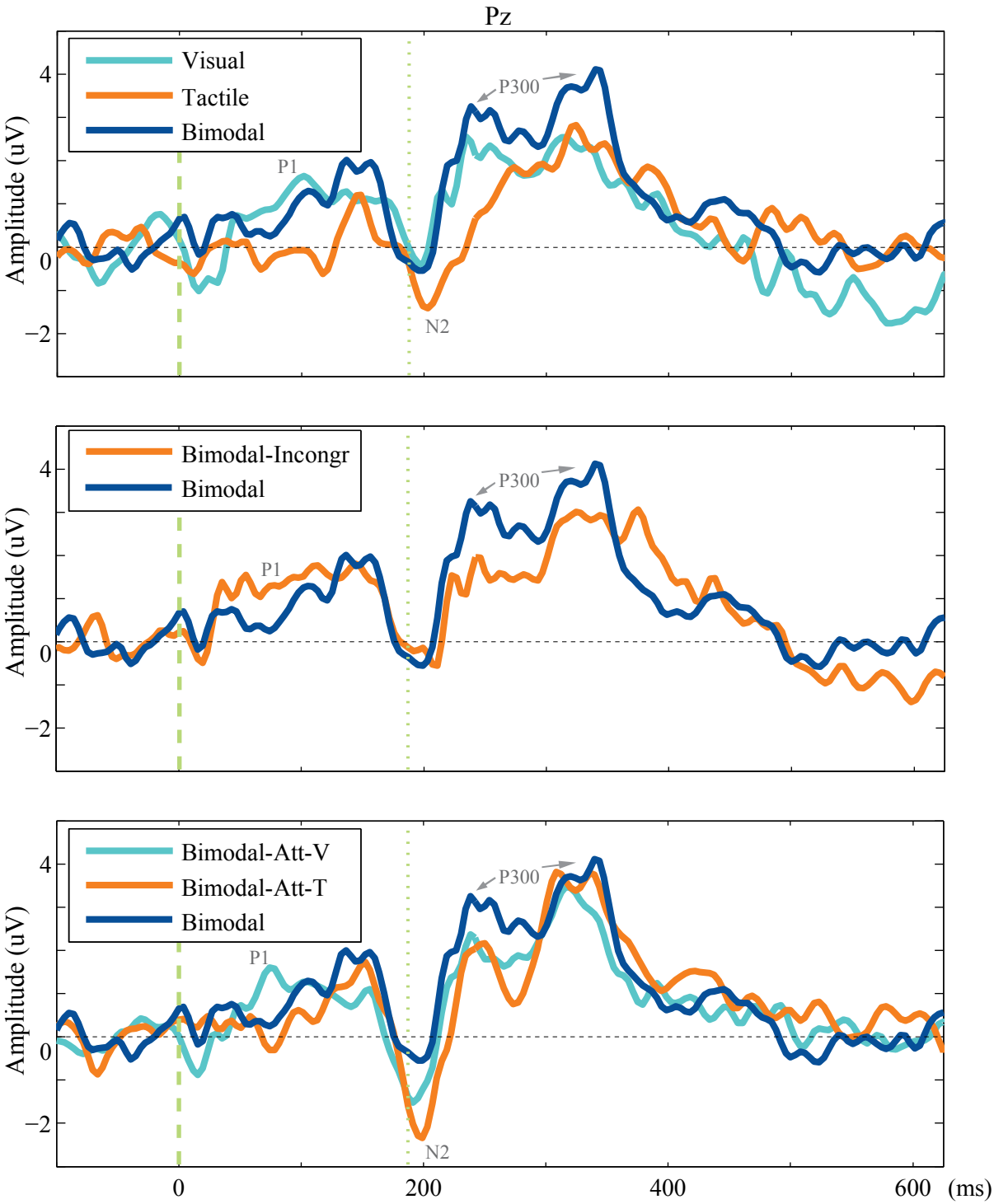

Figure 4.3: Grand average of the endogenous ERP. The averaged endogenous ERP is visualised for electrode Pz for each condition included in the comparison for each research question.

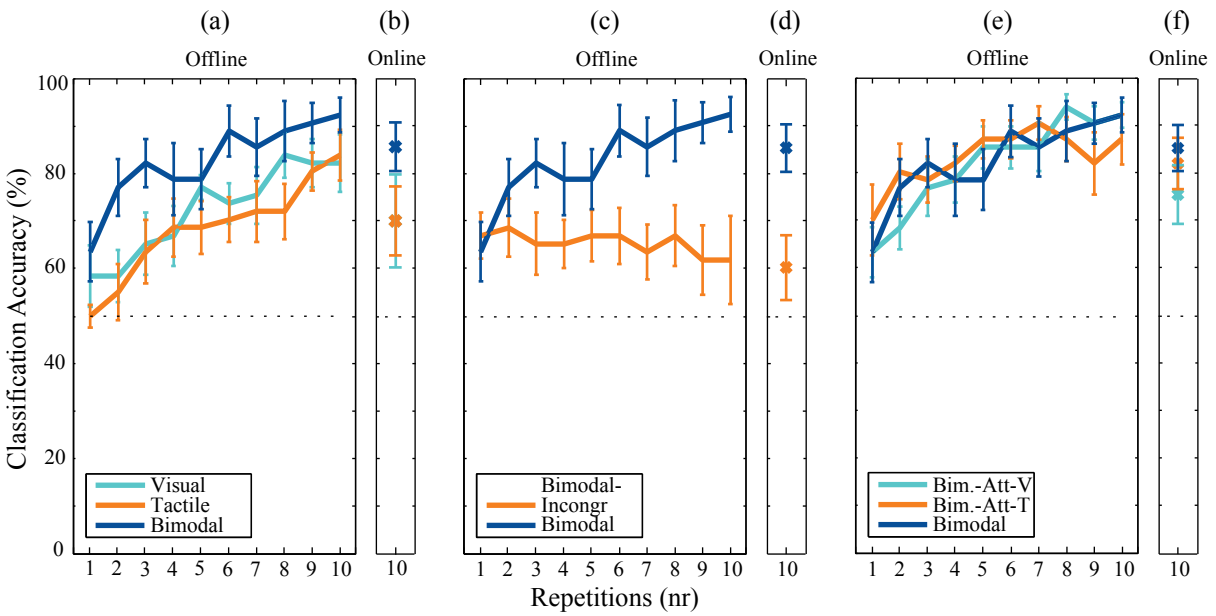

Figure 4.4: Offline and online classification accuracies. (a) Offline and (b) online classification accuracies after each repetition for the conditions involved in the analysis of the first research question (the effect of Bimodality). (c) Offline and (d) online classification accuracies after each repetition for the conditions involved in the analysis of the second research question (the effect of Location Congruency). (e) Offline and (f) online classification accuracies after each repetition for the conditions involved in the analysis of the third research question (the effect of Attending Modality).

ERP component	Visual	Tactile	Bimodal-Incongr	Bimodal	Bimodal-Att-V	Bimodal-Att-T
P1	37,6 *(17,8)*		92,3 *(49,4)*		36,4 *(14,1)*	
N2		56,5 *(27,9)*				44,4 *(22,7)*
P300	168,9 *(63,5)*	237,0 *(73,4)*	351,3 *(140,9)*	526,7 *(223,3)*	534,7 *(125,4)*	265,2 *(168,0)*

Table 4.1: Mean and standard errors averaged over participants of the tAUC-values (µV*ms) of all identified ERP components for each condition.

	Trained on		
Tested on	**Bimodal**	**Bimodal-Att-V**	**Bimodal-Att-T**
Bimodal	83,33 (17,66) *	76,67 (21,08) ^	80,00 (18,92) ^
Bimodal-Att-V	81,67 (12,30) ^	85,00 (14,59) *	73,33 (14,05) #
Bimodal-Att-T	76,67 (17,92) ^	71,67 (26,12) #	86,67 (13,15) *

Table 4.2: Classification accuracies (averages and standard deviations) for each class of cross-conditional classification. Symbols *^# indicate which classes are categorized together, with * for Equal, ^ for Overlap, and # for No Overlap.

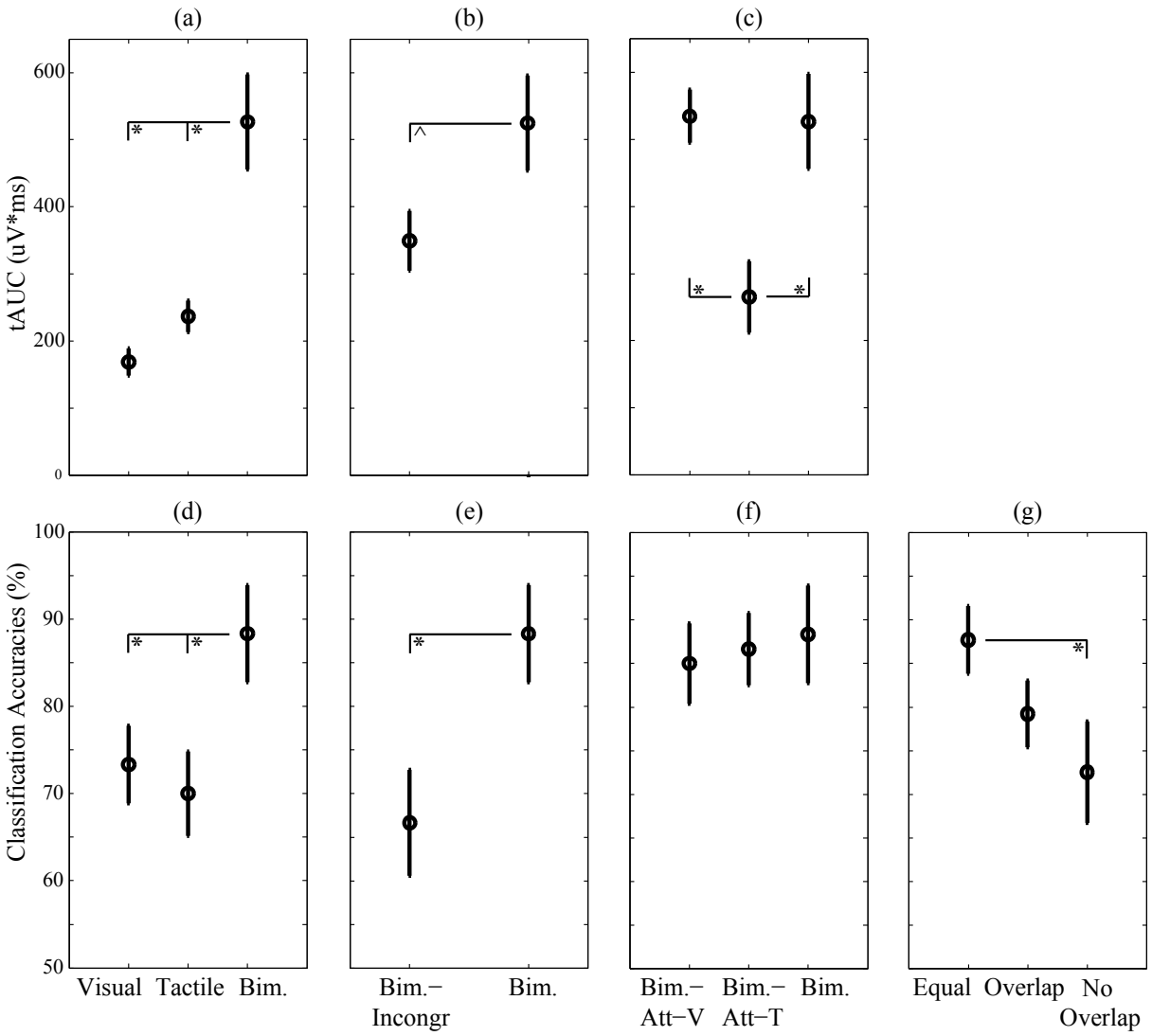

Figure 4.5: Mean and standard errors averaged over participants of the P300 (a-c) and classification accuracies (d-f), for each research question: the effect of modality (a, d), the effect of location-congruency (b, e), and the effect of selective attention to modality (c, f). Condition pairs that significantly differed from each other are indicated by an asterisk (∗) symbol.

4.4. Discussion

4.4.1. Effects of bimodality

The first and main research question addressed in this study was: Are ERP components and corresponding classification accuracies of a bimodal visual-tactile ERP-BCI enhanced compared to its unimodal counterparts? As we hypothesized, we found an enhanced late effect on the ERP (P300) and corresponding enhanced classification accuracies for the location-congruent bimodal compared to the unimodal conditions, using a gaze-independent setup. In our previous bimodal work (Thurlings et al. 2012a), we did not find an enhanced bimodal P300. Instead, the bimodal P300 was even decreased compared to the visual P300. We hypothesized that effect to be a result of location-incongruent bimodal stimuli, as the P300 is affected by spatial attention (Kramer et al. 1988). In this study, we showed that attending to (location-congruent) bimodal (compared to unimodal) stimuli does indeed result in enhancement of the P300. The different findings in these two studies hint that location-

congruency may indeed affect the processing of bimodal stimuli, which we will further discuss in the next section (4.4.2).

In contrast to our expectations, we did not find positive effects of attending bimodal stimuli on the early stage of processing. In fact, we did not detect an early bimodal ERP component at all for location-congruent stimuli when both modalities were attended. However we did observe early ERP components for both unimodal conditions: a visual P1 and a tactile N2. Because the unimodal conditions resulted in early ERP components with opposite polarities, the lack of a bimodal early ERP component in this study may be explained by counterbalanced activity. In (Thurlings et al. 2012a) we did find a bimodal early ERP component (N1), which was not detected in either of the unimodal conditions. The early ERPs of those unimodal conditions, however, appeared much more alike and already showed a slight negative drift. Also in (Talsma et al. 2005) – in which positive effects of audiovisual stimulus attending on early and late stages of processing are reported- the unimodal early ERPs were quite alike. The same is the case in other bimodal studies (e.g., Gondan et al. 2005; Philippi et al. 2008; Teder-Salejarvi et al. 2005). In multisensory literature there is an on-going debate about whether or not superadded activity is elicited when multisensory integration takes place, and how integration effects can be measured (Barth et al. 1995; Boll et al. 2009; Gondan et al. 2006; Senkowski et al. 2011). Perhaps ERP summation is the driving factor behind enhanced effects of bimodal compared to unimodal ERPs in our study.

If unimodal ERP components need to be alike to elicit bimodal effects usable in BCI, it is relevant to understand why in the current study this was not the case. For the tactile condition the early ERP component (N1) resembles the tactile N2 described in (Thurlings et al. 2012a), but occurred slightly (~25 ms) earlier in this study. The P1 from the visual condition also occurs ~25 ms earlier compared to the visual N2 in (Thurlings et al. 2012a), but has a reversed polarity. Possibly, these visual early components do have the same generator: The polarity of the P1 can be reversed if the concerning electrode is measured in reference to for example the nose instead of linked-mastoids (Chiappa et al. 1997). Indeed in this study linked-mastoid references were used (with which a visual P1 is expected: Mangun 1995) while in (Thurlings et al. 2012a) a nose-reference was used. Not every ERP component has to be affected by such a difference: depending on the generator of a certain ERP component and the recorded electrode(s) this can affect polarity.

Bimodal stimuli may have increased exogenous as well as endogenous attention. Therefore the cause of the bimodality effect here could theoretically be either bottom-up, or top-down driven, or by an interaction between the two. In this study Bimodality affected the ERP positively at the late stage. Since Hopfinger and West (2006) found the P300 to be unaffected by increased exogenous attention, we think that top-down controlled endogenous attention may play a role in the Bimodality effect. While this study does not map out the exact mechanism behind the effect, it is clear that BCI performance was much higher when congruent bimodal stimuli were used compared to unimodal stimuli. We therewith provide a way to improve performance of a gaze-independent ERP-BCI.

4.4.2. Effects of location congruency

The second research question concerned the effect of location-congruent compared to location-incongruent bimodal stimuli on the ERP and corresponding classification accuracies in an ERP-BCI. As we hypothesized, we found an indication that location-congruency positively affects the late ERP in response to bimodal stimuli ($p=.056$), and this trend corresponded to increased classification accuracies.

Although we only expected location-congruency to influence the late stage of the ERP, we also found a difference at the early stage: A P1 was observed for the Bimodal-Incongr condition, whereas we did not detect early ERP components for the Bimodal condition at all. This P1 resembles the P1 from the conditions in which the visual modality was relevant (Visual and Bimodal-Att-V). Therefore the occurrence of the P1 in the Bimodal-Incongr condition could be due to (more intense) attending to the visual modality. Although for that condition, participants were instructed to attend both modalities equally, the task may have been too difficult as the locations of the visual and tactile parts of the bimodal incongruent stimuli were rather far apart, and even in opposite hemifields. This could have caused participants to attend more to one of the modalities, in this case, the visual modality. The P1 seems even stronger in the Bimodal-Incongr compared to the Visual condition and compared to the Bimodal-Att-V condition, suggesting that in the Bimodal-Incongr condition participants tried to focus even more on the visual part of the stimulus to not have themselves distracted by the tactile stimulus.

BCI performance was clearly affected by location-congruency. Therefore bimodal BCIs (based on spatial attention) should be based on location-congruent bimodal stimuli for optimal performance. The performance drop caused by location-incongruent bimodal stimuli is expected to depend on the degree of incongruency.

4.4.3. Effects of selective attention to modality

The third research question was does, and if so how does, attending to the visual or tactile modality, or both modalities affect ERP components and corresponding classification accuracies in a bimodal ERP-BCI? We hypothesized a positive effect on the late ERP when both modalities of bimodal (location-congruent) stimuli were attended rather than just one. Indeed attending to both modalities resulted in a stronger P300 compared to attending to the tactile modality alone, but it was equally strong as attending to the visual modality alone. Possibly, and in line with our interpretation of effects on the P1 as discussed in the previous section, (processing of) the visual stimulus was dominant over (processing of) the tactile stimulus.

Selectively attending modality also had an effect on the early ERP. When the visual modality was attended in a bimodal BCI, a P1 was detected, similar as in the visual BCI. Likewise, when the tactile modality was attended in a bimodal BCI, an N2 was detected, similar as for the tactile BCI. Thus, these early ERP effects appear unrelated to multisensory interaction and solely explainable by unisensory bottom-up effects of stimulus processing at attended locations and within attended modalities.

BCI performance was equally good for the three bimodal attention conditions. This means that users can choose a preferred modality to attend to for operating a bimodal BCI when training and classifying occurs using the same attended modalities (attended modality specific classifier). We additionally assessed the effect of switching the attended modality during BCI operation by cross-classifying each one of the three bimodal attention conditions. The results indicate that when the attended modalities are different during bimodal BCI operation and training of the bimodal classifier (attended modality cross classifier), this causes a drop in BCI performance. The size of this drop depends on the degree of overlap in the attended modalities. However, even if there is no overlap, operation of the bimodal BCI is still feasible and performance is similar to that of unimodal BCIs. That means that bimodal BCIs offer the option to be used flexibly, i.e., users can switch the modality to attend to during operation.

4.5. Conclusion

Multisensory effects can be used to enhance BCI performance by employing bimodal stimuli. In this study we investigated bimodal effects in gaze-independent ERP-BCIs, using visual-tactile stimuli. The P300 and corresponding classification accuracies were enhanced when participants were attending to (location-congruent) bimodal versus unimodal stimuli. Unexpectedly, we did not observe early bimodal effects for the specific condition where stimuli were location-congruent and both modalities were attended. This is possibly due to reversed polarities of early unimodal ERP components. We suggest that bimodal BCI performance may further be improved when the early unimodal ERP components are more similar, which may be achieved with different locations of the EEG reference electrode.

Furthermore, bimodal classification accuracies were improved when bimodal stimuli were location-congruent. Thus bimodal BCIs should be designed location-congruent for optimal performance.

Additionally, BCI performance was invariant for the specific modality attended, although the underlying ERP components were affected. When the bimodal classifier was not trained for the specific modality attended, the drop in BCI performance depends on the degree of overlap in attended modalities between training and classifying, but was still at least as good as for the unimodal ERP-BCIs. Thus bimodal BCIs may increase BCI performance and offer more flexibility in use.

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5

Control-Display Mapping in Brain-Computer Interfaces

***Abstract*—**Event-Related Potential (ERP) based Brain-Computer Interfaces (BCIs) employ differences in brain responses to attended and ignored stimuli. When using a tactile ERP-BCI for navigation, mapping is required between navigation directions on a visual display and unambiguously corresponding tactile stimuli (tactors) from a tactile control device: control-display mapping (CDM). We investigated the effect of congruent (both display and control horizontal or both vertical) and incongruent (vertical display, horizontal control) CDMs on task performance, the ERP and potential BCI performance. Ten participants attended to a target (determined via CDM), in a stream of sequentially vibrating tactors. We show that congruent CDM yields best task performance, enhanced the P300 and results in increased estimated BCI performance. This suggests a reduced availability of attentional resources when operating an ERP-BCI with incongruent CDM. Additionally, we found an enhanced N2 for incongruent CDM, which indicates a conflict between visual display and tactile control orientations.

Index Terms: BCI, ERP, CDM, congruency, mapping, conflict, attention, P300, N2, interface, navigation

This chapter is based on:

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5.1. Introduction

5.1.1. Event-Related Potential based Brain-Computer Interfaces

With a Brain-Computer Interface (BCI), people can control a system with their brain signals. In Event-Related Potential (ERP) based BCIs, each option (e.g. the command 'left' or 'right') is coupled to a stimulus (e.g., a left or right pointing arrow on a display). Users can select an option by attending to the related stimulus (*target*) while ignoring other stimuli (*nontargets*), in a sequence of randomly presented stimuli. Attending to and ignoring of stimuli elicits different brain responses, time-locked to the onset of a stimulus, and can be measured with ElectroEncephaloGraphy (EEG). These positive and negative deflections in the EEG can be categorised in different ERP components. The P300 ERP component for example, is of special interest to BCI-researchers, because of its sensitivity to *endogenous* (voluntary) attention: it is stronger for targets than nontargets and occurs after approximately 300 ms after stimulus onset (e.g., Farwell and Donchin 1988). Other ERP components are for example the N1 and N2 and are early negative deflections related to the (perceptual) processing of sensory information (e.g., Hillyard and Kutas 1983; Brandeis and Lehmann 1986). Such differences in brain activity for targets and nontargets are discriminated in a BCI and translated into a command.

ERP-BCIs are only one class of BCIs, yet a substantial one. This type of BCIs is suitable for allowing users to voluntarily and actively control a system as is necessary for tasks like communication or navigation. Besides active control, Human Computer-Interaction may also benefit from passively (no additional user effort) evoked brain signals, as discussed by Zander and Kothe (2011) in state monitoring of for example; affective states (Mühl and Heylen 2009), noise perception (Porbadnigk et al. 2010), error detection (Blankertz et al. 2003; Ferrez and del Millan 2008; Lehne et al. 2009; Schmidt et al. 2011) and the preparation of movement (Blankertz et al. 2003; Haufe et al. 2011; Zander et al. 2011).

The current active ERP-BCIs have already evident benefits for people with severe paralysis. Nevertheless BCIs could become interesting to a large user population, due to the possibility of muscle-independent and concealed interaction. A potential application area is gaming (Nijholt et al. 2009; Muhl et al. 2010), but for this purpose the BCI should be operable without extensive user-training. Future research might lead to the development of BCIs for active control tasks without conscious active user effort, as discussed by Thurlings et al. (2010). This criterion holds for ERP-BCIs but not for an alternative class of BCIs related to actively performing mental tasks like motor imagery (MI; Pfurtscheller et al. 2006). Guger et al. (2009) showed that 89% of a large group of participants achieved effective ERP-BCI-control, which was more than four times higher as with a MI-BCI (Guger et al. 2003).

Most ERP-BCIs use visual stimuli to present the user with options (e.g., Farwell and Donchin 1988). The drawback of visual ERP-BCIs is that the effectiveness of these systems depends to a large extent on the ability of users to gaze at the visual stimuli (Brunner et al. 2010; Thurlings et al. 2010; Treder and Blankertz 2010), which is not for all users (e.g. due to paralysis) or applications (e.g. in gaming, gaze might be required elsewhere) appropriate. Therefore novel approaches are taken to apply covert visual spatial attention in BCIs in general (Allison et al. 2008; Bahramisharif et al. 2010), and more specifically in order to realise gaze-independent visual-based ERP-BCIs (Acqualagna et al. 2011; Liu et al. 2011; Treder et al. 2011b). In addition, interest has grown in employing alternative sensory modalities like audition (Nijboer et al. 2008; Hohne et al. 2010; Schreuder et al 2010). However, in many situations (e.g., in gaming, driving, flying), both the visual and auditory sensory channels are already heavily loaded (Van Erp and Van Veen, 2004), but recent

research has shown that tactile stimuli may also be a viable alternative. Brouwer and Van Erp (2010) demonstrated the feasibility of employing tactile stimuli (*tactors*) around the waist in a tactile ERP-BCI (see also: Brouwer et al. 2010). Tactors around the waist correspond naturally with navigation directions around us (Van Erp 2005), which makes a tactile ERP-BCI especially interesting for navigation applications.

5.1.2. Control-Display Mapping in BCI

Like other interfaces, a tactile ERP-BCI includes a *control* and a *display* device and requires an effective control-display mapping (CDM). For navigation, the display is the device that presents a visual environment and from which users extract navigation information. The control is the device that consists of tactors, each corresponding to possible navigation choices. In such a setup, the user determines the target direction on the visual display and maps this onto the corresponding target from the tactile control.

The roots of CDM research trace back to the work of Fitts and colleagues in the 50's (Fitts and Seeger 1953; Fitts and Deininger 1954). A higher similarity between control and display, in terms of both spatial and nonspatial factors, results in a higher performance in time critical visuo-perceptual motor tasks: faster response times (Zupanc et al. 2007; Chan and Chan 2011) and fewer errors (Zupanc et al. 2007) and more efficient task completion (Phillips et al. 2005). It might also lead to faster learning and a lower mental workload (Wickens 1987) and increased user satisfaction (Tlauka 2004). Basic spatial rules to optimise CDM are that control and display should be parallel and in the same direction in some inertial frame of reference (Worringham and Beringer 1998), here referred to as *congruent* CDM. Training of a specific *incongruent* CDM can improve task performance, but a negative effect remains even after extended practice (Dutta and Proctor 1992).

5.1.3. Possible effects of CDM congruency within a BCI on task performance

We are interested in the effect of CDM congruency within an ERP-BCI, thus using an attention and not a visuo-perceptual motor task. In the tactile ERP-BCI as described by Brouwer and Van Erp (2010), the tactors around the waist were oriented horizontally (parallel to the ground when sitting). For navigation tasks, a visual display presenting the navigation options was added to that setup, and was oriented vertically (perpendicular to the ground). Control and display were thus perpendicular to each other (incongruent CDM), which potentially reduced performance.

Operating a tactile ERP-BCI to navigate consists of two stages. In the first stage, the user maps the target direction on the display onto the corresponding target from the control. We will refer to this stage as the *Target Determination Stage*. This stage is followed by a period of attending to the target and ignoring nontargets, which we refer to as the *Target Attending Stage*. We describe two suppositions how CDM in BCI could affect task performance.

The first supposition is that one might assume CDM takes place only during the Target Determination Stage. This could be because the task of attending to the target in the Target Attending Stage can basically be executed without additional CDM. Similar to effects on response selection in traditional CDM studies (Proctor et al. 2005), incongruent CDM may affect the initial determination of the corresponding tactor, such that a stimulus is erroneously determined as target. This leads to attending to the wrong stimulus in the Target Attending Stage, and thus lower task performance for incongruent CDM.

The second supposition is that CDM does not only affect the Target Determination Stage, but also influences processes during the Target Attending Stage. If for example one would redetermine the target in the latter stage, this would result in a dual-task situation, potentially causing a competition for resources. Because incongruent CDM could lead to a higher level of mental workload (Wickens 1987), it might leave fewer resources available for the target attending task and result in degraded task performance compared to congruent CDM.

5.1.4. Possible effects of CDM congruency in BCI on brain activity

Effects of CDM on task performance are the result of differences in brain activity. If reduced task performance (due to either erroneous target determination and/or a competition of attentional resources due to a dual-task situation) is caused by less attention to the target in the Target Attending Stage, we expect a smaller P300 due to the reverse relation of the P300 and selective spatial attention (Brandeis and Lehmann 1986). Please note that a reduced P300 may negatively affect the operation of a BCI, i.e. BCI performance.

5.1.5. Research questions and hypotheses of this study

In the current study our research questions are:

1. Does CDM affect task performance (counting targets) in a visual-tactile ERP-BCI? And, if so,
2. What are the related differences in electrical brain activity (ERP components)?

Additionally, we endeavour to relate the possible effects of CDM on ERPs to BCI performance, by analysing offline classification accuracies.

Our hypotheses are that determination of and attending to targets in an ERP-BCI using congruent compared to incongruent CDM will result in better task performance, an enhanced P300 and better BCI performance. We hypothesise these results due to a more effective mapping in the Target Determination Stage and possibly due to more available attentional resources in the Target Attending Stage because of easier target redetermination.

5.2. Method

5.2.1. Participants

Ten volunteers (seven men and three women, M_{age}= 29.1 years, age range: 23-39 years), participated in this study. Two of them had participated in a tactile ERP-BCI experiment before. All participants had normal or corrected-to-normal vision.

5.2.2. Task

Participants looked at a screen (see Figure 5.1a) that was divided into hexagons. One hexagon was approximately 3.5 degrees of visual angle in size. Participants navigated a blue disc (representing the participant's position) along a route, visualised by lighter coloured hexagons. The direction from the blue disc to the next hexagon on the route was the target

direction (forward-right in Figure 5.1a). The other directions were the five nontarget directions. Each direction corresponded with a tactor in the tactile control. The six tactors vibrated sequentially. The participant's tasks were to determine the target navigation direction on the visual display, to map this direction to the corresponding target in the tactile control (Target Determination Stage), to pay attention to the target tactor, to count the number of times it was presented and to report the counted number at the end of each step by means of a keyboard (Target Attending Stage). We used the reported numbers as a measure for task performance.

5.2.3. Design

All participants completed the experiment consisting of three conditions, varying in orientations of control and display and thus in CDM (see Figure 5.1b). One condition included the evident (in correspondence with a typical PC setup) display and control orientations, which is a vertical visual display and horizontal tactile control, i.e. incongruence in orientations. Correspondingly, the condition is named: Incongruent. The other two conditions were based on the congruent alternatives of the incongruent setup; visual-display and tactile-control both either horizontal or vertical, named Congruent-Horizontal and Congruent-Vertical respectively. The conditions were recorded in two sessions following after another, and within each session offered in random order.

In each recording, participants were required to follow a route consisting of 18 navigation steps, back and forth over a path of 10 hexagons. We designed routes such that all directions were balanced, and the participants were presented with a different, randomly selected route for each recording. Each of the 18 steps in a route consisted of 10 consecutive sequences of vibrating tactors, i.e. 10 *repetitions*. In one repetition each of the six tactors vibrated once in random order, with the constraint that two target tactors of consecutive repetitions were activated with at least one nontarget tactor in between. Such a setup is typical for ERP-BCIs, and allows an (offline) investigation of the amount of data necessary for robust BCI performance. However, to reliably measure task performance (i.e. the counted number of targets), the number of presented targets for each step should be varied. Therefore, within each step, one dummy sequence of six vibrating tactors was added before, and one after the ten actual repetitions. In a dummy sequence zero to three targets could occur, but also with at least one nontarget tactor in between two target tactors. Thus the number of target tactors within one step varied between 10 (from the 10 repetitions) and 16. The EEG data recorded during the dummy sequences were not used in the analysis.

The participant's position was represented by a blue disc in the centre of a hexagon. At the end of each step, after the participant reported the counted number of target tactors, the blue disc automatically went to the next hexagon on the route as long as the final hexagon was not yet reached. A period of approximately 2.5 seconds during which the disk moved and subsequently a brief pause, was used by participants to interpret the next target direction and map this onto the corresponding tactor. See Figure 5.1 for an overview of the experimental design.

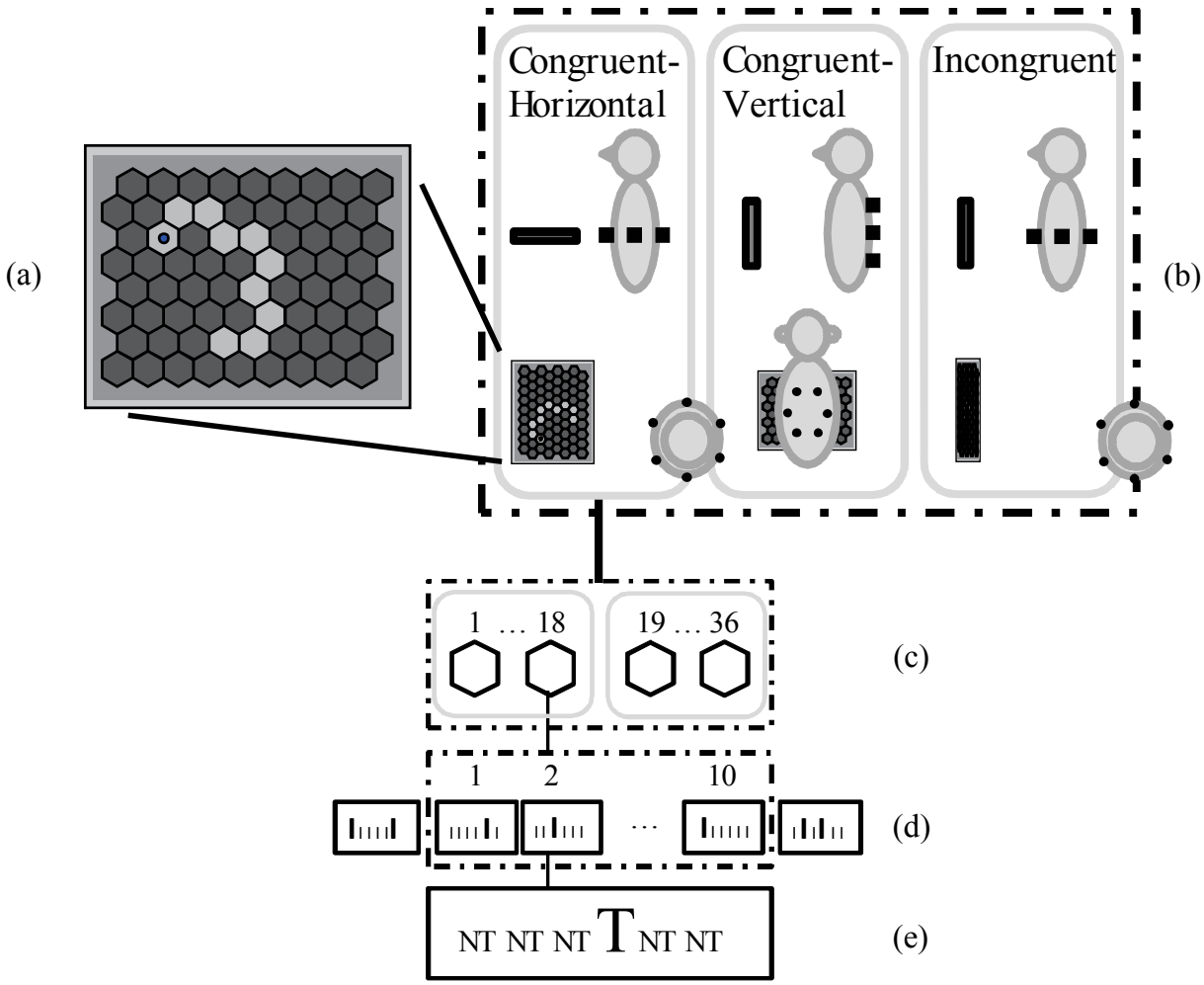

Figure 5.1: Overview of the experimental setup. (a) The path (lighter coloured hexagons) and current location (blue disk) as presented on the visual display. Participants navigated back and forth on the path, by interpreting their current target direction, mapping this direction onto the tactile control on the torso and selecting the target tactor by attending to it and ignoring the other five tactors (nontargets). (b) Overview of the three experimental conditions and the corresponding configurations from the visual-display and tactile-control. Top: Side-view. Bottom: from left to right; top-view, rear-view, top-view. (c) One condition consisted of two recordings, each presenting a different route. A route required 18 navigation steps, going back-and-forth over a path of 10 hexagons, with balanced navigation directions. (d) Each step consisted of 10 repetitions (i.e., related EEG was analysed) and two dummy sequences of stimuli with the purpose to vary the number of targets that had to be counted in each step. (e) Each repetition contained five nontargets and one target.

5.2.4. Materials

Tactile Control

Participants wore an adjustable vest with integrated tactors. The tactors were custom built and consisted of a plastic case with a contact area of 1x2 cm, containing a 160Hz electromotor (TNO, The Netherlands, model JHJ-3; Van Erp et al. 2007). To prevent participants from perceiving auditory information from the tactors, they listened to pink noise via in-ear headphones during the experimental conditions.

For this study the tactors were arranged in groups of two at six locations in a circle-layout, either in a horizontal plane (around the torso at approximately navel-height), or in a vertical plane (on the back) (see Figure 5.1b). The vertical tactor plane was chosen at the back,

because of more anatomical similarity and convenience for both male and female participants. The locations of the tactors corresponded with the navigation directions of the task: left and right, and two directions in between at both the frontal and back side (see Figure 5.1a). The tactors vibrated for 200 ms followed by an off-time of 120 ms.

Visual Display

Routes were presented on a Samsung 19" TFT monitor (1280 × 1024, 60 Hz) which was positioned either horizontally (flat on a table) or vertically (standard monitor position) at a viewing distance of approximately 50 cm.

EEG recording equipment

EEG was recorded from 60 nose-referenced scalp electrodes that used a common forehead ground (Brain Products GmbH, Germany). The impedance of each electrode was below 20 kΩ, as was confirmed prior to and repeatedly during the measurements. EEG data was recorded with a sampling frequency of 1000 Hz and subsequently bandpass filtered. The cut-off frequencies were set to 0.05 and 200 Hz.

5.2.5. Data analysis

EEG, task and BCI performance analysis was done using Matlab 2007b (The Mathworks, Natick, USA).

EEG preprocessing

To prepare the recorded EEG for further processing, the data was sampled with a sampling frequency of 100 Hz and bandpass filtered with cut-off frequencies of 0.5 and 30 Hz (function 'eegfilt' from EEGLAB v6.03b [Delorme and Makeig 2004]). Such a filter reduces influences from artefacts like eye blinks (e.g., Guger et al. 2009; Tereshchenko et al. 2009). We are interested in clean effects of endogenous (voluntary) attention on EEG, and attempted to isolate such effects in the EEG. To this end we maintained two strict rejection criteria, and applied a final preprocessing method to isolate endogenous effects. These methodological techniques are described next.

The first rejection criterion was that EEG data was not further analysed for effects on the ERP, if it was expected to be contaminated by previous or following target responses, relative to a stimulus response of current interest. To this end, we only selected EEG data associated to (non)targets when the three preceding and the three following presented stimuli were nontargets, i.e. there were no (other) target responses between -960 and 1280 ms relative to (non)target-onset. A similar approach was taken by Treder and Blankertz (2010). Please note that such a filter is a non-causal filter, because it depends on future inputs. This is valid for obtaining 'clean' data for interpretation of cognitive processes from ERP components, and for training of a classifier (see section 'Offline classification analysis'), but not for the data entered during the actual classification. Therefore this filter was explicitly not applied to the classification test-data (see section 'Offline classification analysis'). For these selected (non)targets, epochs from all electrodes were extracted from -320 to 1280 ms relative to stimulus onset. For each electrode, this resulted in a total number of target- and nontarget-epochs per condition, averaged over participants: $M_{\text{target-epochs}}$=243.7 (range 227.0-263.0) and

$M_{\text{nontarget-epochs}}$=193.0 (range 166.0-214.0). The epochs were baseline corrected relative to the average voltage during the 320 ms preceding the stimulus-onset.

With the second rejection criterion, we aimed at rejecting EEG data that contained artefacts. Artefacts can have a local (e.g. because of a broken electrode, or bad connection with the skin), or a global (e.g. due to eye blinks or other movements) effect. The safest would be to reject all epochs if *any* type of artefact is detected. However, in this study this would result in the rejection of too much data and a highly varying usable amount of data over participants[1]. Because global artefacts that can be time-locked to the onset of target presentations are the most problematic for the ERP, we applied a global threshold criterion to minimise the influence of such global and time-locked artefacts on the ERP. Therefore all electrodes were rejected if the epochs at both frontal electrodes (Fp_1 and Fp_2) contained amplitude differences that exceeded the threshold of 100 μV.[2] Finally, a number of selected (non)target-epochs remained, with similar means and ranges over participants for all conditions amounting to: $M_{\text{target-epochs sel.}}$= 212.9 (range 88.0-260.0) selected target-epochs and $M_{\text{nontarget-epochs sel.}}$= 174.5 (range 112.0-209.0) selected nontarget-epochs. Subsequently, these selected target and nontarget-epochs were averaged per participant, per condition and per electrode.

The final preprocessing technique was aimed at the isolation of endogenous attention effects in the EEG. This implied the removal of exogenous (involuntary or automatic) attention effects; we subtracted the averaged clean nontarget-epochs from the averaged clean target-epochs, for each participant, each condition and each electrode. We further analysed this difference ERP to identify endogenous ERP components.

Identifying elicited endogenous ERP components

We aimed to identify all endogenous attention ERP components occurring in the interval until 1280 ms after stimulus-onset. We did this as follows: First we identified significant endogenous effects by performing a sample-by sample t-test (or point-by-point or running t-test) on the difference ERP, for each electrode and condition. To correct for multiple testing the method of Guthrie and Buchwald (1991) was applied (Molholm et al. 2002; Rugg et al. 1995; Vidal et al. 2008). In our case, this implied that (at least) six consecutive samples (equivalent to 60 ms) had to be significantly different from 0 in order to consider the corresponding samples as a stable *segment.* Second, we *clustered* these segments over electrodes in order to label the elicited endogenous ERP components, using the cluster's time-interval, topography and polarity. Segments were clustered based on the beginning and ending of their time periods, and their averaged amplitudes (using the following standard parameters: Euclidean distance, single linkage, and maximum 15 clusters; Webb 2002). Also in this dimension (here not over time, but over electrodes) we corrected for multiple testing with the method of Guthrie and Buchwald (1991). Based on that, clusters were considered robust if they contained segments of at least four electrodes. Robust clusters that had overlapping intervals and comparable averaged amplitudes were assumed to be subcomponents of the same ERP component, and combined. These combined robust clusters defined the topographic distribution and the interval of the endogenous ERP components,

[1] For the data reported in this manuscript, we applied a global rejection threshold criterion. To investigate the influence of local artefacts, we also analysed the data using a local rejection threshold criterion (epochs from single electrodes were rejected if amplitudes within a certain epoch exceeded the threshold) and obtained similar results as presented in this manuscript.

[2] Additionally, we inspected the data of the individual participants for large local artefacts. Data from three electrodes (F_2, F_5, and FC_2) from one participant (out of the data from 60 electrodes from 10 participants) were clearly contaminated with artefacts, and rejected for further analysis.

taking the beginning of the earliest segment and the ending of the latest segment in the clusters as ERP component intervals.

Quantifying and comparing endogenous ERP components

After identifying the elicited endogenous ERP components, we quantified these in order to compare them between conditions. To capture the strength of a local (at a certain electrode site) ERP component regardless of its shape, we used the Area-Under-Curve values (AUC: Allison et al. 1999; Luck 2005; Puce et al. 2007). To also allow topographic distributions of an ERP component as a measure of its magnitude, we determined the sum of AUCs to identify endogenous ERP components in each condition and for each participant: Electrode-specific AUCs were calculated and summed. We will further refer to the sum of topographic distributed AUCs from an ERP component as the *tAUC*. With the tAUC we can describe the magnitude of an ERP component, not only taking the averaged amplitude and duration of the component into account, but also the topographic distribution. Endogenous ERP components with overlapping intervals and equal polarities between conditions were considered to reflect the same ERP component. Associated tAUCs were statistically compared. Note that this measure does not necessarily correspond to discrimination as in BCI classification, since the information of neighbouring electrodes in broadly distributed components is redundant. However, it should correspond to perceptual and cognitive processes.

Offline classification analysis

Classification accuracies were analysed offline with a linear discriminate analysis (LDA), because previous BCI research showed good results with this simple method (Krusienski et al. 2008; Blankertz et al. 2011; Zander et al. 2011). We applied a stepwise LDA (SWLDA) with similar parameter settings as in (Krusienski et al. 2008); maximum of 60 features employed in the model, p-value of $<.1$ for features included in the model initially, and p-value of $>.15$ for features removed from the model backwards. The training set was based on the first half of the recorded data from each participant and each condition, and followed similar preprocessing steps as described for the ERP analysis. In contrast, all recorded repetitions were included in the test set (thus neither the threshold rejection criterion nor the rejection of epochs including overlap of target responses criterion was applied to the test data), in order to realistically assess potential online classification performance.

Although SWLDA includes automatic feature selection, it has been shown previously that a reduction of features prior to this procedure, may improve results (Krusienski et al. 2008). Here we do so by comparing different windows and different electrode-sets, so that recommendations can be made for when such extended electrode-recording is not desirable. The windows either include all major ERP components starting from stimulus onset until the P300 or only the P300, and correspond respectively with: 0-750 ms (window 1) and 320-750 ms (window 2). The electrode sets are general sets of electrodes, ranging from 3-60 electrodes, and correspond to the topographic distribution of the major tactile ERP components, and are: Fz, Cz, Pz (set A); $F_{3/4}$, $C_{3/4}$, $P_{3/4}$ (set B); set A and B, and $O_{1/2}$ (set C); and all electrodes (set D).

To evaluate the appropriate parameters concerning window and electrode set, we calculated classification accuracies based on the average of 10 test repetitions, for each combination of window and electrode set. Additionally, we performed an extended offline classification analysis, using the most promising combination of window and electrode set. To this end we

investigated as well the effect of CDM as the number of repetitions for averaging over test repetitions (1-10).

Counting accuracy

The measure of task performance was prepared for statistical analysis, by determining the counting accuracies as the percentage of steps in which the number of targets was counted correctly, for each participant and each condition.

Statistical analysis

Counting accuracy, the tAUC-values of each endogenous ERP component, and classification accuracies were statistically analysed with Statistica 8.0 (StatSoft, Tulsa, USA). We used one-way repeated measures ANOVA with CDM (3 levels) as the independent variable for analysis of counting accuracies and ERP components (or paired t-tests if suitable). For analysis of classification accuracies, a two-way repeated measures ANOVA was applied, with number of repetitions as the second independent variable. Post-hoc analysis was applied using Tukey tests when appropriate.

5.2.6. Procedure

We helped participants into the tactile vest and seated them in front of the screen. We checked for tactor saliency by activating the tactors successively and asking the participants for the corresponding directions. If necessary we tightened or relaxed the tactile vest and/ or repositioned one or more of the tactors.

During EEG preparation, we explained the outline of the experiment, and instructed participants to move as little as possible during tactor presentations. Before each recording, we informed the participants about the type of control-display set-up of the current recording. Then participants accustomed themselves to the current location of the tactile control by activating the six tactors themselves, by pushing keys 1-6, for a maximum period of two minutes. When the participants indicated they were ready to begin, we started the recording.

Each recording lasted approximately 10 minutes. Recordings followed each other with 1 to 15 minutes breaks in between, depending on the participants' preferences.

5.3. Results

5.3.1. Task performance

In Figure 5.4b, the percentage of steps in which the number of presented targets was counted correctly is shown for each condition. Counting accuracy was significantly affected by CDM ($F_{(2,\ 18)}=5.02$, $p<.02$). Post-hoc analysis showed that the percentage of correctly counted targets in the incongruent CDM condition was significantly lower than in both congruent CDM conditions ($p<.05$ and $p<.03$ for comparisons with congruent horizontal and vertical, respectively).

5.3.2. Endogenous ERP components

Spatiotemporal presentations of the amplitudes of the difference ERPs are presented in Figure 5.2a. For all CDMs, endogenous activity was found in multiple time windows within the analysed interval from 0 until 1280 ms post stimulus onset. In Figure 5.2b, spatiotemporal plots show all significant segments. The coloured red and blue areas indicate the polarities (positive and negative, respectively) of the clustered segments which were found to be robust, and thus identified as endogenous ERP components. In Figure 5.3a, these ERP components are visualised by means of scalp plots. We will first report the ERP components that were identified in all three conditions and after that report the ERP components that occurred only in one or two conditions.

Three ERP components were identified in all three conditions (means and standard errors are depicted in Figure 5.4c-e). Starting with the P300, the only ERP component for which we had a hypothesis, it centred around 500 ms post-stimulus. It was widespread and had maximal amplitudes at central areas. Besides the P300, also an N2 was found for all CDMs. It centred around 280 ms at temporal-bilateral sites and seemed attenuated at the left hemisphere. The final ERP component that was found for all CDMs was positive and had an onset after 1170 ms with a fronto-central distribution. We will refer to this component as the P1200.

Some ERP components were identified for only one or two CDMs. An N1 was detected for the congruent-vertical and incongruent CDM and peaked around 140 ms with a central-parietal distribution. For the incongruent CDM a negative frontal component around 740 and for the congruent-vertical CDM a positive central component around 920 ms was detected. We will further refer to these components as the N600 and P800 respectively, indicating their approximate onsets.

The identified ERP components are represented by scalp plots in Figure 5.3a. In Figure 5.4a, the mean tAUC-values and standard deviations from all identified ERP components are presented for all CDMs. The results of the statistical analyses are shown in the final column of Figure 5.4a. Post-hoc analysis revealed that the tAUCs of the N2 for congruent-horizontal and congruent-vertical CDMs were smaller than for incongruent CDM ($p<.001$ and $p<.01$ respectively). The P300 was weaker for the incongruent CDM than the congruent-horizontal CDM ($p<.001$) and congruent-vertical CDM ($p<.05$). The P300 from congruent-horizontal CDM was stronger than from congruent-vertical CDM ($p<.001$). The P1200 was stronger for the congruent-vertical CDM than for both the congruent-horizontal and incongruent CDM (both $p<.01$). Similarly, the N1 was also stronger for the congruent-vertical CDM compared to the incongruent CDM ($p<.001$).

5.3.3. Offline Classification Accuracies

In Figure 5.5a, the offline classification accuracies are presented for each combination of electrode set and window, based on the average of 10 test repetitions. Electrode set and window were evaluated separately, using the average of all results: The 11 electrodes of set C and the window concerning a large timeframe (0-750 ms) are associated with overall best averaged results. This combination of parameters also resulted in the highest averaged accuracies found from all conditions: 59.4% (*SD*16.4) for the Congruent-Horizontal condition.

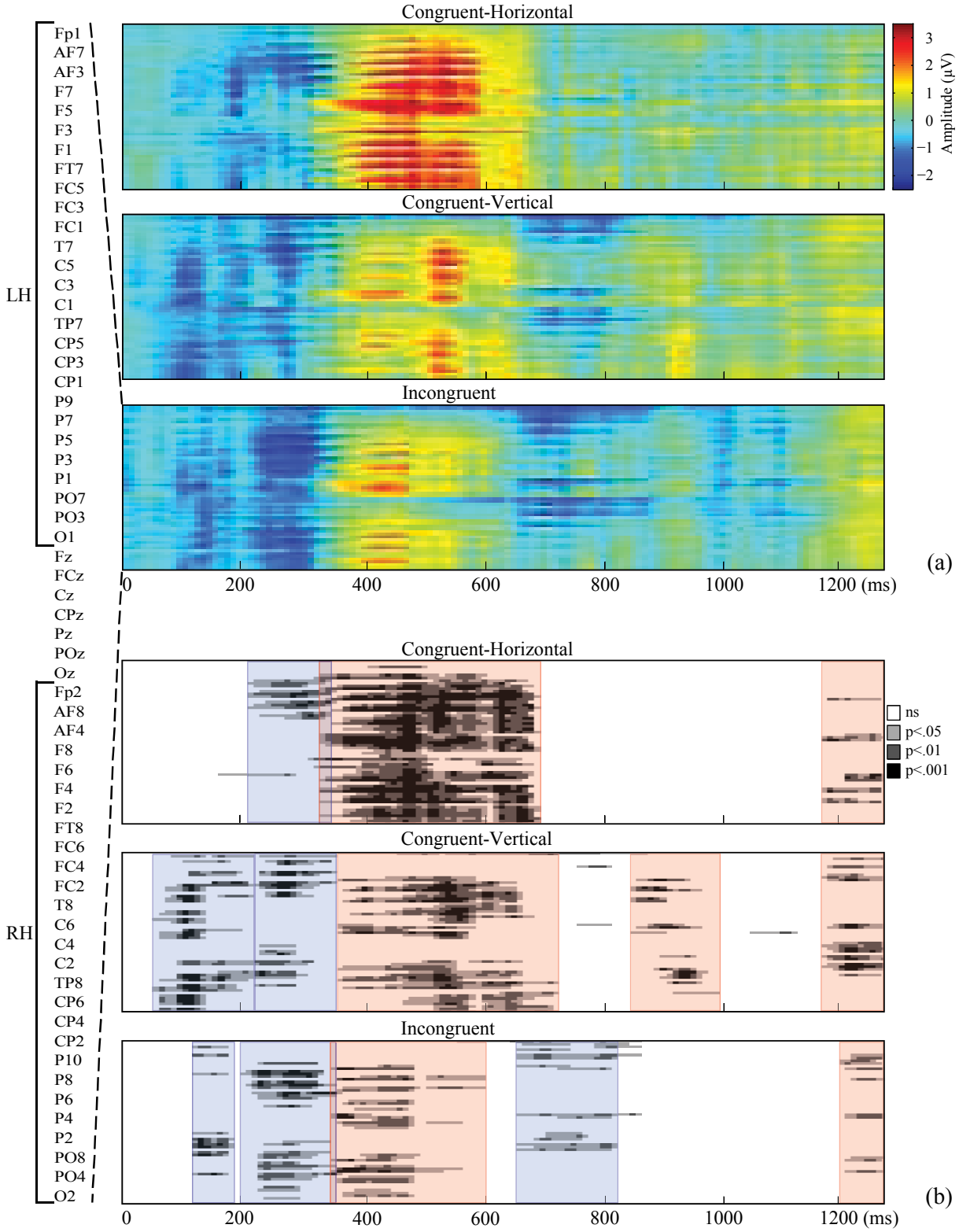

Figure 5.2: Spatiotemporal representations of the difference ERP (based on data from all participants) for each condition, with time (ms) on the x-axis, and electrodes on the y-axis. Electrodes are structured as follows: left hemisphere (LH), midline electrodes, right hemisphere (RH), and substructured with the most frontal electrodes on top and occipital electrodes on the bottom. (a) The Grand Average of the amplitudes of the difference ERP (µV) for each CDM. (b) The statistical significance of the difference ERP from all participants (p-values), resulting in robust segments (i.e., more than 6 consecutive samples of the difference waves significantly differed from zero). The intervals of identified ERP components (i.e., more than four segments within a cluster), are coloured red and blue for positive and negative components respectively.

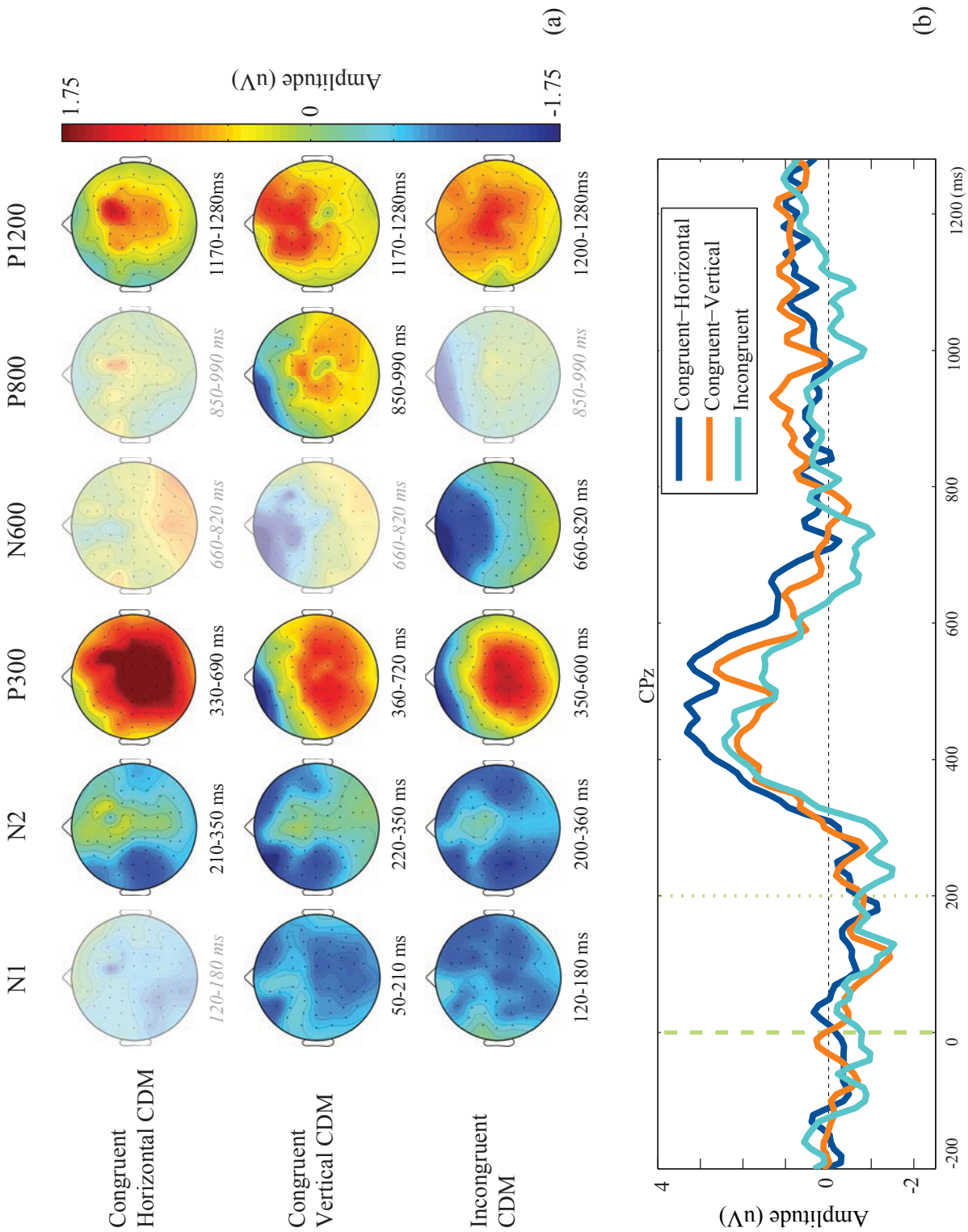

Figure 5.3: (a) Scalp distributions for the identified ERP components (difference ERP). Amplitudes (µV) are averaged within each interval and over all participants for all electrodes. If no ERP component was identified, the corresponding interval was used to visualise that activity for comparison. In that case, the scalp plot is left semi-transparent, and the corresponding interval is shown in grey and italics. For these scalp plots the function 'topoplot' of EEGLAB v6.03b (Delorme and Scott Makeig 2004) was used. (b) The Grand Average of the difference ERP from electrode 'CPz is' visualised for all CDMs.

The classification accuracies of the extended analysis, including the effect of number of repetitions used for averaging, using electrode set C and window 0-750 ms, are presented in Figure 5.5b. Statistical analysis showed a main effect of CDM ($F_{(2,18)}$=4.12, p<.05) and of number of repetitions ($F_{(9,81)}$=28.66, p<.001), but no interaction effect was found. Posthoc analysis revealed higher accuracies for Congruent-Horizontal compared to Incongruent (p<.05). Accuracies were higher for increasing repetition number, but for brevity we only report posthoc results at the 10th repetition, which was significantly higher compared to the first six repetitions (all p's<.05).

(a)

ERP components	Congruent-Horizontal tAUC (µV*ms)	Congruent-Vertical tAUC (µV*ms)	Incongruent tAUC (µV*ms)	Main effect of CDM
N1		310,16 (92,88) *	60,21 (27,48) *	$t_{(9)}$=8,85, p<.001
N2	137,04 (81,38) *	192,19 (73,98) ^	353,42 (175,77) *^	$F_{(2,18)}$=11,62, p<.001
P300	2476,30 (943,56) *	1081,34 (443,35) *	450,04 (233,32) *	$F_{(2,18)}$=47,26, p<.001
N600			136,65 (100,05)	
P800		98,76 (28,36)		
P1200	78,24 (49,27) *^	192,58 (85,16) *	83,65 (40,96) ^	$F_{(2,18)}$=11,64, p<.001

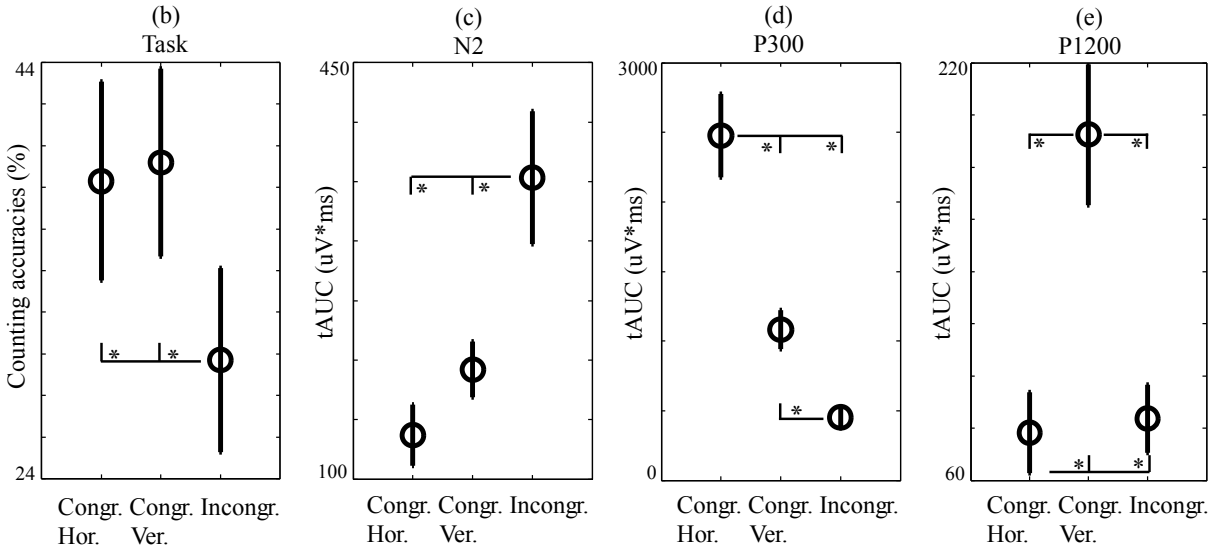

Figure 5.4: Means and standard deviations over all participants of task performance and ERP components for the congruent and incongruent CDMs: Congruent-Horizontal, Congruent-Vertical and Incongruent respectively. Condition-pairs that significantly differed from each other are depicted with an asterisk (*) symbol. (a) Mean tAUCs and standard deviations are presented from all identified ERP components for all CDMs. The results of the one-way repeated measures ANOVA (and paired t-test used for the N1) are depicted in the final column. The symbols * and ^ indicate which condition-pairs significantly differed from each other as shown by post-hoc analysis (b) Results of task performance, i.e., counting accuracies were the percentages of navigation steps in which all targets were counted correctly. (c-e) Results of the magnitudes of endogenous ERP components as reflected with tAUC-values. In these values, the averaged amplitudes and duration per electrode together with the topographic distribution of the components were expressed. In this plot, only the ERP components that were identified for all three CDMs are shown: (c) N2, (d) P300, (e) P1200.

(a)

window	Experimental Condition	Congruent-Horizontal Class.acc. (%)	Congruent-Vertical Class.acc. (%)	Incongruent Class.acc. (%)
0-750 ms	**Electrode Set A (Fz, Cz, Pz)**	55,3 (16,8)	37,8 (15,9)	47,2 (23,3)
	Electrode Set B (F3/4, C3/4, P3/4)	56,7 (18,1)	42,2 (15,1)	40,6 (19,4)
	Electrode Set C (Set A and B, PO7/8)	**63,9 (13,4)**	53,9 (23,0)	**48,9 (23,5)**
	Electrode Set D (All 60 electrodes)	46,1 (14,6)	47,2 (19,6)	38,9 (10,1)
320-750 ms	**Electrode Set A (Fz, Cz, Pz)**	47,8 (18,4)	42,8 (19,6)	38,3 (25,2)
	Electrode Set B (F3/4, C3/4, P3/4)	50,0 (17,6)	46,1 (14,6)	37,2 (21,9)
	Electrode Set C (Set A and B, PO7/8)	52,2 (17,0)	**55,0 (17,1)**	43,3 (18,7)
	Electrode Set D (All 60 electrodes)	51,1 (24,8)	50,0 (23,7)	46,1 (11,7)

(b)

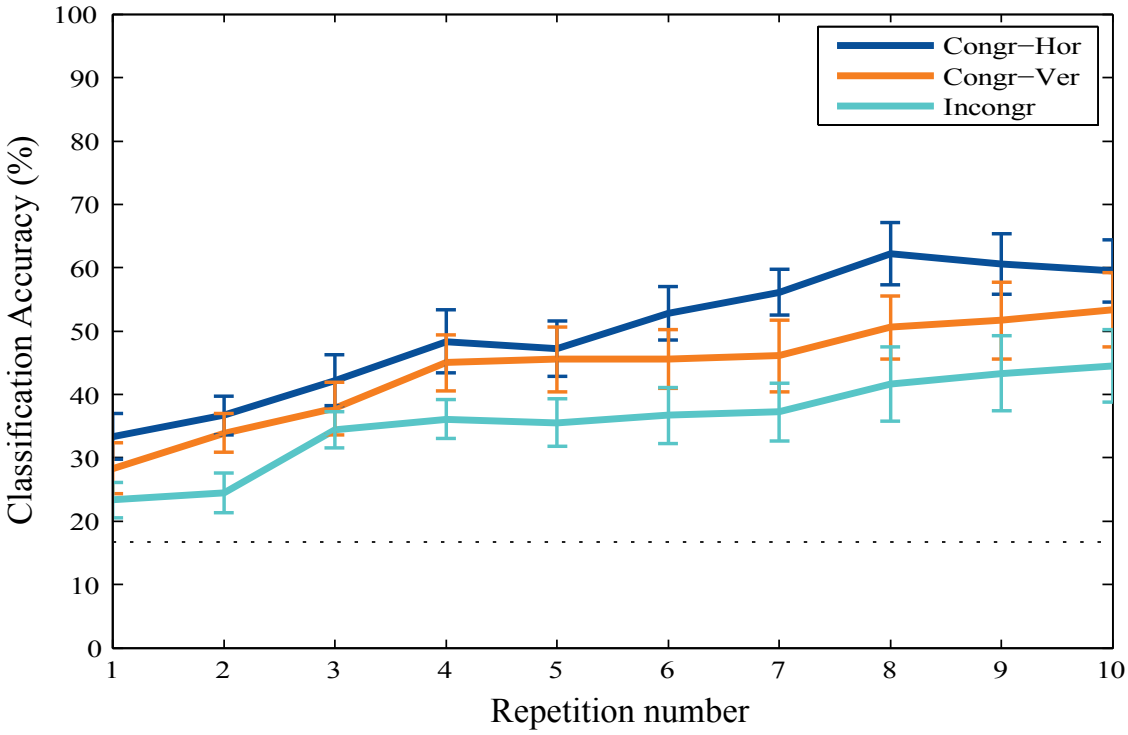

Figure 5.5: Mean classification accuracies and standard deviations over participants, based on SWLDA for all CDMs. (a) Results for multiple combinations of electrode set and window, from which the features were included for training. Accuracies using ten repetitions are presented. (b) Extended analysis using electrode set C (Fz/3/4, Cz/3/4, Pz/3/4, O1/2) and window 1 (0-750 ms), evaluating the effect of repetition number on classification accuracies for each CDM. Mean accuracies over participants and standard errors are plotted.

5.4. Discussion

The results of this study show that incongruence in CDM reduced task performance in a tactile ERP-BCI, confirming the hypothesised answer to our first research question. Correspondingly, we find a decreased P300 ERP for incongruent compared to congruent CDM, which confirms our second hypothesis. This is in line with the offline classification accuracies and thus with predicted BCI performance. The effects on task performance cannot be explained by perceptual differences in tactor characteristics or tactor configuration, because the Congruent-Horizontal and Incongruent conditions employed the same tactor locations.

We discuss the effects of incongruent CDM on task performance and the ERP in the light of the two suppositions offered in the introduction. First, incongruent CDM may yield incorrect target determination and consequently incorrect target attending. Second, incongruent CDM might affect mental processes during the Target Attending Stage, for example related to possible redetermination of the target.

5.4.1. Effect of incongruent CDM during the Target Determination Stage

Task performance

The negative effects of incongruent CDM in the investigated tactile ERP-BCI on task performance (counting accuracies) can be the result of incorrect determinations of targets in the Target Determination Stage. This is in line with the increased errors in task performance for incongruent CDM found by studies involving perceptual-motor tasks (e.g., Zupanc et al. 2007). Similar effects on task performance for both attending and perceptual-motor tasks, confirm effects of CDM specifically on response selection (Proctor et al. 2005; Zhou et al. 2004). This is in line with the first supposition as described in the introduction: CDM seems to affect the Target Determination Stage in a tactile ERP-BCI. However CDM (in)congruence may also influence the Target Attending Stage (second supposition) as we will postulate later.

P300

The most investigated ERP component in ERP-BCIs, the P300, was identified in all three conditions and was the strongest ERP component in this study. It centred around 500 ms, was widespread and had maximal amplitudes at central areas. As we hypothesised, CDM affected P300 magnitude and congruent CDMs result in larger P300 magnitudes than incongruent CDM. The P300 amplitude can be reduced by several cognitive factors, including mental workload in general (Allison and Polich 2008; Kramer et al. 1995), mental rotation (Heil 2002), memory load (Kok 1997) and selective spatial attention (Brandeis and Lehmann 1986). A reduced P300 for incongruent CDM during the Target Attending Stage thus indicates less available attentional resources, possibly directly reflecting incorrect initial target determination.

The results also showed that the P300 differed in magnitude between the two congruent CDMs, which was not reflected in the task performance. More specifically, the P300 was weaker for the Congruent-Vertical condition compared to the Congruent-Horizontal condition. We propose an advantage of horizontal mapping due to navigation experience, which in daily life usually occurs horizontally (e.g., walking, biking, driving). In line with

this hypothesis, initial error rates in a simultaneous 3D tracking task are lowest along the horizontal dimension and corrected sooner, possibly due to attentional prioritising for that dimension as a result of daily experiences with visual horizontal movements (Zhai et al. 1997; Van Erp and Oving 2002)

The effect of CDM on P300 was in line with the effect on BCI performance, while this was different for other ERP components. This indicates that the P300 has the most influence in a tactile ERP-BCI.

Indication for influence of CDM during the Target Attending Stage

If reduced task performance was fully explained by incorrect target determination during the Target Determination Stage one would only expect CDM effects on ERP components during the Target Attending Stage that could be attributed to attentional differences. ERP components are typically enhanced by (spatial) attention, similar as we described attentional effects on the P300. However, the N2 component shows an opposite CDM effect compared to the P300 component: The N2 is enhanced for incongruent CDM compared to both congruent CDMs. This cannot be the result of reduced attention, as the N2 is enhanced by selective (spatial) attention (Wang et al. 2010). Therefore, it seems plausible that incongruent CDM not only affects the Target Determination Stage, but also influences or causes (additional) mental processes during the Target Attending Stage.

5.4.2. Effect of incongruent CDM on mental processes during the Target Attending Stage

CDM effects on mental processes during the Target Attending Stage may be explained by a possible redetermination of the target, related to a higher level of workload for incongruent CDM, resulting in less available attentional resources for target attending during the Target Attending Stage. Furthermore continuous and automatic processing of the navigation display possibly affects mental processes during the Target Attending Stage, as we will discuss hereafter. Next, we will discuss these two possible explanations, starting with the latter one.

Automatic processing of the navigation display

The processing of tactile information is altered when vision is involved (Gillmeister and Forster 2010). Interestingly, if visual task-irrelevant stimuli are presented simultaneously with tactile task-relevant stimuli, participants' responses are slower and less accurate if these are spatially incongruent compared to congruent (Forster and Pavone 2008). Although in our study the visual display can be considered as task-irrelevant during the Target Attending Stage, the incongruent visual-tactile information may have had a similar influence as in the study by Forster and Pavone (2008) and degraded task performance.

This is supported by the elicitation of an N2 component in all three conditions of our study at temporal bilateral sites centred around 280 ms and with a larger magnitude for the incongruent CDM compared to the congruent CDMs. This pattern is reversed from what would be expected due to attentional differences; Allison and Polich (2008) investigated the effect of cognitive workload on ERP components and like us, on counting accuracies. For higher workload involved in another task (besides attending to targets), they found lower accuracies and a reduced P300, but also a reduced N2 amplitude. The affected N2 in our study may not be explained in terms of attentional processes (as indicated by the results from

task performance and the P300), but probably indicated another, more dominant cause: Error detection, mismatch and conflict detection are known to affect early negative ERP components of perceived stimuli. N2-like ERP components were found for conflicts in perceived information resulting in response conflict (e.g., Bartholow et al. 2005), conflicts of stimulus attributes (e.g., colour), mental conflicts, and conflicts in processing in spatial discrimination tasks (Yang and Wang 2002). Importantly, Forster and Pavone (2008) also investigated ERP components and found an enhancement of the N2 for incongruent compared to congruent visual task-irrelevant and tactile task-relevant stimuli, for correct repetitions. They related this to response conflict. Those results indicate us that the visual display did have influence during the Target Attending Stage, and has negative effects when the information is incongruent whether task-relevant or not. Affirmatively, Brouwer and Erp (2010) did not find an N2 in their tactile ERP-BCI study, in which no visual display was used.

Further, we found another early ERP component (N1) suggesting the influence of the visual display during the Target Attending Stage. An N1 was elicited around 140 ms in the Congruent-Vertical and Incongruent conditions, but not in the Congruent-Horizontal condition, and was enhanced for the first mentioned. The N1 is not sensitive to response conflict (Forster and Pavone 2008), but linked to sensory selective spatial attention (Kida et al. 2004b) and crossmodal links (Kennett et al. 2001). An N1 was only found for the conditions that employed a vertical position of the display, and thus required a different gaze direction (i.e., central instead of deviated). Gaze direction influences crossmodal processing such that an endogenous difference of the N1 is only found for central gaze, when tactile spatial attention modulates visual task-irrelevant information (Macaluso et al. 2005). Crossmodal links in spatial attention should be stronger for the Congruent-Vertical compared to the Incongruent condition, which could explain the enhanced N1 for the former condition (Kennett et al. 2001).

Redetermination of the target due to a non-optimal memory representation

Remapping during the Target Attending Stage may be the consequence of non-optimal memory representation. This would result in a dual-task situation, in which the task to attend to targets and the task to determine the target tactor by CDM, compete for resources. Evidence for remapping activities comes from the late occurrence of the P300 in our study (centred around 500 ms) compared with the tactile P300 around 400 ms of Brouwer and Van Erp (2010), who used the same tactile stimulation (in terms of hardware, vibrating frequency, intensity, body locations and similar on/off times). This suggests the presence of additional higher order processes during the Target Attending Stage. Note that the N2 and N1 components were detected at similar latencies as found in many other studies (e.g, Yang and Wang 2002).

Additional redetermination of the target might differ between congruent and incongruent CDM with respect to the level of mental workload (Wickens 1987). Increased mental workload for the task involving incongruent CDM could lead to the availability of fewer resources for the attending task and thus result in reduced task performance and a reduced P300 compared to congruent CDM.

The cause for additional redetermination of the target during the Target Attending Stage may be that the representation of the target in memory became less distinct over time. The quality of the initial target representations in memory might vary for CDM conditions. Naveh-Benjamin et al. (2006) showed that memory performance is reduced if a task with

incongruent versus congruent relations is introduced at either the encoding or retrieval phase. They related this to additional attentional effort for incongruence. Also the late ERP components we found affected by CDM seem to be related to memory processes; our N600 and P800/P1200 resemble the N400 and LPC found in memory studies (Ohara et al. 2006) and in semantics studies (Salmon and Pratt 2002). Although we could only robustly identify the N600 for the Incongruent condition and the P800 for the Congruent-Vertical condition, similar activities were seen in both of these two conditions. Interestingly, a similar pattern was seen by D'Arcy et al. (2005), who investigated incongruence effects in semantic language processing, and found no N400 for semantically congruent texts, and an enhanced N400 for lower compared to higher working memory load. However, it should be noted that the N600 might not reflect brain activity, but ocular artefacts. Although, we did take measures to reduce such influence by means of a bandpass filter and a global rejection threshold criterion, the frontal distribution of this component is suspected (Jung et al. 2000), because of the proximity of eye-muscles. Nevertheless, the prefrontal cortex is also involved in memory processes, and some late far-frontal negative ERP components, for example one between 600-790 ms, which is related to retrieval of episodic information (see for a review: Friedman and Johnson 2000).

We speculate that these results show an advantage of congruent-horizontal CDM due to experience, as suggested in the P300 discussion, and a disadvantage for congruent-vertical CDM due to a possible required remapping of control and display between reference frames. In the Congruent-Vertical condition, the tactile control was fully positioned behind the participant, while the visual display was presented in front, in an egocentric frame of reference. In a dual-task situation, this remapping between reference frames in order to perform the target determination task during the attending task might involve memory more actively (Avraamides and Kelly 2008).

5.5. Conclusion

Congruent CDM results in enhanced task and (offline) BCI performance (an improvement of ~25%), and a stronger P300 than incongruent CDM. Congruent-horizontal CDM may benefit from horizontal navigation experience, which is reflected in the P300. The presentation of a visual display influences the attending of tactile stimuli, even though the visual display seems task-irrelevant during the Target Attending Stage. If the visual display and tactile control orientations are incongruent, the resulting conflict is reflected in an enhanced N2. The late occurrence of the P300 and CDM effects on late ERP components, which could be related to memory, possibly indicate the presence of additional mental processes during the Target Attending Stage. These processes could be caused by additional mapping due to the need to redetermine the target, initiated by the quality of the initial target representation in memory and/or are caused by continuous and automatic visual processing of the navigation display. The implications are that BCIs should be designed using spatially congruent CDM and in compliance to users experiences, to reduce task errors, mental workload and increase available attentional resources and possibly improve BCI-operation and thus facilitate Human-Computer Interaction.

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6

Discussion and conclusions

Our research goal is to understand the underlying mechanisms of multisensory ERP based BCIs with the purpose of reducing the cognitive resources involved, and improving gaze-independent BCI performance. Such knowledge may also generally be applied to improve human-computer interfaces. The main questions of this dissertation are: Does multisensory dual-tasking negatively affect ERP components, and consequently decrease BCI-performance of a tactile ERP-BCI? Do (congruent) multisensory BCIs positively affect ERP components, and consequently increase BCI performance?

In this final chapter we discuss and integrate the results of the studies and answer the main questions of this dissertation. Subsequently, we discuss the implications of the research, reflect on the usefulness of ERP-BCIs, and finalize by making recommendations for future research.

6.1. Effects of multisensory interfaces in ERP-BCIs

To answer the main questions of the dissertation, we derived four research questions. Each research question was addressed in a separate study, and presented in a chapter of this dissertation. The research questions of the studies are:

- *Research question 1:* (How) does (multisensory) dual-tasking affect ERP components, and subsequently BCI performance?
- *Research question 2:* Does attending to bimodal visual-tactile (compared to unimodal) stimuli positively affect ERP components, and subsequently BCI performance?
- *Research question 3:* Does attending to bimodal visual-tactile gaze-independent and location-congruent (compared to unimodal or bimodal location-incongruent) stimuli positively affect ERP components, and subsequently BCI performance?
- *Research question 4:* (How) does (multisensory) control-display mapping (CDM) affect ERP components, and subsequently BCI performance?

In all studies we investigated effects of Target Attending by analysing the difference ERP (target minus nontargets ERP). Thus when comparing conditions where we use terms as "enhancement or increase of an ERP component", such terms refer to a larger difference of that component between target and nontargets responses.

In the next section (6.1.1), we first zoom in to the experimental studies separately; we discuss the corresponding results and answer the research questions of the studies mentioned above. Subsequently, we integrate the results of the four studies and attempt to answer the main questions of this dissertation (section 6.1.2).

6.1.1. Findings per experimental study

Controlling a tactile ERP-BCI in a dual-task

The first research question was (chapter 2): (How) does (multisensory) dual-tasking affect ERP components, and subsequently BCI performance? In accordance with our hypothesis, we showed that when a tactile ERP-BCI is operated alongside a visuomotor (cognitive) task rather than alone, an endogenous P300 is still robustly detected but significantly decreased. In divided attention studies using different perceptual or cognitive paradigms, a reduction of the P300 with increasing workload has been found. These studies showed that the amplitude of the P300 elicited by the rare stimuli of a secondary oddball task depends on the task difficulty of a primary task (for example a visuomotor tracking task) (Isreal et al. 1980a; Isreal et al. 1980b; Kramer et al. 1983; Kramer and Strayer 1988). Consistent with the effect on the P300, bitrates of the ERP-BCI are lower for the dual-task conditions compared to the BCI-only condition. Classification accuracies are still well above chance, but BCI performance may be too low to be considered effective.

In (Friedrich et al. 2011) a secondary task (or distraction) did not affect performance of an active BCI based on mental imagery. One explanation for the different results found in this study and (Friedrich et al. 2011) is that whereas in our study every single stimulus of both tasks needed to be categorized, a mental imagery task may easier allow switching attention between tasks. More importantly, in (Friedrich et al. 2011) participants had to focus on the BCI-task while in our study participants were explicitly instructed to give priority to the non-

BCI task. Therefore relatively few attentional resources may have been allocated to the BCI-task in our study, explaining stronger negative effects of dual-tasking on BCI performance.

As discussed in the introduction, an important motivation to use tactile stimuli to navigate using an ERP-BCI is that the visual (and auditory) channel are often heavily loaded (Van Erp and Van Veen 2004). Even though in our dual-task study the tasks were based on different sensory modalities, we found that dual-tasking affected results of both tasks. We hypothesized that involved cognitive processes to perform the tasks (at least partly) overlapped, causing a competition for resources which affects task performance. Such competition for resources is expected to be even larger when both tasks use stimuli in the same modality (e.g., a visual ERP-BCI for gaming). Competition for resources in our study probably mainly occurred at high-level processing (as apparent from the affected P300), whereas low-level resource competition is (also) expected when both tasks would employ the same modality.

We concluded that control of a tactile ERP-BCI in a dual-task situation is still feasible (i.e., above chance level), but performance is degraded and may be considered ineffective. Therefore, we continued our research by exploring ways of increasing BCI performance, more specifically by increasing ERP activity. One of the possible options to do so is by using bimodal stimuli.

Does bimodal stimulus presentation increase ERP components usable in BCIs?

The second research question was (chapter 3): Does attending to bimodal visual-tactile (compared to unimodal) stimuli positively affect ERP components, and subsequently BCI performance? Confirming our hypothesis, we showed that an early (<200 ms) ERP component, the N1 (70-130 ms), was elicited for attending to visual-tactile stimuli and was enhanced relative to attending either to visual or to tactile stimuli. The input from both sensory modalities contributed to the bimodal N1 through the (sum of the) two separate processes and possibly by additional integration activity due to crossmodal links in sensory processing at that early stage (Foxe et al. 2000). The latency of our bimodal N1 is well in line with previously reported multisensory integration effects modulated by spatial (selective) attention: Talsma and Woldorff (2005) reported the first effect to peak at approximately 100 ms, and ours was present between 70-130 ms after stimulus onset. Furthermore, Talsma et al. (2007) showed that it is required that both modalities of bimodal stimuli are attended for early ERP multisensory integration effects to occur and are not present if one modality is explicitly ignored. This could suggest that the participants in our study correctly followed the instructions to attend to both modalities and did not ignore one modality in the bimodal condition.

In contrast to the early ERP component, the late ERP component, P300, was reduced when attending to visual-tactile compared to visual stimuli, which indicates a reduction in allocated attention to visual-tactile compared to visual targets. In general, it is recommended that stimuli are (or multisensory information is) semantically, temporally and spatially congruent in order to optimize the integration of multisensory input (Driver and Noesselt 2008). The bimodal stimuli in our study may be considered semantically and temporally congruent, but spatially they were only partly congruent. They were congruent in direction, as visual and tactile stimuli were both positioned in a circle-layout in the horizontal plane and indicated a certain direction with the centre of the circle as a starting point. However, because the tactile stimuli were located around the waist, while the visual stimuli were located at a display in front of participants, the bimodal stimuli were not location-congruent (i.e., co-located). Previous research has reported contradicting results regarding the necessity of spatial congruency for multisensory integration. While some researchers have reported enhanced task

performance for spatially incongruent bimodal stimuli compared to unimodal stimuli (Gondan et al. 2005; Philippi et al. 2008; Teder-Salejarvi et al. 2005), others have reported the opposite (Ho et al. 2009). We believe that the spatial incongruence of bimodal stimuli only hampers multisensory integration if the task involves spatial selective attention, which is the case in both our study and that of Ho et al. (2009). In line with our view, Keetels and Vroomen (2007) suggest that location-congruency is not necessary for multisensory pairing to occur, while their employed task included temporal –not spatial- judgment.

We explain the reversal of bimodal effects (positive on the early stage, but negative on the late stage of the ERP) caused by the location-incongruent relation of the bimodal stimuli resulting in affected selective spatial attention. The early effects could be the result of multisensory information processing within the location of attention (possibly only the visual location), which is focussed before the target stimulus is presented. This is bottom-up driven. After sensory processing when top-down driven endogenous selection takes place (Proctor et al. 2005), the tactile part of the bimodal stimulus might have had a distracting rather than supporting effect. It could have attracted attention away from the visual location in the direction of the tactile location, so that attention became more dispersed instead of focused on the target location(s). In line with this explanation, effects of spatial congruency under various circumstances were observed on the intermediate stage of stimulus processing, well after our N1 and related to higher perceptual-cognitive processes (Gondan et al. 2005; Teder-Salejarvi et al. 2005; Zimmer et al. 2010).

In this study we could not show significant improvement of BCI performance for the visual-tactile compared to the visual condition, but trends in classification accuracy suggested that bimodal stimuli could improve the effectiveness of a BCI. For example, only for bimodal stimuli 100% classification accuracy was reached for all participants. This occurred already after four repetitions of stimulus sequences, when for visual stimuli comparable results were obtained by eight out of ten participants. The classification accuracies for tactile stimuli were much lower (e.g., only one participant obtained 100% classification accuracies, after five repetitions). The reason for higher accuracies for visual compared to tactile stimuli is that in this study participants were allowed to gaze at the visual stimuli.

The next study points out whether or not significant improvement is reached when bimodal stimulus presentation is offered location-congruently, and when bimodal and visual BCIs are gaze-independent (and overall performance will be lower).

Bimodal location-congruent ERP-BCIs: Increasing gaze-independent performance

The third research question was (chapter 4): Does attending to bimodal visual-tactile gaze-independent and location-congruent (compared to unimodal or bimodal location-incongruent) stimuli positively affect ERP components, and subsequently BCI performance? Additionally, we investigated the effect of attended modality in a bimodal location-congruent BCI. In our first bimodal study (see chapter 3), we did not observe a positive bimodal effect on the late stage of the ERP, which we hypothesised, due to the use of location-incongruent stimuli. Using bimodal location-congruent stimuli, we indeed found an enhanced late effect on the ERP (P300) for the bimodal gaze-independent compared to the unimodal conditions, which was in line with enhanced BCI performance. The different findings in these two studies hint that location-congruency may affect the processing of bimodal stimuli as hypothesized. Indeed, when directly addressing the effect of location-congruency by comparing the results for attending location-congruent and location-incongruent bimodal stimuli, we observed a trend ($p=.056$) for an increased bimodal P300, which corresponded to significantly increased BCI performance in favour of location-congruent bimodal stimuli.

Bimodal compared to unimodal effects. Based on the early bimodal effect observed in our first bimodal study (see chapter 3) we expected similar results on the early ERP components in chapter 4. However, we did not find positive effects of attending bimodal stimuli on the early stage of processing. In fact, we did not detect an early bimodal ERP component at all (for location-congruent stimuli when both modalities were attended). Nevertheless, for both unimodal conditions early ERP components were detected, but with opposite directions: a visual P1 and a tactile N2. Because the unimodal conditions resulted in early ERP components with opposite polarities, the lack of a bimodal early ERP component in this study may be explained by counterbalanced activity. In our first bimodal study (see chapter 3) we did find a bimodal early ERP component (N1), which was not detected in either of the unimodal conditions. The early ERPs of those unimodal conditions, however, appeared much more alike and already showed a slight negative drift. Also in (Talsma and Woldorff 2005) – in which positive effects of bimodal stimulus attending on early and late stages of processing are reported- the unimodal early ERPs were quite alike. Perhaps ERP summation is the driving factor behind enhanced effects of bimodal compared to unimodal ERPs in our study. To understand the underlying mechanisms further investigation is needed, however bimodal BCI does appear to increase performance of current gaze-independent ERP-BCIs.

Location-congruent compared to location-incongruent bimodal effects. We only expected location-congruency to influence the late stage of the ERP, but we also found a difference at the early stage: A P1 was observed for attending bimodal location-incongruent stimuli. This P1 resembles the P1 from the conditions in which only the visual modality was relevant. This suggests that even though participants were instructed to attend both modalities equally in the bimodal-incongruent condition, the visual modality may have been dominant (at an early stage of processing). Possibly, the task (to attend to two different modalities at two different locations) could have been too difficult as the locations of the visual and tactile parts of the bimodal incongruent stimuli were rather far apart. BCI performance was clearly affected by location-congruency. Therefore bimodal BCIs (based on spatial attention) should employ location-congruent bimodal stimuli for optimal performance. The performance drop caused by location-incongruent bimodal stimuli is expected to depend on the degree of incongruency.

Effects of selective attention to modality. Additionally, we showed that a bimodal location-congruent BCI also offers the flexibility that users can choose to attend to only one modality, without affecting BCI performance (as long as the same modality is attended during training and testing of the classifier). Switching of attended modality during use (i.e., testing of the classifier) is possible too, and depending on the degree of overlap in the attended modalities between training and testing, performance is still at least as good as that of unimodal ERP-BCIs.

The next step in the development of bimodal ERP-BCIs is to study effects in a more realistic setting. Thus effects of Target Attending should not be investigated in isolation, but an actual control such as navigation has to be included, incorporating additional tasks and cognitive processes (see also the study discussed in the next subsection "Control-Display Mapping in Brain-Computer Interfaces").

Concluding, bimodal ERP-BCIs are a promising alternative for gaze-independent unimodal ERP-BCIs. Our results of bimodal BCI performance indicate the importance of congruent design of a BCI. The positive trend in the P300 for location-congruency of bimodal stimuli appears to cause this increase in performance. The mechanisms underlying the effects of congruent design in BCI are not clear yet, and such effects have received marginal attention in the field of BCI so far. Therefore, we continued the study of congruent design in BCI. To assess possible effects of congruency, we investigated an ERP-BCI in a more realistic setting employing a navigation task. Because such a task involves certain cognitive processes and the

visual modality, as a first step we studied the effects of congruent design delimited using a unimodal tactile ERP-BCI.

Control-Display Mapping in Brain-Computer Interfaces

The fourth research question was (chapter 5): (How) does (multisensory) control-display mapping (CDM) affect ERP components, and subsequently BCI performance? Addressing this question we further investigated the effects of congruent spatial relations in BCI. In chapter 5 we focussed on the spatial relation between the tactile stimuli (control) and visual navigation information (display). More specifically we studied how this relation affects mental processes related to the users' tasks to map the navigation direction onto the stimuli to determine the target stimulus and subsequently attend it.

The experiment existed of three conditions: Incongruent (control horizontal, display vertical), Congruent-Horizontal and Congruent-Vertical (both control and display horizontally and vertically respectively). We hypothesized that incongruent CDM may negatively affect the initial determination of the corresponding tactor (Target Determination). This leads to attending to the wrong stimulus in the Target Attending Stage, and thus decreased endogenous ERP components, i.e. P300, and corresponding BCI performance for incongruent compared to congruent CDM. As hypothesized, we found a decreased P300 ERP component for incongruent compared to congruent CDM, which is in line with decreased offline classification accuracies (estimated BCI performance). The effects cannot be explained by perceptual differences in tactor characteristics or tactor configuration, because the Congruent-Horizontal and Incongruent conditions employed the same tactor locations. The position of the display presenting visual navigation information affected the ERP for attending tactile targets, even though participants were not required to process this visual information during tactile stimulus attending. In theory participants could first establish the navigation direction, then map this direction onto the tactile stimuli and determine the tactile target, before the sequences of tactile stimuli presentations started.

We discussed in chapter 5 two possible explanations of how the visual display could have affected attending to tactile stimuli. First, incongruent CDM may yield incorrect Target Determination and consequently incorrect Target Attending. Second, incongruent CDM might affect mental processes during Target Attending, for example related to possible redetermination of the target.

We first discuss possible effects of incongruent CDM during the Target Determination Stage. Incongruent CDM was found to increase errors in task performance by studies involving perceptual-motor tasks (e.g., Zupanc et al. 2007), which is in line with our results on task performance (i.e., counting targets). Such task errors can be the result of incorrect determinations of targets in the Target Determination Stage. Incorrect Target Determination would also explain a reduced availability of attentional resources which results in a reduced P300, as the P300 amplitude can be reduced by several cognitive factors, for example selective spatial attention (Brandeis and Lehmann 1986). However, ERP components are typically enhanced by (spatial) attention, and the enhanced N2 we observed for incongruent compared to congruent CDM can therefore not be explained by reduced attention, as the opposite effect would have been expected (Wang et al. 2010). Therefore, it seems plausible that incongruent CDM not only affects the Target Determination Stage, but also influences or causes (additional) mental processes during the Target Attending Stage.

Next we discuss possible effects of incongruent CDM on mental processes during the Target Attending Stage. The effects on the N2 indicate a different underlying mechanism than

affected spatial attention. Previous studies reported N2-like ERP components for several types of conflicts in perceived information such as response conflict (e.g., Bartholow et al. 2005) and conflicts in processing in spatial discrimination tasks (Yang and Wang 2002). Importantly, Forster and Pavone (2008) also investigated ERP components and found an enhancement of the N2 for incongruent compared to congruent visual task-irrelevant and tactile task-relevant stimuli, for correct repetitions. They related this to response conflict. Those results indicate that the visual display in our study did have influence during Target Attending, and has negative effects when the information is incongruent whether (instantaneously) task-relevant or not. An explanation of why visual information was processed during Target Attending –while theoretically not necessary for the task-, is that the quality of the initial target representation in memory was not high enough (especially for incongruent CDM). That could have caused additional mapping due to the need to redetermine the target in memory. Alternatively, (visual) information of the navigation display may have been processed continuously and automatically.

In conclusion, congruent (horizontal) CDM resulted in the strongest P300 and highest BCI performance, and thus general HCI recommendations concerning CDM are not only relevant for user behavioural task performance, but also for brain-based BCI performance.

6.1.2. Integrating the studies

We conducted four experiments, one focussed on dual-tasking, two on bimodal ERP-BCIs (multisensory interfaces), and one on congruency in CDM. In the second bimodal study the role of congruency was also investigated. Therefore there were three main topics addressed in our research: dual-tasking, multisensory interfaces, and congruency. Interestingly, these topics appeared not only relevant in the studies that were set up for that, but also seemed to play a role in the studies that focussed on the other topics. We will here discuss these three topics and the relation between the studies, leading to answers for the main research questions of this dissertation.

Dual-tasking

As shown in chapter 2, BCI performance is affected by dual-tasking, i.e., when a primary visual (cognitive) task is performed concurrently to a secondary tactile ERP-BCI task. These tasks compete for the same cognitive resources. A concurrent task decreases (spatial) attentional resources needed for the task of Target Attending to operate an ERP-BCI, such that the P300 is decreased, and with that BCI performance.

We did not only find indications of dual-tasking in chapter 2, but also in chapter 5 where participants were only instructed to perform an ERP-BCI task, and no concurrent task. In that chapter we investigated the control of a unimodal tactile ERP-BCI for a visual navigation task. The results indicate that participants process visual navigation information during tactile Target Attending, even though this was theoretically not required to operate the BCI. Possibly, the target needed to be redetermined during the Target Attending Stage, initiated by the quality of the target representation in memory. Such a redetermination of the target is a concurrent task to the task of Target Attending, resulting in a competition for resources. These results highlight the importance of investigating BCI in a more realistic setting, i.e., with all tasks involved and not just the task of Target Attending.

Dual-tasking negatively affects the ERP, and subsequently BCI performance. Our results suggest that a task concurrent to the task of Target Attending (ERP-BCI task) can also occur

as a consequence of a more complicated relation between stimuli and control options. This relation is more complicated when stimuli and control options are presented in different sensory modalities, as is the case in (some of) our studies: visual navigation directions have to be mapped onto tactile stimuli at participants' body locations. When employing a tactile ERP-BCI for navigation on a visual display, the tactile stimuli and visual navigation directions cannot be location-congruent. The (spatial) relation will therefore be more complex than when the BCI is used for real navigation, and visual navigation directions around us are simpler mapped onto the tactile stimuli on our body.

The advantages of employing tactile stimuli to enable gaze-independent ERP-BCI operation (i.e., prevention of sensory overload, natural correspondence with navigation directions, and privately offered), need to be set off to the disadvantage of a more complex relation between stimuli and control option. It will therefore depend on the specific application whether or not using tactile stimuli would be the most appropriate. Operation of a tactile ERP-BCI for a visual navigation task on a display can be considered effective. However, the relation between tactile stimuli and visual information could cause dual-tasking which negatively affects BCI performance, and additional (visual) tasks should not request too many (cognitive) resources.

Multisensory Interfaces

In chapter 3 and 4 we investigated possible advantages of bimodal visual-tactile stimulus presentations in bimodal ERP-BCIs. In both studies we found increased ERP components that may enhance BCI performance. The extent of enhancement seems very dependent on the spatial relation between the visual and tactile parts of the bimodal stimulus: the degree of spatial congruency is expected to correspond to the extent of bimodal positive effects. In chapter 2 and 5 we studied unimodal tactile ERP-BCIs, but visual information was also relevant for the use of these BCIs. In chapter 2 the concurrent task and in chapter 5 the BCI task (navigation) were based on visual information. Therefore also the BCIs in these chapters can be considered as multisensory interfaces. We did not only find multisensory effects for attending bimodal stimuli, but we also observed multisensory effects when attending to unimodal stimuli in such multisensory interfaces.

In chapter 3, when studying a bimodal BCI using gaze-dependent visual-tactile location-incongruent stimuli, we found a bimodal N1. We observed a similar ERP component in chapter 5, for attending to tactile stimuli modulated by visual information. The latter N1 was only found in the two conditions in which visual information may have had the largest (or most direct) influence, and was strongest for the condition in which visual and tactile information was congruent, presumably resulting in strong multisensory binding. In line with these results, we observed an N1 in chapter 2 in a dual-task situation, but only for a condition with a cognitively demanding visual concurrent task, and not for a dual-task condition including a merely visuo-motor task. We explained the different finding between the two dual-task conditions to be caused by visual memory being more severely loaded in the former condition. Visual memory is also a part of the visual system, like visual sensory processing. Surprisingly, we did not find such an N1 in chapter 4, where we expected it the most: That study was designed to elicit multisensory effects and (most) conditions used location-congruent (gaze-independent) bimodal stimuli, so that binding would be expected maximal. We think the lack of such a result is due to the elicitation of early unimodal ERP components of opposite polarities. When both modalities are attended, it appears that unimodal activity is simply counterbalanced, and therefore ERP summation may be the driving force behind the multisensory effects in chapter 4. A red thread through the studies in which the N1 was observed, is that visual information was gazed at. Although early effects of multisensory integration have regularly been found in gaze-independent setups (Gondan et al. 2005;

Philippi et al. 2008; Teder-Salejarvi et al. 2005), the relation between gaze and early multisensory effects on the ERP in BCI deserves further investigation.

The observed effects of multisensory interfaces when attending to unimodal stimuli highlight the importance of investigating BCI in a more realistic setting, as attending to unimodal stimuli is modulated by processing multisensory information. Additionally, the obtained knowledge is of interest to HCI in general, as such effects can provide useful information about the mental processes of a user of a human-computer interface (such as that visual information is processed).

The multisensory interfaces of our studies can be distinguished into three categories, in which multisensory information is used. For:

1. *Multisensory Target Attending*: the BCI task of Target Attending (i.e., bimodal stimuli).
2. *Multisensory Target Determination*: the BCI task of Target Determination (i.e., tactile stimuli and visual navigation information).
3. *Multisensory Dual-Tasking*: the BCI task(s) and a concurrent task (i.e., tactile stimuli and a visual concurrent task).

We showed that the first category (Multisensory Target Attending) can positively affect the ERP, and subsequently BCI performance. However the second category (Multisensory Target Determination) appears to negatively affect the ERP, and subsequently BCI performance (see also previous subsection Dual-Tasking). The third category (Multisensory Dual-Tasking) negatively affects both Target Attending and Target Determination, nevertheless the effects are expected more negative when unimodal dual-tasking (thus positive multisensory effects).

Congruency

In chapter 5 we showed that congruency between tactile and visual information is important for BCI performance also if visual information is theoretically not relevant for attending to the tactile stimuli of the BCI (but only for Target Determination).

Based on the observed effects of congruency in chapter 5, we expect congruency to be even more important for BCI performance when both visual and tactile information are relevant for the main BCI task (Target Attending). Indeed, whereas in chapter 3 using bimodal location-incongruent stimuli we only observed indications that bimodal stimulus presentation may be beneficial, in chapter 4 using bimodal location-congruent stimuli the benefits of bimodal BCIs were shown clearly. In the latter study we found location-congruency to be of significant importance for positive effects on BCI performance. A corresponding trend in the P300 suggests that this advantage is due to higher-level processes. When visual and tactile information are both processed and need to be matched, location-incongruency can lead to additional and more cognitively demanding tasks (Target Determination).

Spatial congruency of multisensory information affects both tasks of Target Attending and Target Determination. Thus (Multisensory) BCIs should be designed according to (spatial) HCI guidelines, i.e., using spatial-congruent multisensory stimuli and task information.

Answers to the main questions of the dissertation

The first main question of this dissertation is: Does multisensory dual-tasking negatively affect ERP components, and consequently decrease BCI-performance of a tactile ERP-BCI?

Yes, the ERP is affected if a tactile ERP-BCI is operated as a concurrent task in a dual-task situation. A dual-task situation is not only caused by an additional (cognitive) non-BCI task, but also by (multisensory) Target Determination. The clearest effect of dual-tasking is a decrease of the P300. Because this is a dominant ERP component in gaze-independent ERP-BCIs (Brunner et al. 2010; Thurlings et al. 2012a; Treder and Blankertz 2010) BCI performance is decreased too. For all dual-task situations in our studies BCI performance was still feasible, but when employing an additional non-BCI task it may be considered ineffective.

The second main question of this dissertation is: Do (congruent) multisensory BCIs positively affect ERP components, and consequently increase BCI performance? Whether or not multisensory ERP-BCIs enhance the ERP depends on two factors. First, the category of multisensory BCI; whether multisensory information is used for the task of Target Attending (i.e., bimodal stimuli), or for the task of Target Determination (e.g., visual navigation information and tactile stimuli), or for the BCI task(s) and a concurrent task (i.e., tactile stimuli and a visual concurrent task). Second, the spatial relation of the multisensory information that needs to be matched within these three categories. Combining these two factors, we conclude the following for each category of multisensory BCIs:

1. Multisensory Target Attending results in an increased (late) ERP and BCI performance (factor one), if the spatial relation of the multisensory stimuli is location-congruent (factor two).
2. Multisensory Target Determination appears to cause a dual-task situation and negatively affect the ERP, and subsequently BCI performance (factor one), but is positively affected by spatial-congruency in multisensory information (factor two).
3. Multisensory Dual-Tasking negatively affects both Target Attending and Target Determination, which negatively affects the ERP, and subsequently BCI performance (factor one). Nevertheless the effects are expected more negative when unimodal dual-tasking (thus positive multisensory effects). The role of the spatial (congruency) relation within a multisensory dual-task needs to be investigated (factor two).

Thus to answer the second part of the main research question: Yes, congruent multisensory BCIs can enhance the ERP and BCI performance. We improved ERP-BCI performance by bimodal stimulus presentation with approximately 20-25% higher classification accuracies (chapter 4), and by congruent CDM with approximately 25% (chapter 5). Whether or not these improvements are sufficient to realise effective BCI control while dual-tasking (as in chapter 2), should be assessed in future research as a next step.

6.2. Implications of the research

The implications of our results are:

- Tactile ERP-BCIs can be used for a visual navigation task, and are thus an interesting alternative for gaze-independent control.
- Dual-tasking negatively affects tactile ERP-BCI performance to such a degree that it may be considered ineffective. Therefore application in a cognitively demanding environment is not recommended.
- Bimodal stimuli can be employed to increase gaze-independent ERP-BCI performance.

- Multisensory BCIs employing bimodal stimuli offer the advantage that users can freely choose to switch the attended modality, without affecting bimodal BCI performance if the classifier is retrained to that situation. If not, performance is still at least as good as that of unimodal ERP-BCIs.
- The spatial relations within multisensory BCIs affect BCI performance and need to be congruent. This includes the spatial relation within bimodal stimuli, and the relation between tactile stimuli and visual navigation directions.

6.3. Reflecting on the usefulness of ERP-BCIs

We were able to improve movement-independent ERP-BCI performance by bimodal stimulus presentation and congruent multisensory CDM design. However, a dual task negatively affects this performance. In this section we reflect on the usefulness of ERP-BCIs and evaluate whether or not these can become successful applications. We first discuss the usefulness of ERP-BCIs for direct control, and subsequently reflect on ERP-BCIs for other purposes, i.e. how ERPs can be used to improve HCI.

6.3.1. ERP-BCIs for direct control (navigation)

In the introduction we described for who and why brain-based control may be beneficial. Firstly, people without the ability to control their muscles would be helped tremendously when they could navigate using an ERP-BCI. Secondly, healthy users may benefit from movement-independent brain-based navigation when using complex interfaces; leaving the eyes and hands free for other tasks. As for the successful application of any other device, the chance to successfully apply an ERP-BCI for navigation depends on the assessment of the whole range of requirements. If performance (bitrate) is the most important criterion, then probably the usefulness of ERP-BCIs is quite limited. Bitrates that we obtained are around 5-10 bits/min. Although we have merely focused on improving performance by comparing conditions with different BCI designs, and performance is expected to be further improved when the classifier is addressed (see also 6.4. “Future research”), these bitrates are not even remotely close to performances of traditional input devices. Even for patients who still have limited muscle-control and could use alternative input devices (for example based on eye blinks), performance may not be interesting enough (yet). With such alternative input devices performances of 150 bits/ min have been achieved for tongue-computer interfaces (Huo et al. 2007), and 17 bits/ min for eye-controlled interfaces (Zheng et al. 2009). Additionally, performance might be even more degraded in a realistic setting, when factors as distraction and perceiving of complex environments affect the ERP. Nevertheless when it is more important that navigation occurs movement-independent, then ERP-BCIs could be considered. Yet, it should be taken into account that when the specific application or context of use requires a large amount of cognitive resources, ERP-BCI control may not be effective. Besides movement-independent control another advantage of brain-based navigation in gaming is the fun-factor. The difficulty to obtain brain-based control may even become part of the challenge, and thus part of the fun for a gamer (Reuderink 2011).

It appears that the main advantage of ERP-BCIs is the possibility of movement-independent control. Hitherto, there are no alternative methods than brain-based interfaces. It is debatable, however, if and when muscle-independent control is really desired. There are no reports yet of completely locked in patients, people who have no remaining muscle-control, who could operate a BCI. Birbaumer (2006) proposed that this is due to the decline of the conscious

mind as the physical ability is declining: When the body stops responding to conscious control, conscious thoughts are extinguished (classical conditioning). For healthy users, there are clear advantages of having the hands and ears free for other tasks. Nevertheless, the disadvantages of required cognitive resources to operate an ERP-BCI and the practical limitations of the necessary equipment form a trade-off with those advantages. Therefore the designers of a specific (navigation) application need to assess the degree of cognitive load of using a BCI in a certain context and to carefully weigh the pros and cons, to choose the most successful method.

Although we still see substantial room for improvement of ERP-BCI performance (see section 6.4. Future research), the successful applications for direct control may be limited as the disadvantages of ERP-BCI control would only be acceptable in specific situations. It is unlikely that in the future ERP-BCIs will replace input devices to control computers. Nevertheless, current ERP-BCI knowledge is also useful in other interfaces. Similar brain signals could facilitate interaction when stimuli are replaced by natural events. Such events could be objects while driving and breaking is desired (Haufe et al. 2011) or specific categories of images (Brouwer et al. 2011). However, such brain-based interaction appears to have other benefits than direct control.

6.3.2. ERP-BCIs for other purposes: BCI to improve HCI

Using ERPs to extract information about users' mental processes

Next, we offer some ideas, based on the results of our research, concerning what type of information could be measured with ERP-BCIs to facilitate interaction for other purposes than direct control. These ideas would fit in the field of affective BCI (Muehl 2012) and passive BCI (Zander et al. 2010); the input of affective or mental states may be used to adapt interaction.

- *The level of workload affects the P300.* Our results support the view that a decrease in the P300 could indicate a reallocation of cognitive resources caused by an increase in required cognitive resources involved in the interaction (e.g., Allison and Polich 2008). Adapting an interface to the level of workload may result in more effectively achieving certain goals (e.g., learning).
- *The degree of conflict affects the N2.* Conflict in interaction hampers effective control and should be avoided. Detection of such a process could be useful information to adapt to. This is in line with ideas concerning the error-related potential (Lehne et al. 2009; Schalk et al. 2000).
- *Multisensory processing appears to elicit an N1.* Such an effect can indicate what type of information is processed. For example that visual information is processed when it is not expected.
- *The latency of ERP components.* In line with reports on delayed latency of the P300 due to increased cognitive load (Kramer and Strayer 1988), the P300 in our studies seemed to start later when an additional task was performed (concurrent task or the BCI task of mapping a target direction onto the tactile stimuli). Thus changes in the latency of the P300 could indicate an increase or decrease in the number or load of mental tasks. Similarly, changes in the latency of earlier ERP components may be indicators of variations in more low-level processes.

- *The occurrence of several late ERP components.* These late ERP components (after the P300) appeared to be related to memory. Adaptation when memory is more heavily loaded may result in more effectively reaching goals (e.g., learning).

Using other signals to extract information about users' mental processes

Besides ERP components, also other types of information from the (brain) signals may be useful to improve HCI.

- *Communication of mental states and processes:* Affective states (Muehl 2012) and mental processes might be derivable from other EEG features too (such as frequency bands).
- *Bio-hybrid HCI:* Possibly the combination of multiple biosignals including EEG can contribute to a better understanding of users mental states (Brouwer et al. 2011; Scherer et al. 2007).

6.4. Future research

In this section, we make recommendations for future research aimed at improving ERP-BCI performance, provide ideas concerning ways to use HCI (knowledge) to improve BCI, and consider some issues concerning moving out of the lab.

6.4.1. Improving ERP-BCI performance

Further improvement of ERP-BCI performance may be realized by:

- *Multisensory stimulus presentation:* By also employing auditory stimuli to create visual-tactile-auditory stimuli. As we found benefits of bimodal compared to unimodal stimuli, trimodal stimuli may offer a greater gain.
- *Order of stimuli presentations:* ERP-BCIs employ sequences of randomly presented stimuli. The reason for a random order is to decrease the level of expectancy when a target is presented with the aim to enhance the P300. Alternative orders of stimuli presentations possibly offer advantages, such as decreased distraction of nontarget stimuli and thus of spatial attention. We are currently investigating this at the BBCI-group at the Berlin Institute of Technology.
- *Tactile hardware:* The employed tactile stimuli in this research were vibrating electromotors (such as in a mobile phone). The saliency of the tactile events might be higher with a different type of hardware. Additionally, electromotors take relatively long to reach maximum intensity (approximately 50 ms in our research). When the start-up time of the hardware would be lower, the required presentation times of the stimuli could probably be decreased, which should result in higher bitrates.
- *Classification algorithms:* While the notion that BCI performance can be improved with a more sophisticated algorithm is quite general, we do believe this is especially true for tactile ERP-BCIs. The characteristics of tactile ERP components differ from the traditional and extensively studied visual ERP components. Thus tactile specific classifiers need to be developed.
- *Continuous classifier feedback:* Continuous feedback on the interim result of the classifier may possibly influence participants attending of targets in ERP-BCIs. Such

feedback is common practice in BCIs based on motor imagery (Blankertz et al. 2008). We started the exploration of continuous tactile feedback in an auditory ERP-BCI (Schreuder et al. 2012).

- *Combining the ERP and the SSEP paradigm (Multi-reactive BCI):* By combining the two types of reactive BCIs, i.e., ERP and Steady-State Potential based BCIs. This specific combination was first suggested in (Allison et al. 2010) for visual stimuli. Initial studies to such a combined BCI, also referred to hybrid BCI (Allison et al. 2012; Pfurtscheller et al. 2010), have recently been made. Panicker et al. (2011) employed the two paradigms in a complementary fashion to communicate different types of commands. The fundamental mechanism underlying the interaction between the ERP and SSEP was studied by Severens et al. (2010). Possible benefits for BCI performance of combined responses deserves further investigation.
- *Training:* The comparison of (ERP-)BCIs with traditional input devices is complicated, since the majority of people have long-term intensive experience with using traditional input devices. Possible effects of long-term training of using ERP-BCIs have not been assessed yet, but training might result in improved performance.

6.4.2. HCI to improve BCI : Effects of congruently designed information in BCIs

Our studies showed that basic HCI guidelines (e.g., spatial relation between control and display should be congruent) also affect brain based interfaces, i.e., BCIs. Such HCI guidelines were already known to affect humans' task performance (speed and accuracy) (e.g., Zupanc et al. 2007). Possible effects in BCI have not previously been addressed. We showed that HCI rules in BCIs not only affect humans' task performance, but also the attending of targets as reflected in the ERP, and BCI performance. To optimize the ERP usable in BCI, the BCI needs to be designed incorporating minimised cognitive effort for using the interface. This entails reducing the number of tasks and complexity of the tasks necessary for operating the BCI, to limit required resources. Thus mappings (from environment to stimuli) necessary to determine targets which have to be attended need to be limited and simplified where possible. Therefore the relation within (multisensory) information that needs to be processed simultaneously should be optimized and as congruent as possible.

Whereas we only investigated (in)congruent spatial relations in ERP-BCIs, HCI rules may affect many relations in BCIs, for example:

- *Semantic relation between stimuli and command options in reactive BCIs:* Not only the spatial relation between stimuli and command options is relevant, also the semantic relation needs to be studied. Such a relation should be simplified as much as possible, meaning that the stimuli should be well-embedded in the environment. For example in the internet browsing BCI reported in (Mugler et al. 2008), the command options are browsing tasks, while the stimuli are letters integrated in the browser. Participants had to map their desired letter (corresponding to a task) onto an additional display presenting a communication matrix from a traditional ERP-BCI. It is likely that mental effort can be reduced when visual elements of the internet browser would directly be used as stimuli.
- *Relation between (arbitrary) mental tasks and command options in active BCIs:* Typically arbitrary sets of mental tasks are offered to participants, and the tasks corresponding to the highest results are used on an individual level. Perhaps this

relation should not be arbitrary and the tasks should be optimized to the command options and/or users' experience (e.g., sportsmen might be better able to imagine body movements, while mathematics could be better off with a mental calculating task).

6.4.3. Moving out of the lab

The majority of BCI research are typical lab studies and are not well generalizable to BCI in realistic use. However, the importance of BCI research out of the lab has been recognized: First studies incorporating factors of influence in a realistic setting have been conducted and demos have been created. To move BCI out of the lab, it is essential that experiments are performed using participants who match the target group. For example traditional BCIs employing visual stimuli targeted at people without the ability to use their muscles were investigated with healthy participants who were allowed to gaze at the visual stimuli. Evidently, such results do not asses performance in a realistic setting. Furthermore the practical limitations of technical equipment (e.g., caps and electrodes) need to be taken into account: whereas it still may be fascinating to wear a designed electrode cap at an exhibition, the motivation to use it at the local bar could be drastically decreased. Not addressed in our research, but online feedback certainly may influence motivation or attending strategies too, and should be considered when designing BCI.

To move BCI out of the lab, our research showed it is crucial to take the following into account:

- *Role of concurrent tasks.* In a realistic setting it is likely that users will not only use a BCI, but will have to perform other tasks too. These tasks may be a part of the BCI itself (e.g., when using a BCI to navigate in a serious game), or from the environment (e.g., attending traffic). Even when no other tasks have to be performed, in a realistic setting the amount of sensory information that needs to be processed is likely much higher than in a lab setting. Such distraction could just as well have influence on the use of BCI.
- *Effects of perceiving information regarding possible command options.* When in BCI studies (such as in some of ours) only effects of attending stimuli are investigated, the following effects can be missed:
    - The influence of perceiving (sensory) information regarding the command options.
    - The role of the relation between stimuli and the corresponding command options.

6.5. Concluding remarks

ERP-BCIs are a promising category of BCIs with which the user can voluntary navigate, without using his/her body. If the required stimuli are presented in the tactile modality, gaze-independent control can be realised and sensory overload could be prevented. When navigating with a tactile ERP-BCI, the user is required to perform the following tasks: plan the navigation direction on the display, map the direction onto the tactile stimuli to determine the target, and attend to target stimuli.

Operation of a tactile ERP-BCI for a visual navigation task on a display can be considered effective, but additional (visual) tasks should not request too many (cognitive) resources. We

showed that Multisensory Target Attending in bimodal ERP-BCIs can positively affect the ERP, and subsequently BCI performance. However Multisensory Target Determination appears to cause a dual-task situation and negatively affect the ERP, and subsequently BCI performance. Spatial congruency of multisensory information affects both tasks of Target Attending and Target Determination. Thus (Multisensory) BCIs should be designed according to (spatial) HCI guidelines, i.e., using spatial congruent multisensory stimuli and task information.

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Samenvatting

Een Brain-Computer Interface (BCI) is een systeem waarmee de gebruiker kan communiceren of zijn of haar omgeving kan aansturen op basis van hersensignalen, zonder het lichaam hiervoor te gebruiken. De ontwikkeling van BCIs is erg relevant voor mensen die hun lichaam niet (meer) kunnen bewegen. Ook voor mensen die dit wel kunnen, zijn BCIs interessant vanwege de mogelijkheid tot bewegingsonafhankelijke controle. In dit proefschrift hebben we ons gericht op breingestuurde navigatie, omdat dit een hoofdfunctie is van vrijwillige lichaamscontrole.

Hersensignalen zijn zeer complex en de signaal-ruis verhouding van de meetbare hersensignalen is erg laag, waardoor intenties op hoger cognitief niveau niet direct te interpreteren zijn. Een bepaald type BCI waarmee men toch dergelijke intenties aan een systeem door kan geven, is de zogenaamde reactieve BCI. De werking van dit type is afhankelijk van de presentatie van zogenaamde externe stimuli en de responsen in de hersenen die worden veroorzaakt door de waarneming en verwerking van deze stimuli op verschillende cognitieve niveaus. Indien iedere stimulus ondubbelzinnig met een commando is verbonden (bv. 'links' of 'rechts'), en de gebruiker zijn of haar aandacht richt op één stimulus (d.w.z. doel stimulus) in een reeks van sequentieel gepresenteerde stimuli en de overige stimuli (d.w.z. non-doel stimuli) negeert, ontstaan er verschillende responsen in de hersensignalen. Een dergelijke response noemen we de Event-Related Potential (ERP), waarvan de P300 ERP component een belangrijke rol speelt in BCI vanwege zijn gevoeligheid voor endogene (d.w.z. vrijwillige) aandacht. De gemeten hersenresponsen worden met behulp van algoritmen ingedeeld in twee of meerdere klassen, en zo wordt via de hersensignalen geïnterpreteerd op welke stimulus de gebruiker zijn of haar aandacht had gericht, en dus wat het gewenste commando is. De mate waarin deze classificatie correct uitgevoerd wordt, kan worden uitgedrukt in het percentage correcte classificaties.

Stimuli van reactieve BCIs kunnen worden gepresenteerd in de visuele, auditieve en tactiele modaliteit. Traditionele reactieve BCIs maken gebruik van visuele stimuli en worden doorgaans geassocieerd met relatief hoge percentages correcte classificatie. Echter, het nadeel van dergelijke BCIs is dat de effectiviteit voor een groot deel afhankelijk is van het vermogen van de gebruiker om zijn of haar kijkrichting te richten op de (relevante) visuele stimuli waarbij oogbeweging noodzakelijk is. Om daadwerkelijk bewegingsonafhankelijke controle te verkrijgen, wordt er in BCI onderzoek naar alternatieve oplossingen gezocht. In veel situaties zijn het visuele en auditieve kanaal al (over)belast, en biedt het tactiele kanaal een interessant alternatief. De tactiele BCI maakt gebruik van tactiele stimuli op het lichaam en is geheel onafhankelijk van lichaamsbewegingen van de gebruiker. Voor een navigatie BCI hebben tactiele stimuli op het lichaam het voordeel natuurlijk te corresponderen met navigatie richtingen om ons heen. Bovendien kan interactie plaatsvinden zonder dat de directe omgeving daar iets van merkt.

Wanneer een tactiele BCI voor navigatiedoeleinden gebruikt wordt, zal de omgeving waarin genavigeerd moet worden visueel worden waargenomen. De mogelijke navigatierichtingen dienen vertaald te worden naar de tactiele stimuli die zich op het lichaam (bijvoorbeeld om het middel) bevinden. Aangezien zowel visuele als tactiele informatie moet worden verwerkt, kunnen we de BCI als een multisensorische interface zien. In dit proefschrift bestudeerden we

de onderliggende mechanismen van multisensorische ERP gebaseerde BCIs, met het doel om de benodigde cognitieve belasting te reduceren en de effectiviteit van bewegingsonafhankelijke BCI te verbeteren. De hoofdvragen in dit proefschrift zijn: Heeft het uitvoeren van een (multisensorische) dubbeltaak een negatieve invloed op de ERP componenten, en vervolgens op de prestatie van een tactiele ERP-BCI? Hebben (congruente) multisensorische BCIs een positieve invloed op ERP componenten, en vervolgens op de prestatie van een tactiele ERP-BCI? We hebben deze hoofdvragen uitgesplitst in vier concrete onderzoeksvragen, die ieder in een apart hoofdstuk in het proefschrift zijn behandeld.

In hoofdstuk twee hebben we onderzocht wat de invloed is van het uitvoeren van een (multisensorische) dubbeltaak op ERP componenten, en vervolgens de BCI prestatie. Wij laten zien dat wanneer een tactiele ERP-BCI wordt bestuurd naast een visueel-motorische (cognitieve) taak, in plaats van in isolement, de P300 ERP-component nog steeds robuust gedetecteerd kan worden, maar significant is afgenomen. In lijn met dit effect vermindert ook de prestatie van de BCI. Hoewel het percentage correcte classificaties kansniveau nog overstijgt, is het wellicht te laag voor effectieve BCI controle. Omdat BCI gebruikers in de praktijk niet altijd hun volledige cognitieve capaciteit kunnen inzetten voor het gebruik van de BCIs, zal de BCI prestatie niet optimaal zijn. Daarom hebben wij ons in de volgende hoofdstukken gericht op het verbeteren van deze prestatie.

In hoofdstuk drie hebben we bestudeerd of het letten op bimodale visueel-tactiele (vergeleken met unimodale) stimuli een positieve invloed heeft op ERP componenten, en vervolgens op de BCI prestatie. We detecteerden een vroege bimodale ERP component, maar een verkleining van de late P300. Een trend in het percentage correcte classificaties wijst op een mogelijk positief effect van de vroege bimodale component voor de effectiviteit van BCI. Mogelijk heeft de incongruentie in locaties van het visuele en tactiele deel van de bimodale stimulus gezorgd voor een verschuiving in spatiële aandacht op een hoger cognitief niveau, hetgeen de verkleining van de bimodale P30 kan zou verklaren. We onderzochten het effect van locatie-congruentie in bimodale BCI verder in hoofdstuk vier.

In hoofdstuk vier stond de vraag centraal of het letten op bimodale locatie-congruente visueel-tactiele stimuli (vergeleken met unimodale of locatie-incongruente bimodale stimuli) een positief effect heeft op ERP componenten, en vervolgens op de BCI prestatie. We vonden een toename van de P300 van bimodaal ten opzichte van unimodaal, die positief beïnvloed leek door locatie-congruentie, wat resulteerde in een verbetering van de percentage correcte classificaties. We concludeerden dat een bimodale locatie-congruente BCI niet alleen beter kan presteren dan een unimodale BCI, maar ook meer flexibiliteit in gebruik biedt doordat de gebruiker zijn of haar aandacht ook op slechts één modaliteit kan vestigen.

In hoofdstuk vijf hebben we verder onderzocht wat de rol van congruente spatiële relaties in BCIs is. Meer specifiek bestudeerden we het effect van de spatiële relatie tussen tactiele stimuli enerzijds en anderzijds een scherm waarop navigatierichtingen zijn afgebeeld. Wanneer deze relatie richting-congruent was (d.w.z., parallelle richtingen gezien vanuit een centraal punt in hetzelfde vlak), observeerden we een sterkere P300 dan wanneer die relatie richting-incongruent was. Tevens vonden we voor de incongruente relatie een sterkere N2 ERP component, die mogelijk wijst op een conflict tussen het scherm en de tactiele stimuli. De toename in de P300 correspondeerde met een verbetering in de BCI prestatie. We concludeerden dat algemene richtlijnen uit het gebied van Human-Computer Interaction (HCI) niet alleen relevant zijn voor gedragsprestatie, maar ook voor brein gestuurde BCI prestatie.

In hoofdstuk zes hebben we de resultaten van de experimenten apart besproken en de studies geïntegreerd om de hoofdvragen van het proefschrift te beantwoorden. Tevens bespraken we

de implicaties van de resultaten, we reflecteerden op de bruikbaarheid van ERP-BCI voor directe controle en andere doeleinden, en we deden aanbevelingen voor toekomstig onderzoek. We sloten af met de conclusie dat het bedienen van een tactiele ERP-BCI voor een visuele navigatie taak effectief is, maar niet te veel additionele (cognitieve) bronnen mag aanspreken. Het letten op multisensorische doelen in bimodale BCI kan een positieve invloed hebben op de ERP, en vervolgens de BCI prestatie. Echter, multisensorische doelbepaling kan leiden tot een dubbeltaak, wat een negatieve invloed heeft op de ERP, en vervolgens op de BCI prestatie. Spatiële congruentie van multisensorische informatie heeft invloed op zowel de taak van het letten op doelen, als de doelbepalingstaak. Daarom adviseren we dat (multisensorische) BCIs ontworpen moeten worden volgens (spatiële) HCI richtlijnen, d.w.z., gebruik makende van spatieel congruente multisensorische stimuli en informatie.

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This is it, the last section I am writing for this dissertation. I am looking back with mixed feelings. The last years have been like backpacking for a long time, which is actually my favorite hobby. My first travel was to India, and the trip was amazing, interesting, and a life-enriching experience. Yet, I was exhausted and deprived of both energetic and financial resources, overwhelmed, and perhaps a different person when I came back. This is how I feel now too, I have learned a lot –workwise and personally- and all experiences have helped me grow. I have enjoyed this research trip and immensely appreciate the experience, but am happy that this chapter in my life is almost done. Since India I have made quite a few other travels, and will continue to do so, but I am not planning to go back to India any time soon. This work could not have been accomplished though without the help of many others. I would like to thank each and every one of you. I am very grateful to you, even if I forget to mention you here.

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Curriculum Vitae

Marieke Elise Thurlings was born in Aalst-Waalre, the Netherlands, on December 24, 1981 and graduated from secondary school Sint-Joris College (VWO) in 1999 in Eindhoven (the Netherlands) at the age of 17. She obtained a Bachelor of Science degree in 2006 and a Master of Science degree (average 8.1; top 3%) in Industrial Design (Design for Interaction) in 2007 from the Delft University of Technology (the Netherlands). During her studies she was involved with various extracurricular professional activities, such as teaching, research and international collaboration. Additionally, in 2003/2004 she studied a semester abroad at the Polytechnical University of Valencia (Spain). She initiated her own graduation project, for which she got the opportunity to work on at Philips Design Eindhoven (the Netherlands). The project was aimed at the concept-development of a biofeedback product that helps people to influence their stress level, based on extensive qualitative research.

Marieke decided to extend her engineering and Human Factors skills and knowledge, with a scientific training. From 2008-2012, she was a PhD candidate within a collaborative project between the Department of Information and Computing Sciences at Utrecht University and the Department of Perceptual and Cognitive Systems at TNO (the Netherlands). Her research on Brain-Computer Interfaces resulted in this dissertation entitled 'Brain-Computer Interfaces based on multisensory Event-Related Potentials'. At both TNO and Utrecht University, she extended her teaching experience and supervised Master graduation students. During her research she collaborated nationally (amongst others in consortia Gate and Braingain) and internationally (e.g. summer-school eNTERFACE on multimodal interfaces at the University of Genoa, Italy). Furthermore she collaborated with a leading research group at the Berlin Institute of Technology in Germany (under supervision of prof. Blankertz), in which she is currently continuing her research on Brain-Computer Interfaces as an invited guest researcher.

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