MTBalance: Assisting Novice Mountain Bikers with Real-Time Proprioceptive Feedback

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Fig. 1. MTBalance, a system aimed to improve the balance and technique of novice mountain bikers with real-time feedback.

Mountain Biking (MTB) is an increasingly popular outdoors activity which offers a unqiue connection to nature along with the health benefits of cardiovascular exercise. Yet, complex MTB technique is an entry barrier that often prevent novices from enjoying the sport. Developing interactive systems, which can support developing MTB proficiency can augment the outdoor experience and make the sport available to a larger group of users. To that end, we designed, implemented and evaluate MTBalance—a system which provides body posture feedback for beginner mountain bikers. Based on inertial tracking, MTBalance informs the user about how to correct their posture to improve MTB performance. We conducted a study in which we compared different feedback modalities for MTBalance. We observed that the system increased perceived balance awareness. Our work provides insights for designing body awareness systems for outdoor sports.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**.

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1 INTRODUCTION

While most cyclists use their bicycles as a means of commuting on paved roads, mountain biking offers an experience of exploring forest paths at a breathtaking pace. The complex terrain in which MTB takes place, demands a wide variety of skills from riders. Mountain bikers need to find a right posture, the correct stance, properly using the brakes, while at the same time maintaining stability. Adjusting posture to maintain balance is often a difficult skill to master for novice bikers. Supporting bikers in developing balancing skills could potentially lower the skill entry barrier, which could make MTB available to a wider audience.

Previous studies in the field of Human-Computer Interaction (HCI) explored the use of technology during everyday [41] or at-home [21] cycling. Past research efforts explored solutions for increasing cyclist safety [25], navigating city environments [8] and controlling mobile devices [57] when cycling. Even though these interactive technologies are useful in a regular cycling context, we note that MTB requires a different type of technological support. In contrast to everyday cyclists, MTB riders tend to push the boundaries of their capacity, riding increasingly challenging trails while improving their skills. These aspects are part of the thrill and therefore arguably essential to the MTB experience. Currently, to our knowledge, no studies have explored how technology can support mountain bikers in developing such technical riding skills. To address this gap, our work explores how interactive technology can aid novice mountain bikers.

To this end, we explored how novice mountain bikers can be aided in adjusting their body posture during an MTB ride. We designed a system called MTBalance, which models the rider's posture during a ride and provides real-time feedback on how to adjust posture to attain optimal balance. We compared three feedback designs for MTBalance: two designs of visual feedback on the helmet and feedback using a vibrotactile belt. We found that the vibrotactile belt provided the best perceived sense of balance and it was preferred by most users.

Our study offers an exploration of technology-supported mountain biking, focusing on the key skill for novice mountain bikers: maintaining balance. Furthermore, this paper contributes (1) the design and implementation of MTBalance: a posture feedback system for MTB; (2) a comparative user study conducted on a MTB track which compared feedback modalities for MTBalance and (3) insights for future systems which augment the users body awareness in sports.

In this paper, we first discuss relevant related work. We then report on the design and implementation of our system. Next, we describe the user study and provide its results. Finally, we discuss our findings and relate them to past results in designing interactive technologies for physically active users and discuss how our system constitutes a start for exploring the design space of mountain biking.

2 RELATED WORK

In this section, we situate our work in the HCI for sports field and report on past research which inspired our work. First, we discuss HCI work which focused on increasing bodily awareness. Next, we report on past examples of designing feedback in context of HCI for sports. Finally, we present previous work on designing interactions for cyclists.

2.1 Bodily Awareness in HCI

The HCI field has an established track record of designing body-centred technologies for increased awareness [30]. Lopes et al. [23] explored using proprioception as a means of interaction, using relative body posture as input. This method was extended by Asplund and Jonsson [2], who used physical visualization to help users stay balanced. Despite a number of applications, there is no consensus on on the effectiveness of feedback modalities for body awareness. Turmo Vidal et al. [48] helped users achieve body alignment by implementing vibrotactile feedback and *Haptic Radar* [6] used 360-degree vibration motors. In contrast, Newbold et al. [28] used visual and auditory feedback to increase awareness of movement. These works show that there is a need for further investigating how feedback for body awareness can aid users in body-oriented tasks. Further, most examples in past research focused on static postures. Feedback for more dynamic movements requires further research. Body awareness is a recognised design goal, and our work explores new ways in which it can be achieved.

2.2 Feedback in HCI for Sports

A number of feedback solutions were designed to help users during physical activity. Vibrotatctile feedback is the most prominent form of haptic feedback HCI for sports. Erp et al. [50] investigated the use cases of tactile feedback by defining proof-of-concept cues that indicate where, how and when to move within the tactile feedback paradigm in rowing training. Stewart et al. [46] designed a wearable training device for roller derby, which allowed skaters to reflect on their technique in real time. Feeken et al. [11] built *ClimbingAssist*—a tactile display attached to the shin of amateur climbers. The device provided real-time feedback to support users in improving their technique. These examples show teat vibrotactile feedback is often a strong candidate for designing output in sports applications.

Visual feedback was also effectively used in sports. Fothergill [13] found that visual cues were effective especially when athletes became fatigued or experienced extended absence of additional coaching in rowing. Park and Lee [35] developed the *Motion Echo Snowboard*, which help users understand their body movements when snowboarding. Finally, Niforatos et al. [29] built the *s-Helmet*, a smart ski helmet, which alerted users about skiers approaching from behind with peripheral feedback. Based on these works, we observe that there is potential to effectivey use visual feedback in the context of dynamic exercise.

Auditory feedback was also extensively explored. Rheden et al. [51] contributed a literature review of sonification approaches for HCI in sports, analyzing the use cases and implementations of auditory solutions during physical exertion. They reported that auditory feedback was successfully used in running [27], swimming [42], dance [14] and cycling [43]. Further, sound was used in combination with other feedback modalities. Nylander et al. [32] explored the effectiveness of peripheral interaction for cross-country skiing and golf with a combination of vibrotactile and audio feedback. Later, they implemented both audio and visual feedback to raise the movement awareness of runners [31].

While there is a rich body of work on designing feedback for sports, there are no established guidelines or design procedures to choose the correct modalities for a specific activity. Works which compare modalities often do not offer clear-cut conclusions or modality choice or suggest using multiple modalities. For instance, Wozniak et al. [56] reported that different modalities offered different advantages in supporting maintaining golf posture. Consequently, this work explores the modality design specific to the dynamic body positioning task involved in MTB rides to further understand how we can design feedback in HCI for sports.

2.3 HCI for Cycling

There is a limited history of designing for interaction while riding the bicycle in HCI. A key design consideration within this area is the fact that the user's perception of stimulus is diminished compared to a stationary activity. Pakkanen et al. [34] studied how the perception accuracy and reaction times are influenced by tactile pulses while biking. They found that depending on the bodily position of the tactile cue, the ability to perceive cues was significantly affected. Bial et al. [3] have shown how tactile feedback was able to support cyclists in fulfilling a user-defined training program. This was done by communicating the desired pedal cadence with tactile pulses.

Bicycle navigation also explored as a design case. Steltenpohl and Bouwer [45] used a tactile belt and a two-stage waypoint design to help participants with anticipating upcoming turns. *Vibrobelt* was able to guide all participants to their end-goals via an unfamiliar route. Moreover, it made the occurrence of (near) accidents less common, though traditional navigation systems were generally faster. Poppinga et al. [38] shifted the focus from precise navigation towards a more exploration-focused navigational aid. *Tacticycle* helped users orient themselves without influencing the cycling experience, focusing on improving the overall sense of direction. Two vibrotactile actuators were placed on the handlebars of a bicycle, where the intensity of the vibration depended on the target position and the current orientation. The study was extended by renting the prototype to tourists, which showed that the system could be used to navigate in a playful manner [37].

Further research explored different modalities for providing additional feedback while cycling. Schneiders and Skov introduced *CyclAir* [44], a visual feedback system mounted on the handlebar of bicycles, which allowed users to monitor traffic-related air pollution in their proximity. Dancu et al. experimented with projecting navigational information on the road, allowing users for safe interaction with a navigational task whilst cycling [8]. However, this solution required a flat surface for projection. Okugawa et al. [33] built a sonified training system for bicycle pedaling, which guided users with clicks. Zwinderman et al. [58] designed a navigation method for cyclists based on 3D-audio. Yet, audio feedback and warnings were deemed less suitable in cycling environments as they could be obtrusive and irritating to the user [9].

While the HCI field did contribute a number of designs and studies where cyclists were the primary users, the majority of the work focused on tasks, rather than cycling technique. Further, past results indicate no consensus on which feedback modalities are optimal for in-ride use while cycling. This is work is, to our knowledge, the first to explore feedback on body position while cycling.

3 DESIGN

The design process of MTBalance involved several steps and iterations. We aimed to build a system that would support novice mountain bikers to improve their technique. Our inquiry began with conducting interviews with mountain bike coaches to identify the key areas that our system should address, resulting in a set of design requirements. Thereafter, the feedback modalities were chosen and evaluated through an online user survey.

The following subsections describe our design process, and explain the decisions that underlie the design of MTBalance.

3.1 Expert Interviews

We began our design process with expert interviews, in order to establish an understanding of current techniques, practices and needs for mountain biking. Three professional mountain bike trainers were recruited, each of them having more than five years of experience with training novices. We conducted three individual semi-structured interviews (total duration: 131 minutes).

In the interviews, we discussed what difficulties novice mountain bikers experience, additionally exploring the requirements and possible effects of new technologies in the context of the sport. We paid particular attention to difficulties which novices experienced in the sport and the ways to support the transition from novices to active practitioners. We inquired specifically about initial problems with MTB and the content of coach feedback during initial MTB training sessions. Subsequently, we presented an initial conceptualization of the MTBalance system in order to receive feedback on design decisions in this premature stage.

Three themes emerged from these interviews: (1) the importance of balance, (2) the significance of coaching for correct posture, and (3) a current lack of evaluation technology for mountain biking.

3.1.1 The Importance of Balance. All trainers specified that bike balance is an essential skill in order to improve mountain biking technique and to avoid accidents. The coaches voiced that altering posture to retain stability and balance is possibly the most difficult aspect for novice mountain bikers. A focus on posture guidance in the MTBalance system could resolve this. Yet, this type of feedback is only effective when the rider is conscious of the underlying techniques in the first place, indicating that coaching plays an important role in improving the nuances of mountain biking, such as having a correct posture.

3.1.2 Significance of Coaching for Correct Posture. The experts mentioned that coaching allows for quicker progression since this feedback enables reflection on the nuances of mountain biking. Progress could stagnate if bikers do not comprehend how and what to improve; thus, professional training such as following a clinic is often recommended. It was stated numerous times that practice is crucial to improve the underlying techniques needed to preserve balance. The experts also noted that real-time feedback should be limited to dire circumstances, since distractions affect concentration and increase the likelihood of perilous situations, which is something that should be taken into consideration for the design of MTBalance.

3.1.3 Lack of Evaluation Technology for Mountain Biking. Finally, the trainers mentioned that there is currently a lack of technology that supports users in the technical aspects of mountain biking:

> "There are devices that are able to measure distance and height, though there are no options that focus purely on providing technical feedback".

This lack of technology used for technical feedback is due to three reasons. First of, *impracticability*; since mountain biking is a sport of high intensity and uses a large range of motion, devices could limit the mobility of a rider which negatively impacts performance. Secondly, due to *obtrusiveness*. A tool could shift the attention of the rider away, leading to negligence of their posture and viewing behaviour. The experts expressed concerns regarding this possible focus shift since cycling computers have similar effects, leading to unsafe and unenjoyable rides. Finally, given the non-deterministic nature of the sport, there tends to be *variability*. Devices evaluating technical aspects need to consider an abundance of variables such as bike orientation, velocity, the positioning of the rider, surface types and weather conditions. However, regardless of these technical challenges, our experts did show interest in devices aimed at giving feedback on balance and posture during mountain biking. Through these interviews we constructed a set of design requirements that should be taken into account for the design of MTBalance.

3.2 Design Requirements

Based on our review of previous work and the interviews with professional mountain bike instructors we formulated requirements that could guide our design process. From a functional perspective, the system needed to be wireless and non-restrictive to the range of motion, in addition to being compact, lightweight and durable.

From an interaction perspective, the system should provide feedback both post-hoc, as well as in real-time. The post-hoc feedback should provide the user with rich data regarding proper balance, handling different orientations along with any environmental noise present during mountain biking. Real-time feedback on the other hand, should solely be used for dire situations. Furthermore, real-time feedback should be unobtrusive in order to avoid jeopardizing safety, caused by distraction. In our discussions with the coaches, we decided to focus on the balance of the rider because adjusting posture to the terrain configuration was the key skill, which novice MTB riders needed to develop. Improper balance often led to other issues with technique and may have caused abandonment of the sport after an initial interest. Concurrently, understanding balance when riding on a bike was an area of past study in kinematics and sports mechanics, e.g. [40]. This enabled us to applied the modelling techniques available in research to a pragmatic problem faced by novice riders.

3.3 Choosing Feedback Modalities

We investigated tactile, visual and auditory modalities for real-time feedback solutions, as these are the most common options within the HCI research field. Auditory modalities are considered to be less suitable in the context of mountain biking as it tends to be obtrusive, irritating or even dangerous [9, 54]. Therefore, we did not further consider audio-related designs as viable solutions.

Tactile displays on the other hand, do not overload cognitive processes, thereby lending itself as an unobtrusive feedback option [50]. Previous work showed several examples of providing vibrotactile feedback through modified belts [17, 19, 36, 45]. These studies attached the belt to the waistline of users, which is a suitable location for several reasons: the waistline has a relatively high perception rate of tactile cues [34], the waistline receives the least amount of jerk during rides which limits environmental vibrations [19], and a belt does not restrict movement during mountain biking [45]. Given the repeated success in providing vibrotactile feedback through waist belts, we chose a similar approach for one of the two designed feedback devices, as illustrated by Figure 2. While we wondered if vibrotactile feedback would be effective in an MTB scenario, past research strongly indicated that it was a viable design alternative. Thus, we decided to investigate it further.

Next to tactile feedback, also visual feedback could be a suitable feedback mode for MTBalance. However, as on-screen alternatives could be distracting, we decided to implement peripheral visual feedback in the second feedback device, due to its repeated success in context of HCI [20, 29, 47]. The *LeaD* and *s-Helmet* solutions inspired the design of the real-time visual feedback, both augmenting a helmet with a LED strip; the helmet possibly being the most ubiquitous gear used while mountain biking. By using a LED strip, we can provide feedback to the peripheral view of the user without drastically obfuscating or impeding sight [7]. This minimizes the impact of the system on obtrusiveness, usability, portability and comfort. These factors, together with the fact that past helmet-based interfaces were successfully deployed [52], implied that we needed to consider a helmet interface as a possible design choice for our system.

3.4 Defining Feedback Modes

We developed three different feedback modes: a vibro-tactile feedback mode, and two visual feedback modes. The *vibro-tactile feedback* (VTF) mode uses the waist belt to give the user feedback. The belt consists of several vibration motors that are spaced apart equally over the length of the belt in an ordinal set-up, with motors for each direction [17, 36, 45]. As the feedback intensity of the vibration motors needs to be modified based on user exertion [34], we decided to set the vibrotactile intensity high by default to account for the general mobility and the impact of the rough terrain during mountain biking. Furthermore, the vibratory stimuli increase as the user deviates more from the optimal balance zone.

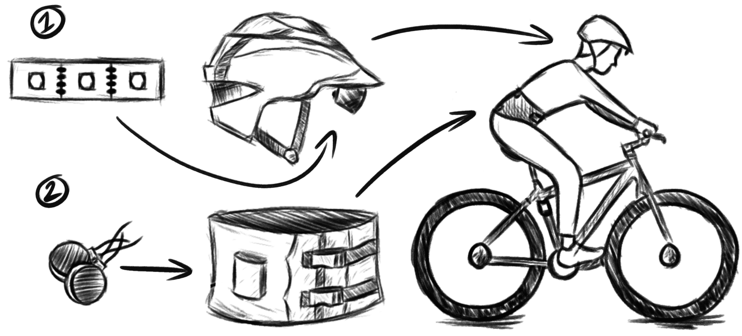


Fig. 2. The initial feedback devices of MTBalance. The visual feedback device (1) has a LED strip attached to the front end of a helmet. The vibrotactile feedback device (2) is a belt lined with vibration motors, worn above the hips.

The *Visual-Directional Feedback* (VDF) mode uses a combination of colored light patterns to convey the feedback. This mode is based on a binary traffic-light color scheme, denoting forward-directed feedback with green, and backward-directed feedback with red. To make sure that the design of MTBalance is inclusive, we decided to use cyan instead of 'pure green', so that the light signals are also distinguishable for users with Deuteranopia (red-green color blindness), which is the most common form of color blindness [55].

The *Visual-Color Feedback* VCF mode uses the RGB color spectrum to visualize the feedback directions. In the VCF mode, each of the eight directions is represented by a single color. As the RGB color spectrum is not a standardized model, we assigned the color mapping for each direction based on default occurrences in mainstream computer software (e.g. Adobe Photoshop). The color mapping is in line with previous work that mapped hue to cardinal directions in an effective manner [5, 20]. Furthermore, past work indicated that fixed color patterns were easy to recognize, even for people with some form of color blindness [5]. Since none of the feedback directions has priority, this mapping translates well to the circumstances present while mountain biking.

3.5 User Survey

In the next phase of our design process, we conducted a study with low-fidelity prototypes to determine the preferred feedback modes. This is a pragmatic approach as based on past work in the sports area, e.g. Wozniak et al. [56]. Choosing feedback modalities for sports where in-activity feedback was not explored before is a task with often divergent design alternatives, cf. [10]. An experimental vignette approach [1] was used to receive feedback on the design in its early stages and assure a user-centred design process.

3.5.1 Participants. We distributed the survey on the social media site *Reddit*, with a focus on user groups with affinity for mountain biking, preferably novices. In total, we recorded 50 survey responses (47 male and 3 female), aged from 14 to 42 years old ($M = 27.96, SD = 7.43$). We recorded entries from 23/06/2020 to 30/06/2020, with a survey completion rate of 58%. The 21 partially completed surveys are solely taken into consideration for the introductory and open-ended questions; to prevent skewing the quantitative data parts.

3.5.2 Survey Content. We employed the *Qualtrics*[1] survey software to create an online survey. The survey acquired insights on the feedback design concepts, and took approximately 15 minutes to complete. These feedback design concepts consisted out of the introduced real-time feedback devices and modes, along with a post-hoc application prototype that works in conjunction with the direct feedback. The survey utilizes the UMUX usability metric questionnaire to target the effectiveness, efficiency and satisfaction of the elucidated solutions. The full questionnaire is available as auxiliary material.

3.5.3 Results. In the survey we presented the real-time and post-hoc feedback modes to the participants. We showed the real-time modes in a counterbalanced fashion to minimize possible group effect.

Per participant, an UMUX score (0-100 point scale) is calculated for each of the modes. ANOVA procedures could be used for the analysis of the data since UMUX is a standardized scale for which normality is shown [4]. Figure 3 presents the scores for each mode.

The survey data showed that the post-hoc feedback solution is significantly preferred over most real-time feedback proposals. A reason for this might be that users are familiar with this feedback type, since many participants acknowledged the usage of a dedicated device or application during their rides to track statistical data such as distance and speed. This familiarity could make the post-hoc application less daunting. Some participants noted that the preference was due to the solution being the least generalizing and most unobtrusive option; post-hoc feedback is processed over a longer time-frame compared to the real-time alternatives and does not directly influence biking behaviour. Furthermore, participants struggled with comprehending the continuous nature of the real-time feedback after the threshold is reached. A common suggestion was to limit the amount of feedback directions so that each signal was easier to recall.

Additionally, participants were probed to state a preferred real-time feedback solution. The vibrotactile solution got the majority of the votes (62.07%). However, the results are not significant due to a high variance within the data. Therefore, both the vibrotactile and visual designs will implemented in the final system.

Overall, the statements made by the participants line up with the advice received from the expert trainers. Participants assessed that an automatic coaching and feedback system could be particularly useful for novice mountain bikers. The results of the user survey have been combined with the expert advice and previous work, leading to the final design of the feedback in MTBalance.

3.6 Final Prototype

Based on related work, expert interviews, the user survey, design requirements and design principles, we finalized the design of the feedback devices in the MTBalance system.

As result of the poor performance of the VCF mode in the user survey, we replaced it with an alternative visual mode that is comparable to the VDF mode. Visual-Positional Feedback (VPF) relies solely on light patterns to convey the feedback directions as each feedback direction uses the color blue.

Due to suggestions from the user survey, the feedback modes now use a discrete set of balance directions instead of continuous direction feedback [10, 11]. This discrete implementation provides feedback in the relative ordinal directions around the user, resulting in a set of 8 possible feedback signals per mode. This increases the clarity of feedback whilst making it easier to comprehend [20]. Naturally, this means that we updated each mode to have a specific signal per direction. Each predefined signal per mode is shown in figure 4.

[1] https://www.qualtrics.com/

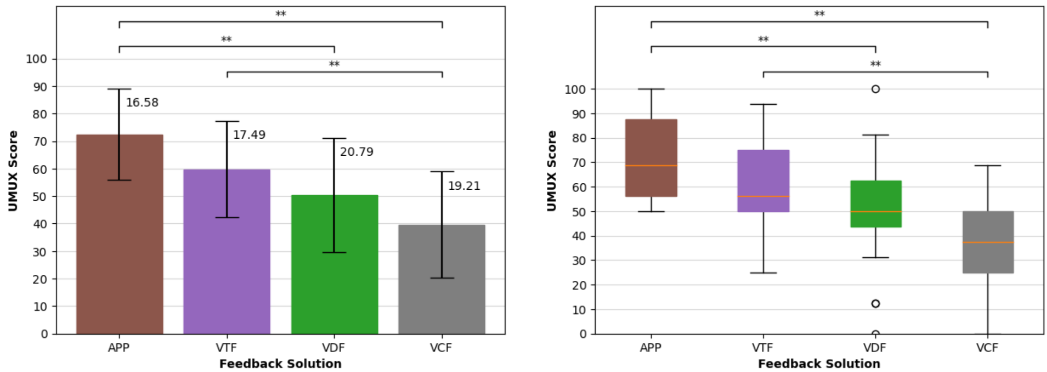


Fig. 3. The one-way within-subjects ANOVA results, detailing the significance of the UMUX scoring on the proposed feedback modes. The bar plot (left) shows the average means of each of the proposed solutions, including errors bars indicating the standard deviation. The box plot (right) illustrates the spread of the UMUX scores. These plots are displayed side-by-side to represent the counts and distribution characteristics of the results respectively. The annotations signal the significant pairs. A single asterisk in these plots denotes a significance of ($p < .05$), with double asterisks representing a significance of ($p < .01$).

Figure 5 demonstrates the final design of MTBalance. The definitive implementation of the vibrotactile feedback features a customized running belt which we lined with coin vibration motors [17, 19, 36, 45].

The visual feedback device of MTBalance uses a standard mountain bike helmet, which we further augmented with electronic components. We attached a LED strip to the topside of the helmet, in the peripheral vision of a user to provide the visual feedback cues, similar to the design of *LEaD* and *s-Helmet* [29, 47]. By utilizing equipment which is standardized within the sport, unobtrusiveness, usability, portability and comfort are ensured, staying in line with the design requirements. The LED strip is in turn attached to custom-made electronics which we mounted on top of the helmet. Switching between the modes is done by simply changing the desired feedback in the main application. There are no additional buttons to operate the device; the battery is connected to the microcontroller and further settings can be accessed in the developed application similar to the vibrotactile feedback device, streamlining and simplifying the MTBalance system.

4 IMPLEMENTATION

In this section, we describe the design of our final prototype to ensure the reproducibility of our study. The auxiliary material contains a video file that demonstrates the implementation of MTBalance.

4.1 Sensors Used for Balance Information

Taking a similar approach to Fitzpatrick and Anderson, Marin-Perianu et al. and Morris et al., we collect the directional balance information with IMU sensors [12, 24, 26]. Ultimately, we integrated the *Xsens DOT*[2] IMU environment into MTBalance seeing that the *DOTs* are small, lightweight and wireless, and are designed specifically with sport and health applications in mind. Each IMU sensor incorporates an accelerometer, a gyroscope and a magnetometer to provide an accurate

[2]https://www.xsens.com/xsens-dot

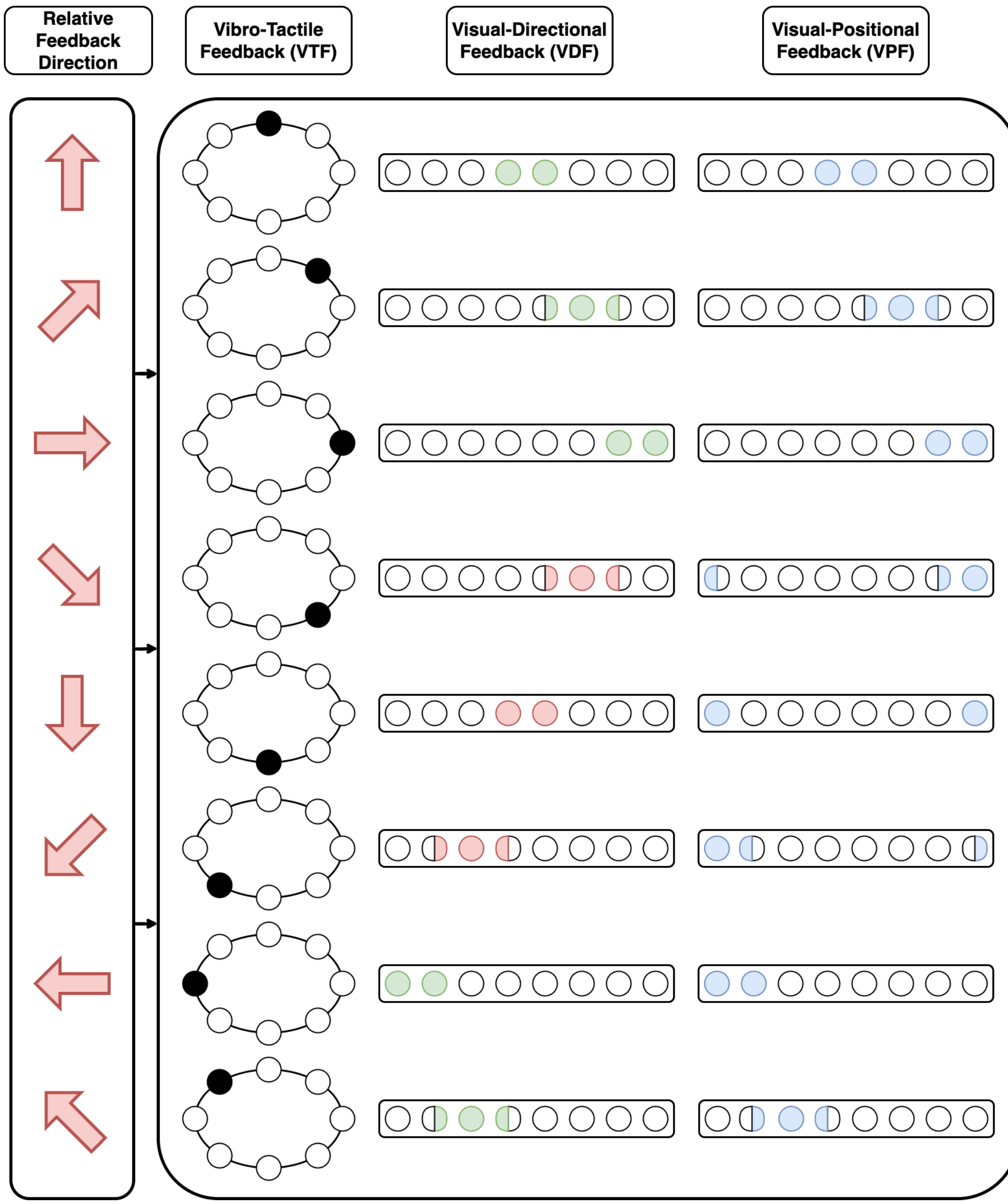


Fig. 4. Overview of all the feedback modes in the MTBalance system. The arrows denote the feedback direction relative to the user from a top-down view. Feedback is only provided in discrete ordinal directions. A fully colored circle either stands for a group of 2 vibration motors in VTF mode, or for 2 LEDs in the visual modes.

Fig. 5. The final feedback device prototypes used with the MTBalance system; the visual feedback device (top left) and the vibrotactile feedback device (top right).

3D orientation. Furthermore, each IMU has an embedded processor that handles the sampling, calibration, the integration of the inertial data and a custom Kalman filter algorithm which is able to provide sensor orientation within 1 degree of accuracy. The calculated data is communicated using Bluetooth Low Energy (BLE) 5.0, ensuring that calculated orientation data can be streamed in real-time to a custom-made mobile application for the MTBalance without explicit pairing.

We use five *Xsens DOT* sensors in the MTBalance system. Three IMU sensors are attached to the bike, the other two to the user (one on the user's ankle, the other onto the knee). The sensors are wrapped inside the pockets of custom-made straps, made of foam and velcro. This makes wearing the IMUs more comfortable to the user.

4.2 Assessing the User's Balance from Sensor Input

To calculate the user's balance from the sensor input, we followed the approach used by Redfield [40], who studied the motion of mountain biking dynamics. Redfield created a bond graph model depicting maneuvers specific to the sport, such as banks, drops and rough terrain riding. We use this model to estimate the body mechanics present during mountain biking. Implementing the model in MTBalance, enables accurate balance assessment, which we determined to be key for beginner MTB riders through the expert interviews. The model is especially applicable to novice mountain bikers, as the relation between body and bike movements is more rigid (i.e. beginner riders react more profoundly to changes in bike alignments) for novices in contrast to more experienced riders, according to both Redfield and the expert coaches [40].

Our approach involved six calculation steps, as depicted in Figure 6. Through these steps, we calculated the balance difference, from which the feedback direction could be derived as the correction required to return the rider to an equilibrium state. This correction served as the input for the different feedback modes. A more detailed description of the implementation and used formulas has been added to the supplementary material.

4.3 Vibrotactile Feedback Device

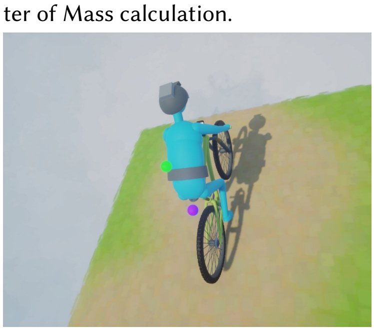
We implemented the vibrotactile feedback based on previous work which successfully integrated vibration motors into a belt for directional feedback [17, 19, 34, 45]. Especially Kiss et al. influenced the design; coin vibration motors (Parallax 28821) are applied in an 8x2 grid, with each set evenly spaced over the length of an elastic running belt [19]. We chose this grid design due to the high vibrotactile intensity it provides compared to related work [36, 37, 39, 45]. We hot-glued each set

(a) Quaternion rotations to create vectors.

(b) Yaw corrections are applied to properly align the vectors.

(c) Optimal balance line and user Center of Mass calculation.

(d) Finding the intersection point and distance.



(e) Flattening of the Center of Mass and intersection to calculate the balance difference.

(f) Angle partitioning, resulting in an ordinal feedback direction.

Fig. 6. The MTBalance application uses quaternion rotations to create vectors, yet, as figure 6a illustrates, these vectors are displaced. This is caused by the reference frame for the IMU's, which are earth-fixed, thereby not taking heading displacements into account. To correct the placement of the vectors, we applied yaw corrections (figure 6b). After this correction, the vectors can then be used to calculate the bike balance. MTBalance does so by calculating the Center of Mass of the user and the ideal balance direction, i.e. the state where the body of the rider would be closest to equilibrium. Next, the system calculates for the closest intersection, i.e. the point where the CoM to intersect with the optimal balance direction. Then, the distance between the CoM and this intersection is obtained. If the distance is larger than an empirically determined threshold, the feedback direction for the real-time feedback is calculated and sent to the used feedback device.

of motors at a different ordinal direction on the belt to provide vibrotactile cues in 360 degrees around the user.

We based the vibrotactile feedback prototype on an Arduino-compatible Microcontroller Board (MCU), the Seeeduino Lotus V1.1 - ATMega328[3]. It can receive directional feedback information from the mobile application with a Bluetooth Low Energy module (Grove - BLE V1.0 HM-11[4]). This module is directly attached to the Microcontroller Board using a Grove connector to limit soldered connections, keeping hardware accessible. Eight data pins from the MCU are in turn connected to a custom designed Printed Circuit Board (PCB). The MCU, BLE module and custom PCB are connected to each other with jumper wires and are tucked away in the pouch on the front end of the running belt. A generic lithium-ion battery is used to power the vibrotactile feedback device (2600mAh, 5V/1A), directly supplying power to the USB input on the MCU.

4.4 Visual Feedback Device

Inspired by the *LEaD* and *s-Helmet* approaches of Tseng et al. and Niforatos et al, we display the visual feedback using a high-brightness Adafruit NeoPixel LED strip, housing a total of 30 LEDs (SK6812) over 0.5 meters[5] [29, 47]. The stript used RGB LEDs, allowing for quick customisation or desiging user-specific colour coding, e.g. for users with a specific kind of colourblindness. We chose this specific strip since the LEDs are spaced apart adequately and are uniformly distributed, limiting the possibility of confusing users with the different feedback cues [29]. Since the amount of LEDs do not necessarily influence accuracy [47], we cut the strip to a total length of about 26 centimeters resulting in 16 usable LEDs, matching the amount of vibration motors in the vibrotactile feedback. The LED strip was held in place at the front end of a generic mountain bike helmet with cable ties, properly centered around the circumference of the helmet. We encapsulated the LED strip with a removable IP20/65 weatherproof casing to further protect it. The visual feedback device uses the same MCU[2] and BLE[3] module as present in the vibrotactile feedback, in order to keep programming between the two devices consistent and to simplify troubleshooting if needed. Once again the BLE module is directly attached to the MCU using a Grove connector (4 pin), making communication with the MTBalance application possible. We powered the visual feedback device with a 2500mAh lithium-ion battery (RealPower PB-2500 Slim), directly attached to the Microcontroller Board to ensure a constant 5V power supply with a current of 1A. The MCU, BLE module and battery are contained within a small, waterproof plastic container lined with protective foam. This container is fixed on top of the helmet with cable ties through small holes in the bottom of the container and the venting holes of the helmet. This gave us easy access to the electronic components whilst keeping them protected from environmental factors such as rain and impacts.

5 EVALUATION

In order to evaluate MTBalance, we conducted a within-subject experiment with repeated measures, which was performed on a mountain bike trail in a local forest. We wanted to evaluate how the feedback modes performed and to observe how novice mountain bikers used the system in conditions that test the robustness and the capabilities of every mode.

5.1 Participants

We used social media and snowball sampling to recruit participants for the study. Our experiment call was distributed via instant messengers (e.g. WhatsApp), along with emails to dedicated mountain

[3]https://www.seeedstudio.com/Seeeduino-Lotus-V1-1-ATMega328-Board-with-Grove-Interface.html
[4]https://wiki.seeedstudio.com/Grove-BLE_v1/
[5]https://www.adafruit.com/product/3919

bike groups. This ensured that a range of (preferably novice) mountain bikers was recruited with similar levels of experience. In total, we recruited 20 participants (18 male and 2 female), aged from 22 to 32 years old ($M = 26.95, SD = 3.02$). Participants were asked for their perceived skill level (beginner, intermediate or expert), with all but one classifying themselves as novices. This high rate of beginners was favorable since the MTBalance system is designed with inexperienced mountain bikers in mind. None of the participants reported being colourblind. We did not give any remuneration to participants, aside from providing drinks and snacks during the study. The study lasted around 75 minutes per participant.

5.2 Apparatus

The participants completed a predefined mountain bike course, with a length of 500 meters, for each of the conditions, whilst focusing on their balance during the ride. The trail was located in a forest as this is a typical environment to practice the sport in. To ensure that we tested the MTBalance system in a setting with circumstances that would naturally occur while mountain biking, the chosen trail contained many common elements and obstacles; it included technical challenges such as banks, (sharp) turns and uneven terrain with mud, leaves, roots and rocks. These elements were featured throughout a downhill section with small drops, along with an uphill segment including varying slope angles. We took extra care to ensure that the trail was not too difficult for novice mountain bikers. We laid the course out as a closed circuit; participants ended the route at the same location from where they initially started. Not only did this simplify the testing process, it made the route easier to explain to participants as well; the trail route featured solely 2 right turns at distinct crossings on the route. The auxiliary material contains a video file that demonstrates the entire course.

5.3 Hypotheses

Using this set-up for the experiment, we evaluated the following hypotheses:

(1) The balance performance of the vibrotactile solution will be significantly higher than the balance performance of the visual solutions;
(2) The response time of visual solutions will be significantly faster than the response time of the vibrotactile solution;
(3) Using real-time feedback leads to a significantly better perceived balance awareness compared to the no feedback conditions.

We based *Hypothesis 1* on related work, which indicates that tactile systems have a high performance in cycling environments, especially in navigational context [3, 36, 45]. *Hypothesis 2* builds upon visual related work that shows the effectiveness of visual cues, most notably for reaction times [25, 29, 35, 47]. *Hypothesis 3* refers to the heightened sense of bodily awareness present in past real-time feedback systems using the proprioceptive abilities of humans [6, 23, 28, 48].

5.4 Conditions and Measures

For the evaluation of MTBalance we asked participants to complete the course four times, once for each of the following conditions:

- *Base:* solely post-hoc feedback (denoted as *APP* in further plots);
- *VTF:* Vibro-Tactile Feedback, no post-hoc feedback;
- *VDF:* Visual-Directional Feedback, no post-hoc feedback;
- *VPF:* Visual-Positional Feedback, no post-hoc feedback;

Next to general variables such as the start time of each condition, participant number and the current condition, we collected six different metrics for each condition: balance performance, balance deviation, response time, Task Completion Time (TCT), a score describing how aware participants were of their balance (balance awareness) and perceived task load.

We express balance performanceas a percentual value, that indicates how long a participant has been in a balanced state ($T_{balanced}$) over the total ride time (T_{total}). The *MTBalance* system deemed a participant to be in balance when their CoM is within the desired threshold (set to 50 centimeters in this study, based on extensive testing and related work [22, 40]) and unbalanced when they overshoot this threshold. As such, we calculate the balance performance *BP* in the following manner:

$$BP = \frac{T_{balanced}}{T_{total}} * 100 \tag{1}$$

Balance deviation is the average deviation of the participant from the balance threshold, measured in centimeters. During each measurement, the *MTBalance* system determines if the participant is unbalanced. If so, we add the current deviation from the threshold to a cumulative moving average (*CMA*) in order to process the metric in real-time:

$$CMA_{n+1} = \frac{x_{n+1} + n * CMA_n}{n+1} \tag{2}$$

where:

n	current iteration
x_{n+1}	value added to the CMA

The response time denotes the average recovery time of a participant going from the unbalanced state to the balanced state, in milliseconds. We measured TCT with a digital chronometer present in the application. The chronometer began automatically at the start of a condition and was manually stopped as participants finished the circuit. The balance awareness is a score on a 10-point Likert-type rating item, where participants stated how conscious they were of their balance during the trail; the score ranges from completely unaware (1) to fully aware (10). Task load was determined by using the NASA Task Load Index (TLX), which is an assessment tool that allows for quantifying and analyzing the workload required to complete a task [15]. After completing a condition, participants filled in a questionnaire consisting out of six sub-scales on a 21-point Likert scale adaptation [16]. Individual opinion on MTBalance and the whole proposed interaction was collected in semi-structured interviews.

5.5 Procedure

We welcomed and briefed participants before the experiment. Once again we asked for explicit consent regarding the processing gathered data and study participation in general. We strictly advised participants not to jeopardize their safety during the experiment; they were explicitly informed to finish the trail at their own pace, to not take unnecessary risks by being aware of their own capabilities and to watch out for other people using the trail.

We explained the experiment in depth whilst walking to the trail. Next, we collected demographic data and questioned participants about their perceived mountain biking experience. Once the starting area of the course was reached, we adjusted the bike saddle to match the participant's height. Since each participant has a different person-specific level of balance performance, we first assessed each participant's baseline balance performance by running the MTBalance application whilst participants sat on the bike in a stable position, and made adjustments if needed. Each participant was then assigned a starting condition and equipped with the corresponding feedback

	BalPerf [%]		BalDev [cm]		RespTime [ms]		TCT [s]	
Condition	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Base	92.17	7.79	0.65	0.81	10.7	7.89	164.55	17.55
VTF	96.54 †	3.24	0.23 ‡	0.27	8.09 †	5.82	165.88	17.04
VDF	93.88	4.75	0.55 †	0.55	12.52	9.77	175.09	23.96
VPF	89.68 †	8.47	2.68 †‡	3.74	17.49 †	15.98	174.07	20.47
ANOVA	($F_{3,57} = 4.842, p < .005$)		($F_{3,57} = 7.695, p < .0005$)		($F_{3,57} = 3.565, p < .05$)		($F_{3,57} = 2.741, ns$)	

Table 1. The mean value and standard deviation for every Dependent Variable: the balance performance (BalPerf), balance deviation (BalDev), response time (RespTime) and Task Completion Time (TCT). Moreover, the results from the respective ANOVAs are presented as well. Except for the TCT, each of the results are significant. † and ‡ show significantly different pairs, calculated using Tukey HSD at the $p < .05$ level.

device. Condition order was counterbalanced using Latin squares. Our study replicated the within-subjects design used in past HCI for sports work, e.g. [10, 56] For conditions with feedback, we allowed participants to test the real-time feedback, making sure that participants could see the LED strip in their peripheral view and that the belt was in the right position. Once the participant had a confident understanding of the feedback, they were allowed to start their ride.

When the participant finished the course, we manually stopped the measuring process. The participant was given time to recover and was offered drinks and snacks. During this recovering period, we asked them to fill in a questionnaire containing the balance awareness scale and NASA TLX measures. Afterwards, we conducted a short, open interview to ask about personal findings for the tested condition. Once rested, the participants started their next condition in the same fashion. After completing all the conditions, we asked some final questions regarding their thoughts on all conditions to investigate which condition was preferred and if a certain style of feedback was endorsed. Finally, we debriefed the participants and thanked them for their cooperation.

6 RESULTS

We collected four dependent variables the balance performance (as a percentage), balance deviation (in centimeters), response time (in milliseconds) and the total time required to complete the task (TCT, in seconds). Additionally, participants reported their balance awareness on a scale and the perceived load of each task using NASA TLX.

The four dependent variables were analyzed using ANOVAs, with the most relevant results summarized in Table 1 and Figure 7. We did not standardize the results of the quantitative measures; aside from a single participant, each test subject belonged to the novice category, ensuring differences in mountain biking proficiency were minor. Confounding variables such as the physical condition, level of exhaustion and track conditions were considered to be comparable. Normality tests for the quantitative data have been excluded due to the relatively small sample set (20 participants). For all measures we also run alternative models where the order of the conditions was a factor. The order was not a significant factor in all the models, which may suggest that the conditions were counterbalanced effectively.

The grand mean for the balance performance was 96.07%, with the highest mean recorded for the VTF mode ($M = 96.54\%$) and the lowest mean for the VPF mode ($M = 89.68\%$). The effect of the feedback mode on the balance performance was statistically significant ($F_{3,57} = 4.842, p < .005$).

For balance deviation, the grand average deviation from the threshold was $M = 1.03cm$. The lowest average balance deviation was measured for the VTF mode ($M = 0.23cm$), followed by the VDF mode ($M = 0.55cm$). This shows an increase in deviation of over 239% between the two

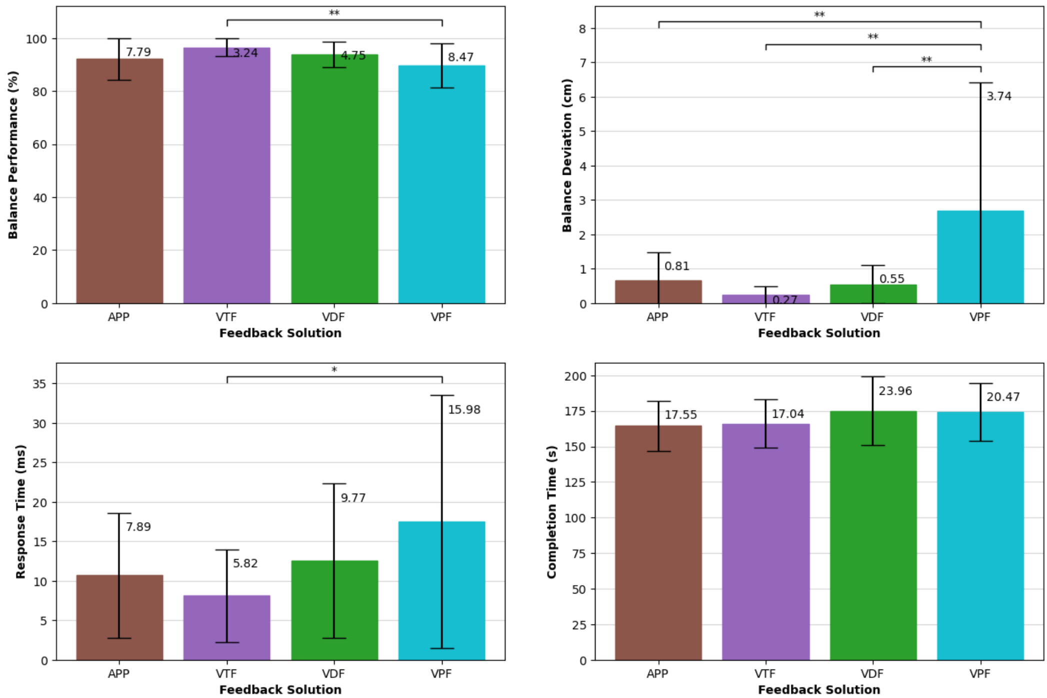


Fig. 7. The mean and standard deviation of each Dependent Variable. Significant pairs are marked with annotations. Note that aside from balance performance, a lower value is better. A single asterisk in these plots denote a significance of ($p < .05$), with double asterisks representing a significance of ($p < .01$)

modes. The effect of the conditions on the balance deviation was statistically significant as well ($F_{3,57} = 7.695, p < .0005$).

Next, the ANOVA of the response time showed a significant effect of the conditions on the DV ($F_{3,57} = 3.565, p < .05$). Both the base and VTF condition ($M = 10.70ms$ and $M = 8.09ms$ respectively) showed a mean below the measured grand mean ($M = 12.20ms$).

Finally, the Task Completion Time (TCT) was examined. The ANOVA showed that the completion time was not significantly affected by the feedback condition ($F_{3,57} = 2.741, ns$).

6.1 Balance Awareness and TLX

Since balance awareness is based on a 10-point Likert score, the measurement scale for the data is ordinal. As such, parametric tests are typically are not suitable for this type of data. However, aligning and ranking the data allows for the execution of a non-parametric ANOVA such that interaction effects can be examined. We transform the balance awareness data using the Aligned Rank Transform procedure [53].

The lowest mean was recorded for the base condition ($M = 4.95$), the highest mean for the VTF mode ($M = 8.30$). A one-way ANOVA on the transformed data displays that the effect of the feedback conditions on balance awareness was statistically significant ($F_{3,57} = 31.438, p < .0001$). A post-hoc Tukey HSD test revealed five significant pairs. Each of the real-time feedback modes had a significantly higher balance awareness when compared to the post-hoc (base) condition.

	Mental Demand		Physical Demand		Temporal Demand		Performance		Effort		Frustration	
Condition	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Base	20	20.71	61	16.59	24.75	19.83	25.75	16.08	66.5	16.79	23.75	20.89
VTF	21.25	17	57	17.43	21.5	15.99	20	8.43	59.25	18.3	18.5	15.9
VDF	32.25	17.51	60.25	16.82	28.5	20.53	24.5	7.76	60	21.82	39.75	21.79
VPF	58	19.49	60.5	16.21	27.25	17.73	34.25	18.16	66.75	17.11	52.75	25.47
ANOVA	($F_{3,57} = 22.809, p < .0001$)		($F_{3,57} = 0.907, ns$)		($F_{3,57} = 1.518, ns$)		($F_{3,57} = 4.123, p < .05$)		($F_{3,57} = 2.281, ns$)		($F_{3,57} = 13.799, p < .0001$)	

Table 2. The mean value and standard deviation for every sub-scale of the TLX questionnaire. The results from the respective ANOVAs are presented underneath each sub-scale. The mental demand, performance and frustration sub-scales scores are significant. Signifcantly different pairs shown were obtained using Tukey HSD.

Furthermore, the VTF mode yielded a balance awareness which was significant compared to both the visual feedback modes (VDF and VPF respectively). Figure 8 demonstrates the box plot of the balance awareness results.

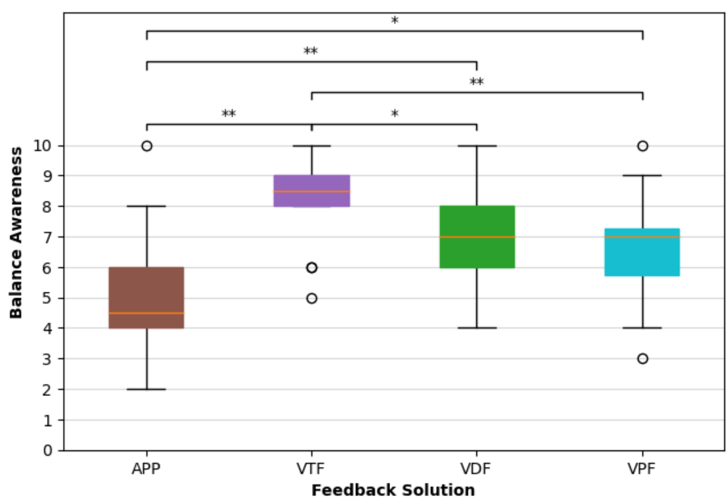


Fig. 8. Box plot detailing the spread of answers on the balance awareness scale for each condition. Note that the plot shows the non-transformed data for readability. The significance annotations are based on the transformed data. A single asterisk in this plot denotes a significance of ($p < .05$), with double asterisks representing a significance of ($p < .01$)

For the NASA TLX scores, we used one-way ANOVAs to compare the scores of the full scale and each sub-scale to the four feedback conditions, which is in line with the approach used by Wozniak et al. [56].

We acquired the full TLX scale score by taking the mean of the normalized sub-scales per condition and participant. This ensured that each sub-scale was rated evenly. The ANOVA revealed that the feedback condition was statistically significant for the TLX score ($F_{3,57} = 12.923, p < .0001$).

6.2 Qualitative Feedback

Post-study interviews were used to acquire more insight into the preferred feedback mode. All post-study interviews were recorded and transcribed verbatim.

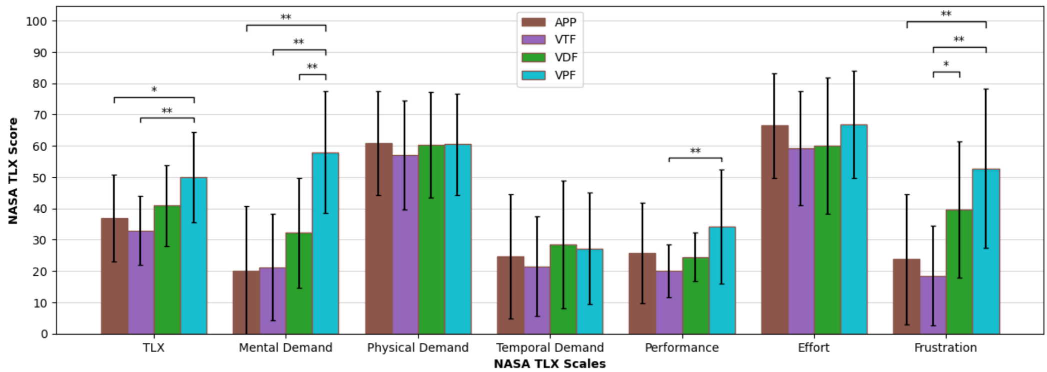


Fig. 9. The normalized NASA TLX scale and sub-scales from the task load questionnaire. Error bars show the standard deviation of each condition per sub-scale. Significant pairs are annotated. Lower scores indicate a lower task load, which is favorable. A single asterisk in this plot denotes a significance of ($p < .05$), with double asterisks representing a significance of ($p < .01$)

6.2.1 Preferred Feedback Mode. Out of the 20 participants, 14 preferred the VTF feedback mode. The other 6 participants had a preference for the base condition. VTF mode was considered a popular choice due to several factors. Most notably, the Vibro-Tactile Feedback was often described as natural and intuitive, allowing for subtle corrections in balance; the feedback being compared to an instinct by some participants:

> "When I received feedback while using the vibrotactile belt, it almost felt as if I automatically steered my center of mass towards the feedback direction. (...) The belt felt like an extension of my natural reflexes".

Directions in the vibrations were deemed clearly separable due to the motors being evenly spaced around the belt. Furthermore, participants noted that the mode is not visually limiting which allowed for complete focus and awareness on riding posture, balance and the trail without constantly thinking about the device or received feedback. Participants recognized that this made the mode less distracting overall:

> "I felt very confident and supported by the device. I did not constantly have to remember what certain vibrations meant or process the feedback to make sense out of it, so correcting myself was a breeze. Nothing was limiting my view or my movements. (...) The ride was very enjoyable, as if I had a hand on my shoulder guiding me".

Participants that favored the base condition showed an appreciation for the non-obtrusiveness and accessibility present in this method; it allowed riders to practice and enjoy the sport as usual without wearing or worrying about additional devices, receiving feedback in a way that is familiar to other sport applications:

> "I like that everything feels familiar and straightforward. I can just enjoy the sport while not getting distracted and get detailed feedback afterwards at my own pace. It is a lot like applications I use for other sports".

Furthermore, since the application gives feedback on the full ride in detail, deeper analysis is possible :

> "Looking back at the full ride gives me the possibility to go over it in my head. 'Oh, here is when I leaned too far over that tree trunk. And I think this is where I took the

corner too sharp', and so on. It is less specific to single moments than the real-time feedback. (...) I could use this to train and analyze multiple rides together, see what I do wrong and track progress as I better my posture and balance".

The measurements and corresponding plots were described as interesting, detailed, valuable, educational and easy to process. Participants noted that the plots showed fluctuations in body movement well, and give additional insight for balance improvements during mountain bike rides. When we asked about a preference for post-hoc or real-time feedback during mountain biking, participants' preferences showed more variety. Although some participants based their preference on their favored mode, 13 participants indicated that using both real-time and post-hoc feedback at the same time would be the best solution:

"Real-time feedback aids during the ride, so you can already tell if you are doing well. However, if you only use the real-time feedback, you could have cases where you are barely balanced but won't get any feedback. If you also have the post-hoc app, you can precisely verify how balanced you really are. (...) It could make the association of the feedback in post-hoc stronger when you know where you had feedback during the ride. It is the best of both worlds".

None of the participants reported a preference for visual feedback.

6.2.2 Noticing Patterns. The visual solutions had various levels of reception. This predominantly had to do with the types of patterns and colors used in the feedback modes and how well they were noticed during the ride. The VDF mode was the most preferred out of the two, since the color scheme made it easy to differentiate between forward and backward feedback directions. This contrast helped to distinguish the feedback patterns as well. According to many participants, the cues were less clear in the VDF mode:

"In the VDF mode, I felt like the colors gave you at least a sense of direction that was easy to translate to movements. In VPF mode, the signals for all directions use the same colors, so you really have to know the patterns in order to make use of it. Especially the separation between frontwards and backwards movements was confusing".

In general, the LEDs on the extreme ends of the strip were hard to notice during exertion. Weather conditions effected the visual modes, as glare from sunlight could make noticing feedback harder. This made some participants nervous as they did not want to miss feedback, making them explicitly check their peripheral view for signals which led to balancing problems. However, the LEDs within the extreme boundaries were easily visible in the peripheral view, with participants noting that visual feedback could lead to more immediate responses.

6.2.3 Feedback Processing. Several participants indicated that it was difficult to process the visual feedback. Both visual modes (VDF and VPF) confused participants:

"The visual modes had signals that were not always immediately pointing towards a certain direction and they were difficult to remember. I had to think about the received feedback whilst riding, which was irritating and makes the ride less enjoyable".

This in turn made participants focus on the feedback modes instead of on the trail, overthinking their balance and the received feedback. At times, this made them over-correct or ignore the feedback altogether. A participant noticed that they did not want to think about translating the feedback into directions:

"The visual feedback started to feel like an obstacle or a distraction. First I tried to just turn off the lights, so I started to move my body so that I would not see them anymore,

> not really thinking about the direction of the feedback. Eventually I just ignored it and focused on the ride. (...) The feedback sometimes felt more like a hindrance. More time is needed to learn these feedback methods for them to be useful".

In contrast, the base condition made people forget about balance completely at times, since no real-time feedback was present. Hence VTF was the preferred solution for most participants, as it provided balance feedback in real-time while being unobtrusive.

7 DISCUSSION

Here, we summarise the findings from our study and reflect on the difference between feedback modalities to understand how they impact the design of systems which provide real-time feedback for physical activity. As HCI studies for mountain biking to date are limited, we note that the design of MTBalance is a pragmatic choice. We hope that our system can serve as a generative contribution and a starting point for future sports interfaces for MTB. As we interpret the results of our study in detail, we are aware that the findings are only fully applicable to our specific design. While this is a generic challenge of artefact-driven work in HCI [18], MTBalance offers an exploratory contributing and a beginning for understanding the design space of technology for MTB.

7.1 Using MTBalance did not cause significant objective improvements in balance performance

Our study showed that adding additional feedback to the MTB ride experience did not result in a significant improvement in balance performance or the time in which participants responded to terrain changes. Therefore, the results of the study do not allow us to make conclusions in terms of **H1** or **H2**. We can, however, observe that VPF is a suboptimal solution. Thus, our results suggests that future systems that feature real-time visual feedback for dynamic solutions should use directional encoding. Similarly to results in other domains, e.g. golf [56] there is no clear choice in terms of feedback modality. We hypothesise that there are two reasons which could explain these results. Firstly, the duration of the ride in which the study participants engage could have been to short to show performance effect. Secondly, our feedback design could have been too disruptive for the beginner MTB experience—this is, however, not supported by TLX results.

7.2 Users reported a increased sense of balance awareness when using MTBalance

Our study showed that all versions of MTBalance provided the users with a significantly increased subjective perception of balance awareness. Therefore, H3 was confirmed. This suggests that, when using MTBalance, the bikers felt more in control of their bodies. Qualitative results show that this state was desirable and led to increased satisfaction of the users. In light of these findings, future systems for body awareness in sports can focus on providing an increased feeling of awareness even if it is not directly linked to performance. The subjective feeling of balance awareness appears to have produced a positive user experience when using MTBalance. Thus, providing a subjective feeling of remaining in control may be enough to effectively augments the experience of beginners in sports. These results echo findings by Turmo Vidal et al. [49]—the subjective perception of performance in an activity may often be the key design goals for a system which supports physical activity.

7.3 Vibrotactile feedback produced the least frustration and required low cognitive load

NASA TLX results in our study showed that VTF produced the lower cognitive load, outperforming VPF. While this study did not collect enough data to make definite conclusions about the mental load caused by the different modalities, there is limited evidence which suggests that the vibrotactile modality may have delivered the extra balance information at a minimised cognitive cost. This is further supported by the fact that the majority of the participants preferred VTF over the other versions of MTBalance and the baseline solution. This would suggest that the complexity of the visual signals in MTBalance may have been to high. The inherent spatial nature of the relative directional balance correction may be better communicated with 360-degree haptic feedback, analogously to past navigation solutions [36].

7.4 Limitations

We recognise that our systems and study are subject to certain limitations. First, we remark that the study was conducted on a single trail. The route, although quite challenging for beginners, did not incorporate more extreme elements often present during mountain biking such as steep drops, gaps, jumps and other highly technical sections. This limited the risk for participants and allowed us to fulfill the ethical standards required by our institution. It is uncertain how the system will function under more extreme conditions and whether the feedback can be processed at even higher speeds. Thus, we believe that the insights from our work are primarily relevant for beginner MTB bikers. Based on expert feedback, balance was the focus of the design of our system. However, we recognise that a more robust MTB training system should include other parameters such as cadence or pedalling technique.

The performance of the visual feedback was hampered by the weather conditions during the field study. Participants indicated that direct sunlight made the LEDs less noticeable, which limited the visibility of the feedback cues. Even though we took extra care to have each participant test the system under comparable conditions, the variable time slots and the unpredictability of the Autumn season affected the effectiveness of the device. To make the visual device more robust, we would recommend to test different positions for the LED strip, or to use a different type of apparel for attachment.

Finally, we recognise that our study had an exploratory character. The system was tested at a single instance of its use. Consequently, we cannot conclude what the influence of MTBalance on developing mountain biking proficiency is. To analyze this, the system should be used by a larger user group and during a longer time period. In the context of past work in the HCI for sports area, we can conclude that an increased feeling of body awareness contributes positively to the overall experience of engaging in a new sport [10, 56]. Consequently, future studies should investigate if systems like MTBalance can lead to increased performance and skill acquisition when utilised in regular training. When used over a longer time period, the systems can also be evaluated by expert coaches to better understand its role in MTB skill development.

8 CONCLUSION

In this work, we reported on the design, implementation and evaluation of MTBalance, a system designed to provide augmented balance awareness to novice MTB riders. Our systems uses inertial sensing to estimate the position of the rider and suggest ways in which they could correct the posture in accordance with the traversed terrain. We designed three feedback forms for MTBalance, which we compared in a user study on an MTB trail. The study showed that while MTBalance did not cause significant increases in objective performance, the users felt more aware of their posture. Further, vibrotactile feedback was reported as causing the least perceived cognitive load. We hope that our work not only inspires more developments in building interactive systems for mountain biking, but also contributes further insight into understanding feedback design in HCI for sports.

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