Animal-Computer Interaction (ACI): An Analysis, a Perspective, and Guidelines

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Abstract

Animal-Computer Interaction (ACI)'s founding elements are discussed in relation to its overarching discipline Human-Computer Interaction (HCI). Its basic dimensions are identified: agent, computing machinery, and interaction, and their levels of processing: perceptual, cognitive, and affective. Subsequently, three seminal studies are discussed, the ACI community should be become acquainted with. Next, three guidelines are defined that could help ACI to gain further maturity. We close with a brief conclusion.

Introduction

The previous two years, the first two International Congresses on Animal-(Human-)Computer Interaction (ACI) have been organized[2]. As such, a new vibrant subfield of HCI has emerged [10], which is sustained with various follow-up initiatives, including the current symposium. However, since its origin HCI itself has always been a research field on the move, lacking a single, stable, generally accepted definition. As such, HCI provides a fragile foundation for ACI. Recently, Carroll [4] gave the following definition: "*Today, HCI is a vast and multifaceted community, bound by the evolving concept of usability, and the integrating commitment to value human activity and experience as the primary driver in technology.*"

Directly derived from HCI and ACI's names, three basic dimensions can be identified:

- agent
- computing machinery
- interaction

and, subsequently, the following levels of processing can be distinguished:

i) intra (e.g., attention / uptime):
   a. low level perceptual (e.g., pattern recognition [2,18]);
   b. high level cognitive (e.g., models [19,20]); and
   c. affective (e.g., emotions), which interacts with all other levels [6,7,15,16];
ii) inter (e.g., as in social media [9] and cooperative annotation [20]); and
iii) role-based (e.g., functioning within an organization [17]),

where with the latter two a network perspective should be taken, the first process concerns one agent. Each of these three levels hold for both agents and machinery, except for affective processing. As such, HCI and ACI can increase our understanding of both its agents (e.g., via computational models) and computing machinery as well as their interaction, which should be considered as ACI's primary focus [10]. Note that, although generally assumed, the agent does not have to be human or animal, it can be any agent, including even computing machinery (e.g., a robot [14]).

Although the decomposition in three levels of processing is valid for any agent, in the vast majority of cases the agents have been humans. Moreover, animals differ from human users on each of these levels and animal species have far from homogeneous characteristics [10]. So, knowledge transfer from HCI to ACI should be considered

[2] The ACI URL: http://animalcomputerinteraction.org [Accessed 25 March 2016].

with the utmost care! Starting directly from this concern, this article will describe initial ideas to extent Mancini's research agenda [10], consisting of two components: i) some studies that deserve attention from the ACI community (and seem to be overlooked, so far) and ii) some concrete initial suggestions for a methodological foundation for ACI research. Last, a brief conclusion is provided.

Some … studies that deserve some attention

This section presents by no means an exhaustive survey. It should be considered as a sample from scientific literature highly relevant for ACI; but, perhaps, overlooked if not discussed. Three scientific articles from the last 25 years to 10 years. For reasons of brevity, only a triplet of studies is discussed, many, many other seminal studies can be considered as at least equally important for ACI (e.g., Harlow's work on "the nature of love" [14]) and, more recently, the work of Van Eck and Lamers, who studied whether or not it is possible to play computer games against animals [22].

ACI is a very interesting idea, not only from a HCI perspective; but, also, from an Artificial Intelligence (AI) perspective. In 2011, Mancini [10] stated *"... quite literally, the elephant in the room of user-computer interaction research. The time has come to acknowledge the elephant, to start talking about ACI as a discipline in its own right, and to start working toward its systematic development."* 21 years before, Rodney A. Brooks already noted that "Elephants don't play chess" [3]: "*There is an alternative route to Artificial Intelligence that diverges from the directions pursued under that banner for the last thirty some years. The traditional approach has emphasized the abstract manipulation of symbols, whose grounding in physical reality has rarely been achieved. We explore a research methodology which emphasizes ongoing physical interaction with the environment as the primary source of constraint on the design of intelligent systems.*" His claim helps us to identify three important notions for ACI, namely:

1. Brooks [3] shows to be an advocate for empirical computer science, more specifically: empirical AI. In particular, he stresses the importance of the interaction of agents (e.g., a human, animal, and robot) with each other and their environment.
2. He also explicitly distinguishes two branches of AI, that process information on entirely other levels: symbols and signals. This is very interesting as both levels are of importance for ACI, although the latter seems to outrun the former. The symbolic level is considered as typically and even exclusively linked to human intelligence.
3. Throughout its complete existence, AI has struggled in its attempts to fulfill its promises. Implicitly, Brooks seems to suggest that AI has taken the wrong turn or, at least, should divide its attention. Up to this day, the former is a topic of debate. However, there is a general agreement on that at least the latter is needed. From that perspective, ACI should perhaps even be preferred over HCI. Humans claim to be much more advanced than animals should make it simpler to understand the latter than the former and, hence, should make it simpler to understand ACI than HCI. As such, ACI could be a model for HCI, as is the case with many other sciences, where specific animals (e.g., rats and monkeys) serve as a model for humans or robots (cf. [1]).

In the 80s, an interesting HCI initiative was implemented at the MIT Media Lab [5]. It concerned an artificial animal they named Noobie (short for "New Beast") that interacted with children. Noobie looked like furry Sesame Street's Muppet (cf. Sesame Street's Pino). So, it is HCI or human-animal interaction and no ACI. Druin [5] concisely describes Alan Kay perspective on animal models: "*the use of animal agents is a wonderful way of stretching what we already know about representing animal behaviors, as well as what we know about rendering and animating figures. Therefore, if we are able to give children the tools to explore animal behavior, then we as tool-makers may learn just as much about our tools as about animal behavior.*" This is on par with what ACI aims: continuously learn about animals, adapt the animal models embedded in the computer, and, consequently, improve the actual ACI [10]. In other words, there are many possible paths that can be followed to realize and improve on ACI. Noobie's team took five evaluation criteria, which can be adopted by ACI as well [5]:

1. Comprehension: How much time did it take the animal to figure out what to do with the computer?
2. Ease of use: How easy was it to use the computer?
3. Interaction styles: How does the animal interact with the computer?
4. Attention span: How much time did it take before the animal lost interest?
5. Expectations: What did the animal want or expect to do with the computer (if anything at all)?

In 2006, Kerepesi et al. [8] reported on a study that is highly relevant for ACI. They compared human-animal (dog) and human-robot (AIBO) interactions. So, as with [5], no ACI; but, nevertheless, work that is highly relevant for ACI. Let us mention three concerns addressed in this article that are of interest to the ACI community:

1. The importance of interaction. Kerepesi et al. [6] conclude "*... that more attention should be paid in the future to the robots' ability to engage in cooperative interaction with humans.*" So, again, as with the other two articles, interaction is posed central in understanding the agents involved and their relations.
2. Levels of complexity of the agent and the computing machinery. In addition to Kerepesi et al.'s work [8], a few years ago a vivid discussion on robot nannies emerged [14]. Although it concerned human children and, hence, involved HCI or, more specifically, human-robot interaction, it can be conceived as an interesting intermediate step between HCI and ACI. In some aspects, children are closer to some animals (e.g., apes and, even, monkeys) than they are to adult humans.
3. Study temporal structures. Kerepesi et al. [8] stress the importance of detecting temporal patterns (or T-patterns). They conclude that *"whether humans were playing with dog or AIBO had a significant effect on the structure of the patterns. Both children and adults terminated T-patterns more frequently when playing with AIBO than when playing with the dog puppy, which suggest that the robot has a limited ability to engage in temporally structured behavioural interactions with humans. As other human studies suggest that the temporal complexity of the interaction is good measure of the partner's attitude ..."* (e.g., cf. [15]).

Taken together, ACI would benefit from historical reflection (cf. [16]). Next to HCI literature, knowledge from biology, psychology, communication science, AI, and robotics should be reviewed. Moreover, ACI articles should take a clear position in how they want to contribute: i) The animal can be a model of humans and as such help us to understand humans, ii) ACI can learn us about the animal in a semi-controlled manner, iii) ACI can also learn us about the computer's pros and cons, and, last, iv) it can learn about the interaction between animals and computers.

Some … suggestions

To conduct valid, replicable studies, ACI needs to meet some guidelines or as Mancini baptized it: a research agenda [10]. This section provides three of such guidelines, which is by no means an exhaustive list; but, perhaps, it could serve as starting point. These guidelines link directly to Mancini research agenda [10], extending this agenda. These guidelines are derived from a set of guidelines introduced in the context of affective computing [15].

Context

When animals and humans interact with each other, they are able to use implicit situational information, or *context*, to increase the conversational bandwidth. Unfortunately, this ability to convey ideas does not transfer well to animals interacting with computers. In traditional interactive computing, human users have an impoverished mechanism for providing input to computers. Consequently, computers are currently not enabled to take full advantage of the context of the animal-computer dialogue. By improving the computer's access to context, we increase the richness of communication in ACI and make it possible to produce more useful computational services (cf. [7]).

As is stated above, capturing context is easier said than done. Handling context is even considered as one of AI's traditional struggles [15]. Perhaps this can be attributed partly to the fact that in the vast majority of cases, research on context aware computing has taken a technology-centered perspective as opposed to an animal or human-centered perspective. This technology push has been fruitful though, among many other techniques, sensor networks, body area networks, GPS, and RFID have been developed [2,4,6,7,14,15]. Their usage can be considered as a first step towards context aware computing. However, not only the gathering is challenging but also processing (e.g., feature extraction) and interpretation are hard [15,16].

Potentially, context aware computing can aid ACI significantly. Biosensors can be embedded in jewelry (e.g., a belt or necklace), in consumer electronics (e.g., a cell phone or music player), or otherwise as wearables (e.g., embedded in cloths or as part of a body area network). Connected to (more powerful) processing units they can record, tag, and interpret events and, in parallel, tap into animals' reactions through our physiological responses.

Validation

In the pursuit to study animal behavior in a more or less controlled manner, a range of methods have been applied: multimedia (e.g., images, audio, and multimedia), games, agents, and real world experiences [15]. However, how to know what these methods actually triggered with the animals studied? This is a typical concern of validity, which is a crucial issue for ACI. Validity can be obtained through various approaches. Here, we will discuss four of them [15].

Content validity refers to the degree …

- of expert's agreement on the domain of interest (e.g., limited to a specific application or group of animals);
- to which a feature (or its parameters) of a given signal represents a construct; and
- to which a set of features (or their parameters) of a given set of signals represents all facets of the domain.

Criteria-related validity handles the quality of the translation from the preferred measurement to an alternative, rather than to what extend the measurement represents a construct. Interactions are preferably measured at the moment they occur; however, measurements before (predictive) or after (postdictive) the particular event are sometimes more feasible. The quality of these translations is referred to as predictive or postdictive validity. A third form of criteria-related validity is concurrent validity: a metric for the reliability of measurements applied in relation to the preferred standard. For instance, the more types of interaction are discriminated the higher the concurrent validity.

A *construct validation* process aims to develop a nomological network (i.e., a ground truth) or an ontology or semantic network, build around the construct of interest. Such a network requires theoretically grounded, observable, operational definitions of all constructs and the relations between them. Such a network aims to provide a verifiable theoretical framework. The lack of such a network is one of the most pregnant problems ACI is coping with. Often a statement such as "*The term animal(s) is loosely used throughout to refer to nonhuman animals.*" [10] is made to cover this[1]. However, better would be: "*any of a kingdom (Animalia) of living things including many-celled organisms and often many of the single-celled ones (as protozoans) that typically differ from plants in having cells without cellulose walls, in lacking chlorophyll and the capacity for photosynthesis, in requiring more complex food materials (as proteins), in being organized to a greater degree of complexity, and in having the capacity for spontaneous movement and rapid motor responses to stimulation.*" [11].

Ecological validity refers to the influence of the context on measurements. We identify two issues:

- Natural ACI events are sparse, which makes it hard to let animals cycle through a range of interactions in a limited time frame; and
- The interactions that occur are easily contaminated by contextual factors; so, using a similar context as the intended ACI application for initial learning is of vital importance.

From a measurement-feasibility perspective, an easy way out would be to conduct interaction measurements in controlled laboratory settings. However, even this by itself could be a stressor for animals. Moreover, it makes results poorly generalizable to real-world applications.

Triangulation

Triangulation is the strategy of combining multiple data sources, investigators, methodological approaches, theoretical perspectives, or analytical methods within the same study [9]. In the operationalization, this provides methodological instruments to separate the construct under consideration from irrelevancies. We propose to adopt this principle of triangulation, as applied in social sciences for ACI.

Five types of triangulation can be distinguished [12], namely:

1. *Data*: Three dimensions in data sources can be distinguished: time, space (or setting), and the recorder. Time triangulation can be applied when data is collected at different times. In general, variance in events, situations, times, places, and persons are considered as sources of noise. Extrapolations on multiple data sets can provide more certainty in such cases and anomalies can be detected and corrected.
2. *Investigator*: Multiple observers, interviewers, coders, or data analysts can participate in the study. Agreement among these researchers, without prior discussion or collaboration with one another, increases the credibility to the observations. Par excellence, this type of triangulation can be employed on including context and unveiling events.
3. *Methodological*: It can refer to either data collection methods or research designs. Its major advantage is that deficiencies and biases that stem from a single method can be countered.
   Multiple data sets (e.g., both qualitative and quantitative) and signal processing techniques (e.g., in the time and spectral domain) can be employed. Moreover, multiple features extraction paradigms, feature reduction algorithms, and classification schemes can be employed. Further, note that methodological triangulation is also called multi-method, mixed-method, and methods triangulation.
4. *Theoretical*: Employing multiple theoretical frameworks when examining a phenomenon.
5. *Analytical*: The combination of multiple methods or classification methods to analyze data. This facilitates (cross) validation of data sources.

In general, we advise to record at least 3 signals for each construct under investigation. In ambulatory, real-world ACI research much more noise will be recorded. To ensure this noise can be canceled out, we advise to record even more signals. As a rule of thumb for ambulatory research we advise to record as many signals possible, without that they interfere with the animal's natural behavior. However, a disadvantage accompanies this advice, as "*a `more is better' mentality may result in diluting the possible effectiveness of triangulation*" (p. 256) [12]. Moreover, qualitative and subjective measures should always accompany the signals (e.g., video-based ethnography). On the one hand, with animals, the use of many traditional HCI measures (e.g., questionnaires and cooperative annotations [22]) is challenging, if possible at all. On the other hand, Rhesus monkeys, pigs, and rats have already been successfully trained to use a joystick and perform computerized game-like tasks [22]. This calls for a base of biology's empirical methods for ACI, in addition to psychology's methods, as are often used in HCI.

Conclusion

ACI is interesting and a research field full of promises. However, it also requires a true interdisciplinary approach, which makes it vulnerable for criticism from all of its founding disciplines, as was discussed in the introduction (cf. [10]). This requires an interdisciplinary historical reflection and, consequently, identification of crucial scientific notions, which we perhaps all know; but, sometimes forget to apply [14-16]. Moreover, guidelines on ethical issues should be developed [14]. Väätäjä and Pesonen [13] provided an excellent starting point for this. By no means this article can be considered as an exhaustive treatment of the subject; but, perhaps, it can serve as that one more building block for a solid foundation for ACI. And this is very much needed, as undoubtedly ACI's progress is accelerating. ACI is here to stay and is heading towards a bright future, quickly emerging throughout a plethora of societal contexts.

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