HCI needs to embrace reverse self-organization and decide if computers are equipment or agents

DOBROMIR DOTOV, McMaster University, Canada

HCI is poised to face dynamic interaction and complexity by virtue of the rising speed, coupling, and abundance of computing devices. Our proposal is that it will be conceptually and methodologically beneficial to embrace reverse self-organizing in analogy to reverse engineering. Using examples from human movement science, we show how to design a task space affording spontaneous dynamic interaction, how to measure the interaction between user and complex tool with transfer entropy, and how to study the breakdown of skillful user-tool interaction. Next, we briefly raise two theoretical questions that need to be considered in the future. First, are computers agents or equipment? Second, what is the precise domain where the theoretical principles of complexity and enaction become relevant?

CCS Concepts: • **Human-centered computing** → **Auditory feedback**; **HCI theory, concepts and models**.

Additional Key Words and Phrases: autonomy, dynamic systems, emergence, real-time interaction, robotics, self-tool integration

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1 INTRODUCTION

During one of the first blooming summers of AI research Dreyfus famously proposed an anti-Cartesian, anti-cognitivist critique based on Heidegger's phenomenology [11]. After that, Winograd and Flores introduced similar ideas to human-computer interaction [18]. One key notion was that the intuitive separation of subject and object only emerges as a special, aberrant case of skillful action due to some malfunction in the workspace. This implied a re-emphasis of different theoretical primitives from systems science. An example for this is the idea that interaction in a nonlinear path, instead of sequential linear path, can give rise to emergent properties that exist only as dynamic patterns over this interaction. Arguably, this was needed to explain how skills and activities in the background enable the sort of purposeful action that mainstream cognitive science was focused on.

Since then, technology has been providing an ever increasing range of ways to interact with computing machines. There are different sensory modalities, levels of abstraction, and time scales. Computers try to play games and talk to us while impersonating different characters. There are also different levels of embeddedness - from the traditional arrangement with a desktop computer to smart tools, cloud computing, wearable devices, and even implantable task-specific computing.

The proposal for an emergent HCI (eHCI) advanced in this workshop [1] comes in a timely manner to suggest a new wave of principles from 4E cognition (embodied, embedded, enactive, extended) and the other E (ecological

Author's address: Dobromir Dotov, dotovd@mcmaster.ca, McMaster University, 1280 Main Street W, Hamilton, Ontario, Canada, L8S 4K1.

psychology). From this perspective, cognition arises in the midst of the back-and-forth between an agent and a layer of the environment. Specifically, this is the part of the environment that the agent is predisposed to interact with through its physical constraints and sensory capacities. The 4E approach emphasizes the spontaneous creation of functionality or meaning, defined over the dynamic agent-environment system, rather than the flow of information between pre-determined and encapsulated modules.

What does this imply for HCI, what would the application of such principles look like in practice, and what new methods will be involved? In what follows, a few examples from past projects illustrate how to study the properties of such interaction and the coupling between user and tool. In addition to that, it is suggested that a better intuition pump for eHCI is to think of it as *reverse self-organizing* rather than reverse engineering [7]. Next, discuss two theoretical questions that arise from the proposal for eHCI are discussed. First, does the C in eHCI stand for equipment or another agent? Second, is eHCI alternative to tradition or a complementary approach that addresses specifically the forms of HCI that involve fast, non-symbolic forms of interaction and learning machines?

2 REVERSE SELF-ORGANIZING A CUEING DEVICE FOR GAIT IMPROVEMENT IN PD

Rhythmic auditory cueing is a well-known method for improving gait in patients with Parkinson's disease. One limitation with most methods is that they can only provide fixed rhythms. This requires patients to fiddle with their cueing device while walking to ensure comfort and synchronization. Instead, we sought to design interactive cueing that created the opportunity for spontaneous synchronization [9]. The device sampled foot steps in real-time to adjust the phase of the musical beat. To achieve the desired outcome, we modeled the stimulus and the walker as two oscillators that each had a preference for given frequencies but there was also mutual coupling nudging them to synchronize. We constrained the stimulus by taking each participant's preferred cadence into consideration. This allowed us to set some of the parameters and find what is needed for stable synchronization. In short, we configured the apparatus for each participant such that mutual entrainment was not forced but occurred spontaneously. Thus, we set the conditions that made it possible for a self-organized synchronized pattern to emerge over the system comprising of walker and cueing device.

3 MEASURING COUPLING WHILE CONTROLLING A COMPLEX TOOL

There is a lot of talk about dynamic interaction in the 4E literature, yet the problem how to measure the interaction is not discussed as much. One possibility of addressing this gap is to directly apply methods from complex systems that are well-suited for the coupling between elements of a network of dynamic components [3]. Granger causality and Transfer Entropy (TE) are popular for multi-channel neural data [17] but also have been applied to map the sensory-motor networks of mobile robots [16]. We used TE to measure the coupling from the user to a stimulus and from the stimulus back to the user in a motor learning experiment [5, 6].

The experiment is interesting for the present purposes because it involves a more realistic scenario, namely a user trying to control a tool that has its internal functionality, or hidden degrees of freedom, see Figure 1. The task was to learn how to move so as to stabilize an intrinsically unstable tool. More specifically, participants were coupled through their hand movements and auditory feedback to one of the dimensions of a 3D chaotic system. The goal was to move in such a manner as to push the intrinsically chaotic trajectory onto a periodic trajectory. Imagine balancing a pole on one's finger by finding the pattern of finger movement that keeps the pole predictable and under control.

The task was performed under different coupling scenarios. As expected, the best performance and learning was observed in the bi-directional coupling scenario. Importantly, as performance improved with practice, TE from user to tool and back from tool to user increased and converged to similar values, see Figure 1C. We propose the idea that such an equilibrium of functional connectivity could serve as a distinguishing feature of eHCI principles.

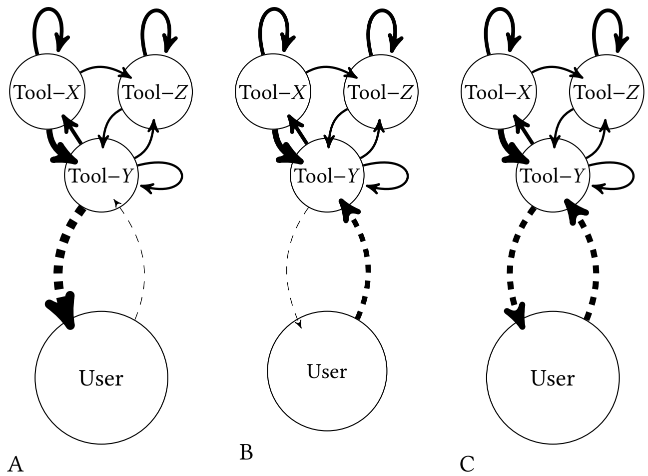

Fig. 1. A user trying to synchronize with and control a dynamic system with two hidden degrees of freedom. The system was a chaotic oscillator. Thickness of the dashed arrows represents the functional connectivity estimated with transfer entropy. A) Control condition with one-directional coupling from tool to user. B) Control condition with one-directional coupling from user to tool. C) Bi-directional coupling. The estimated transfer entropy agrees with the conditions. Importantly, with learning and improved performance in C) transfer entropy converged to a balanced level in the two directions.

4 STUDYING BREAKDOWN IN HUMAN-COMPUTER INTERACTION

As stated, Dreyfus and Winograd and Flores brought revolutionary ideas. One of these was that the user of a smoothly functioning equipment is not a subject. Similarly, equipment does not appear as a separate, detached object with various intrinsic properties. In fact, it does but only when it no longer functions in the way that the background of skillful action intends it. In other words, equipment becomes an object only when it is broken and as such interrupts the nonlinear dynamic pattern. This turned the artificial intelligence program on its head and probably the implications for HCI are similar.

Our study involved a version of an inverted pole balancing task that participants performed on the screen using the computer mouse. In the middle of the trial the coupling between the hand holding the mouse and the workspace was perturbed. Perturbation is interpreted as kicking a user-tool extended system out of its preferred trajectory. Indeed, dynamic properties of hand movement before and during this perturbation suggested a special kind of organization. It was consistent with the idea that the tool and the user made a single dynamic system [10]. Using the same task we also found that participants remembered more task-irrelevant features about the workspace when it was being perturbed. This suggested that they engaged a more cognitive attitude towards their workspace [8]. This research constituted an attempt to bring Heidegger to the experimental psychology lab by coming up with testable predictions about human-tool interaction [4]. To be fair to other approaches inspired by the phenomenology of tool use, predictive processing accounts for this perturbation in terms of a prediction error [2].

5 THEORETICAL ISSUES

There are certain theoretical questions that eHCI may need to address to make itself more definite.

5.1 Autonomy: Do computers stand for Equipment or an Other?

> *"Our lives are not our own. From womb to tomb, we are bound to others, past and present, and by each crime and every kindness, we birth our future."*—Sonmi-451

Enactive AI [14] and dynamic interactive AI [7] attempted to enrich AI research with theoretical ideas comparable to the present workshop. Among others, we proposed that autonomy and the need for generalization of learning might be exaggerated, leading to a range of practical and theoretical problems [7]. It stands as a contradiction to the original inspiration, yet it could be more productive in the short term to work on AI that does not "think for itself" but merges in a dynamic system with the user. Even with those constraints, however, eHCI will have to take a stance on the problem of agency and autonomy because of how richly interactive computers are trying to become. Traditional individualist accounts treat social cognition as two or more cognitive agents modeling each other. Yet, if the enactive arguments are correct, social interaction emerges more easily than that [12, 13, 15]. When is it suitable to treat the C in eHCI as another agent and when as transparent equipment?

5.2 Is eHCI an alternative or a complementary approach?

If eHCI rests on a broad theoretical statement about the nature of human interaction with the world, is it then relevant to all forms of human-computer interaction? Does eHCI define itself as an alternative to traditional approaches? Or, would it rather define relevant problems characterized by mutual coupling and rich dynamics? In other words, does eHCI want to follow a colonialist or an explorer agenda? And do we even want computers that are always sensitive to every fluctuation in user performance?

Defining its relevance will help eHCI avoid the conceptual mess that will inevitably ensue from throwing its principles at everything that can be described qualitatively as interactive and complex. This will also help eHCI make its relevance understood by a wider audience. To give an example, the burgeoning and exciting field of 4E cognition has made very little impact on otherwise relevant fields such as movement science and the neuroscience of motor control. This could be a matter of time, of course, but it could also be because 4E made too many, too strong, and too far-reaching theoretical statements, making it difficult for potentially interested researchers to reconcile 4E with their existing programs of research.

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