Mutual Information as a Measure of Coordination in Collaborative Interaction

Dari Trendafilov
University of Hertfordshire
School of Computer Science
Hatfield, UK
d.trendafilov@herts.ac.uk

Alexander Maye
University Medical Center Hamburg-Eppendorf
Department of Neurophysiology and Pathophysiology
Hamburg, Germany
a.maye@uke.de

Daniel Polani
University of Hertfordshire
School of Computer Science
Hatfield, UK
d.polani@herts.ac.uk

Roderick Murray-Smith
University of Glasgow
School of Computing Science
Glasgow, Scotland, UK
roderick.murray-smith@glasgow.ac.uk

Andreas K Engel
University Medical Center Hamburg-Eppendorf
Department of Neurophysiology and Pathophysiology
Hamburg, Germany
ak.engel@uke.de

We present an information-theoretic approach for quantifying the level of coordination between cooperating parties engaged in a computer-mediated collaborative interaction. The approach builds on Shannon's mutual information, as a task-independent objective measure, which captures the level of corelation between the actions of interacting agents. We introduce the approach through two characteristic examples and discuss the challenges in designing a reliable measure and the amount of modelling effort required. Our initial results suggest the potential of this measure in supporting designers of collaborative systems and in providing more solid theoretical foundations for the science of Human-Computer Interaction.

1. INTRODUCTION

A fluid, engaging collaboration between people connected remotely via a computer has long been a goal of technology-mediated interaction. Modern hardware increasingly facilitates the emergence of exciting high-bandwidth, tightly-coupled, continuous interaction styles by getting new sensing, processing and feedback capabilities. Multi-player games, taking place in virtual environments, are just one example of such systems. More recent work expands further the research towards human–robot collaboration.

Cooperation in the real world emerges as a distinct combination of innate and learned behaviour according Tomasello (2009), and collaborative systems tap into both individual and social processes such as mutual perception, joint attention, turn-taking, and mutual entrainment. Research on the interactive dimensions of mutual perception (Auvray et al. (2009)) show that rich perceptions are possible even with a minimal channel of communication, which has direct practical implications. Causes and consequences of disrupted coupling between agents is studied in the context of deficits in social cognition abilities like in people with autism spectrum disorders. However, in order to analyse such social contingencies we need coupling measures in place. Standard performance metrics, such as success rate or completion time, might not be applicable, nor descriptive for a particular system, hence, in order to evaluate such systems we need new objective measures.

One current challenge is the development of a formal measure, quantifying the level of coordination between participants of computer-mediated environments. A rigorous measure of coordination could help provide a firm foundation for designers to treat and evaluate collaborative systems in a general fashion. An analytical tool, characterising coordination in real time, could give direct insight into the detailed interactions that evolve as people engage and disengage from contact with each other. In this paper we present initial results of the application of the information-theoretic approach introduced in Trendafilov et al. (2015) to a labyrinth game scenario and discuss its sensitivity and potential for characterizing the dynamics in social interaction. Variants of Shannon's mutual information are typically used in the identification of the 'flow of information' in a given system (Ay and Polani (2008), Wheeler (1990)), where the joint information stems from a common past (Matsumoto and Tsuda (1988); Schreiber (2000)).

Proceedings of International Workshop on Ubiquitous and Collaborative Computing (iUBICOM'15) – Lincoln, UK

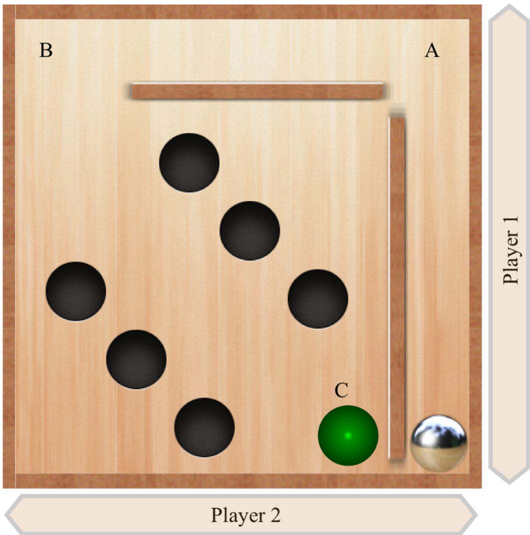

Figure 1: *In this example each of the two players controls only one axis of the labyrinth game. First, player 1 brings the ball to position A without any interaction from player 2. By reversing the roles, player 2 then brings it to position B. Finally, both players need to cooperate in order to pot the ball in the green target and not in one of the wholes.*

2. COLLABORATIVE INTERACTION

Real-time collaborative systems enable the simultaneous interaction between multiple participants; however, for simplicity we will consider the bidirectional coupling of two agents only and will focus on the perceptual crossing in what Tomasello et al. (2005) call a 'dyadic engagement'. Collaboration could take place in proximal interaction, involving a jointly manipulated physical object, or in distal interaction, where the agents are not in direct physical contact with each other.

An example of proximal interaction is presented in Figure 1, which shows a collaborative labyrinth game, consisting of a maze with holes and a ball. The goal is to guide the ball through the maze by slating the board while preventing it from falling into holes. By constraining the dimensionality of the sensorimotor coupling, this scenario facilitates the emergence of cooperative strategies.

An example of distal interaction is presented in Figure 2, depicting a collaborative target acquisition game, which requires partners' coordinated actions and is performed in a shared mediated environment. In recent studies (Trendafilov et al. (2014, 2011)) we investigated the dynamics of social interactions, building on the minimalist experimental paradigm of Lenay et al. (2007), and exploring the emergence of cooperative strategies using limited modes of communication. In these studies the interaction was limited to scrolling a finger on a touch-sensitive tactile device. Given the all-or-none nature of the

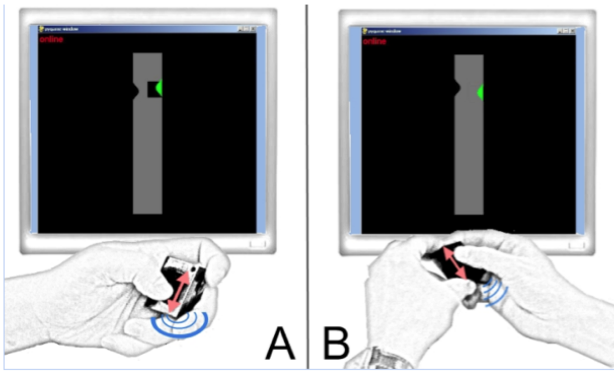

Figure 2: *An example of perceptual interaction, involving the exploration of a shared one-dimensional space, utilising touch-sensitive tactile devices. When the avatar of an agent (green/black) overlaps with a fixed object (black square, on the left), the object is perceived by that agent. When the avatars of A and B (opposite in black and green) meet, the agents perceive each other.*

sensory feedback, the perception of an object was possible only by means of dynamic exploration of the shared one-dimensional space. More precisely, the spatial characteristics of an object could be defined by specific 'laws of sensorimotor contingencies', which make it possible to anticipate the sensory consequences of one's actions in the course of an active exploration (O'Regan and Noë (2001), Noë (2005)).

In both of the examples, standard performance metrics may not be descriptive for the level of coordination, since high levels of coupling may achieve low levels of performance, and vice versa, as suggested in Trendafilov et al. (2015). For example, a smooth coordinated performance (Figure 2), may be slow in locating objects, resulting in a lower score. Alternatively, jumping from one object to the next, could appear as a less coordinated behaviour, but at the same time lead to a higher score.

3. MEASURE OF COORDINATION

In recent work (Trendafilov et al. (2015)) we proposed an information-theoretic approach to quantify coordination, based on mutual information, which is defined for random variables X_A and X_B given X_S as follows

$$I_p(X_A : X_B|X_S) = \sum_{x_S} p(x_S) I_p(X_A : X_B|x_S), \quad (1)$$

where

$$I_p(X_A : X_B|x_S) = \\ = \sum_{x_A} p(x_A|x_S) \sum_{x_B} p(x_B|x_A, x_S) \log \frac{p(x_B|x_A, x_S)}{p(x_B|x_S)}.$$

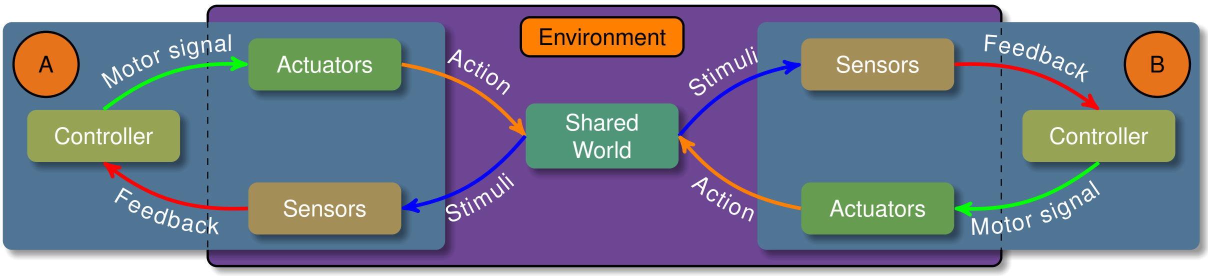

***Figure 3:** Schematic diagram of a dyad cognitive sensorimotor loop in a shared computer-mediated environment.*

Furthermore

$$I_p(X_A : X_B | X_S) \leq min(H_p(X_A), H_p(X_B)), \quad (2)$$

which gives a characteristic upper bound, provided by the minimum of the two entropies. In this formalism X_A and X_B denote the actions of the agents A and B respectively, and X_S denotes the state of the shared environment. Intuitively, the mutual information in Equation 1 captures how well we can predict the behaviour of A, if we know the behaviour of B, for a given state of the shared environment S. If X_A and X_B are conditionally independent, then the coordination is zero, meaning that there is no corelation between the actions of A and B. Equation 2 provides the range of this measure for a particular stochastic model and can serve as a benchmark in system evaluation.

4. STOCHASTIC MODEL

In order to apply Equation 1 to experimental data, we need an empirical approximation of the probability distribution. This, in turn, requires the definition of a discrete stochastic model (i.e. random variables X_A, X_B, X_S) for a particular system, and the population of conditional probabilities from empirical data. The approach relies to a great extent on the quality of the model – the more accurate the model, the more reliable the measure it implies. In the discretisation of the continuous sets of actions and environmental states, we need to find a trade-off between space granularity and measure reliability, which is influenced by the density of our empirical data. Higher resolution spaces usually require larger amounts of data to provide a reliable empirical distribution, as data sparsity could bias the model.

Feedback in the perception–action loop is subject to disturbances, such as noise and delays, which affect the quality of experimental data and have implications on the modelling process. Lag is inevitable and can be attributed to properties of the human cognitive and sensorimotor system, input/output devices and software (Figure 3). Sampling rates of input and update rates of output devices are major contributors. Lag is increased further due to 'software overhead' – a loose expression for a variety of system-related factors. Communication modes, network configurations, number crunching, and application software all contribute. In human–human mediated interaction, however, we also have to account for the variable response time of a human decision maker, which – unlike machines – varies across individuals and depends on various factors, making it unpredictable. Other sources of disturbances are different types of noise due to digital sensor imprecision, human sensorimotor inaccuracy, transmission interference, etc. In order to tackle the effect of these factors on experimental data, we need to apply advanced filtering and delay compensation techniques, prior to the computation of this measure.

5. RESULTS

We applied the above method to data collected in a labyrinth game study. A sample of force data, derived from the electromyograms (EMG) of the players' fingers, is shown in Figure 4 (top).

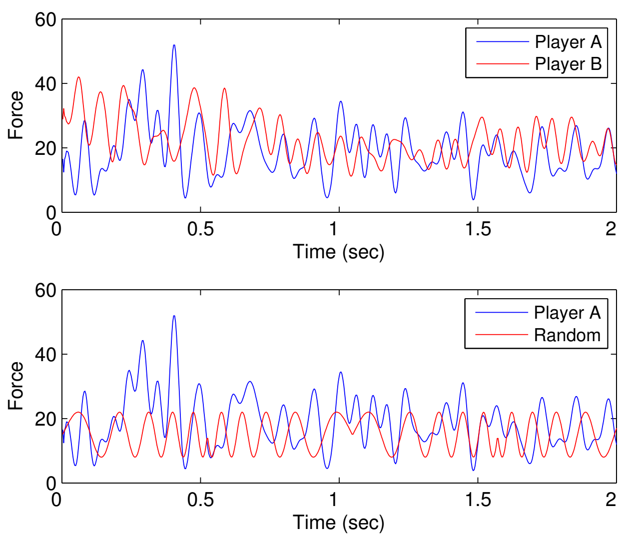

***Figure 4:** Time series from an experimental trial yielding 0.42 bits of coordination (top). Player A vs. a quasi-random sine wave yielding 0.27 bits of coordination (bottom).*

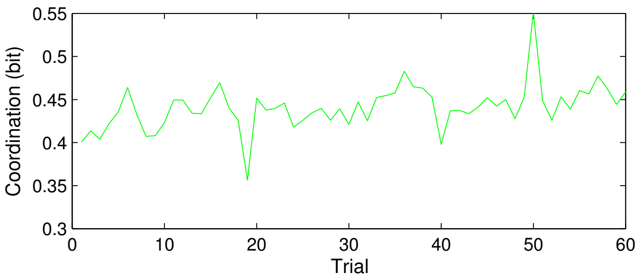

Figure 5: *Levels of coordination of 60 consecutive trials suggesting the learning effect.*

Using a variant of Equation 1, which ignores the ball position as environmental state (X_S), we computed the mutual information of X_A and X_B, representing both players' switches in finger force trajectories. Encoding switches with binary random variables in our stochastic model implies a theoretical upper bound of 1 bit. Applying a delay compensation in the range of 20ms, we computed the corelation between switches across trials. To validate the results, we generated a quasi-random sine wave with similar frequency characteristics (Figure 4 bottom), and computed the corelation between this artificial curve and player A's data, which resulted in 0.27 bits of coordination, whereas the coordination between player A and player B measured 0.42 bits. The evolution of the coordination level across all 60 trials of one pair shows signs of a learning effect (Figure 5), represented by a gradual increase from 0.4 to 0.45 bits. Further analysis is required to determine the precise relationship between our measure and standard performance metrics.

The corresponding results of the distal interaction experiment can be found in Trendafilov et al. (2015).

6. CONCLUSION

In this paper we present an application of mutual information to measure coordination between collaborating parties in the context of two representative computer-mediated systems. Our initial results show interesting trends, however, detailed sensitivity analysis is required to further explore the properties of this approach. A rigorous measure could give direct insight into the convergence properties of mutual entrainment and could help provide a firm foundation for designers in making informed decisions when evaluating collaborative systems. Applying our method, however, requires prior modelling – the more accurate the models, the more costly they are to create, but the more reliable the measure they imply. The aim of this paper is to raise the awareness of the research community about the potential of systematic quantification of coordination in computer-mediated environments.

ACKNOWLEDGMENT

The authors would like to acknowledge support by the H2020-641321 socSMCs FET Proactive project.

REFERENCES

Auvray, M., C. Lenay, and J. Stewart (2009). Perceptual interactions in a minimalist virtual environment. *New Ideas in Psychology 27*(1), 32–47.

Ay, N. and D. Polani (2008). Information flows in causal networks. *Advances in Complex Systems*.

Lenay, C., I. Thouvenin, A. Gunand, O. Gapenne, J. Stewart, and B. Maillet (2007, August). Designing the ground for pleasurable experience. In *Conference on designing pleasurable products and interfaces*, Helsinki, Finland.

Matsumoto, K. and I. Tsuda (1988). Calculation of information flow rate from mutual information. *J. Phys. A: Math. Gen. 21*(6).

Noë, A. (2005). *Action in perception*. Cambridge MA: MIT Press.

O'Regan, J. K. and A. Noë (2001). A sensorimotor account of vision and visual consciousness. *Behavioral and Brain Sciences 24*, 939–973.

Schreiber, T. (2000). Measuring information transfer. *Phys. Rev. Lett.* (85), 461–464.

Tomasello, M. (2009). *Why We Cooperate*. Boston Review Books.

Tomasello, M., M. Carpenter, J. Call, T. Behne, and H. Moll (2005). Understanding and sharing intentions: the origins of cultural cognition. *Behavioral and Brain Sciences 28*, 675–735.

Trendafilov, D., S. Lemmelä, and R. Murray-Smith (2014). Negotiation models for mobile tactile interaction. *Mobile Social Signal Processing*, 64–73.

Trendafilov, D., D. Polani, and R. Murray-Smith (2015, March). Model of coordination flow in remote collaborative interaction. In *IEEE UKSim-AMSS 17th International Conference on Computer Modelling and Simulation, UKSim2015 (UKSim2015)*, Cambridge, United Kingdom.

Trendafilov, D., Y. Vazquez-Alvarez, S. Lemmelä, and R. Murray-Smith (2011). Can we work this out?: an evaluation of remote collaborative interaction in a mobile shared environment. *Proc. MobileHCI*, 499–502.

Wheeler, J. A. (1990). Complexity, entropy and the physics of information. *Santa Fe Studies in the Sciences of Complexity*, 328.