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Prospects of Inter-brain Synchronization with a Virtual Agent: Preliminary Considerations

Chen Lam Loh[1†] and Tom Froese[1]

[1]Embodied Cognitive Science Unit,
Okinawa Institute of Science and Technology Graduate University,
Okinawa, Japan
(E-mail: chen.loh@oist.jp, tom.froese@oist.jp)

Abstract: The recent discovery of the occurrence of inter-brain synchronization during social interaction tasks has led to interests to investigate its benefits and mechanisms. This conceptual paper proposes a paradigm to study inter-brain synchronization in a way that offers more control over hyperscanning methods. Specifically, this paradigm involves a human interacting with a virtual agent (VA) endowed with a connectome-based model. Accordingly, the virtual agent (VA) tracks the human movement and generates its next execution based on pre-simulated data. Furthermore, the VA has a connectome model which simulates neurophysiological data that synchronizes with the human subject's recorded neurophysiological data in real-time. Following the proposal, we show our first step in an attempt to implement the paradigm without the neurophysiological component and report example results of the implementation using a fingerpointing task. Then, we further discuss our views on the paradigm and the next steps for realization.

Keywords: Cognitive science, Artificial brain, Human machine interaction and collaboration

1. INTRODUCTION

Expansion in neuroimaging methodologies over the past two decades has allowed the simultaneous neuroimaging, otherwise termed hyperscanning of two individuals engaged in social behaviour using techniques such as electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) [1]. This has led to several significant findings, one of which is the discovery that the neural signals between interacting individuals exhibit phase synchronization during interaction [2-4]. This has motivated a shift in the philosophical framework of social cognitive neuroscience to move from an internalist approach to an embodied, interpersonal and interactive approach [5]. For example, recently there has been a call to utilize multi-brain stimulation to study social interaction in a multi-person framework [10]. The exact mechanism for inter-brain synchrony is yet to be clarified, although it can yield communicative, predictive and affective benefits [6]. However, current evidence points to the involvement of mirror-neurons and mentalizing systems[11-13], and the findings of spatiotemporal correspondences in inter-brain dynamics are usually task-dependent[14].

There has been a substantial body of research in coordination dynamics since the development of the Haken-Kelso-Bunz model [15]. Since coordination dynamics could play an important role in dictating the inter-brain dynamics, the study of inter-brain synchronization should go hand in hand with the study of coordination dynamics. For instance, there are interests to clarify the relationship between inter-brain dynamics and behavioural dynamics[17-19]. Moreover, the recent development of a human-machine paradigm, known as the human dynamic clamp (HDC) has permitted the grounded, principled study of human neurophysiology and behaviour[16]. This is achieved through the embedding of well-studied theoretical models into a machine and closing the loop through real-time interaction with a human subject.

Individual brain dynamics is inherently complex, in the sense that it is a mixture of both chaos and stochasticity [20, 21]. Thus, the investigation of inter-brain dynamics with two real interacting humans would further complicate the purpose of understanding inter-brain synchrony. Furthermore, it would be difficult to have full control over the perturbation of desired parameters. In a dynamical systems sense, the perturbation of parameters is important for the study of the transition between different patterns of behaviour, which is also known as phase transition.

As an example, if we want to modulate a brain region at a certain oscillatory frequency, we would need to stimulate the brain using transcranial currents at that particular frequency [10]. Although multi-brain stimulation may allow us to study the causal effects of inter-brain synchronization, there we are only indirectly controlling the oscillatory phase and amplitude of the brain region. Our independent variable would then be at best the frequency of the stimulation and not the real oscillatory properties of the brain region. On the other hand, despite assumptions that the neurophysiological recording artifacts generated by transcranial alternating current stimulation (tACS) could be corrected for[23], it i+s difficult to determine whether all of the artifacts are completely rejected due to the non-linearity of the interaction between the subject and the stimulation [22]. It could also be argued that multi-brain stimulation is not the only way to study the causal mechanism of inter-brain synchronization [24]. As the research on inter-brain synchronization is still at its early stage, a multitude of approaches is required for the understanding of behavioural and neural dynamics which will benefit the development of a general model for inter-brain synchronization. A connectome-based model of inter-brain synchronization was published in Dumas *et al.* (2012) [28] which studied the relationship between anatomical con-

† Chen Lam Loh is the presenter of this paper.

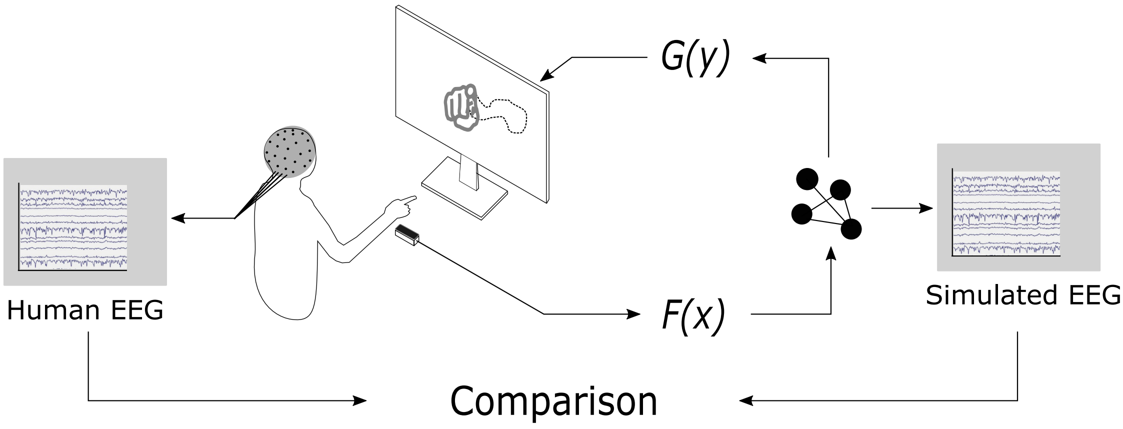

Fig. 1. Conceptual Design of the Proposed Paradigm. The paradigm involves a human subject coupling with a virtual agent (VA) through sensorimotor interactions. $F(x)$ and $G(y)$ transforms the inputs to and outputs from the connectome-based model respectively. The EEG simulation of the VA and analysis of inter-brain synchrony can be done online or offline. The human EEG and the simulated EEG can then be compared.

nectivity and inter-brain synchronization. This connectome-based model, combined with the HDC paradigm would allow us to study empirically the causation structure of inter-brain synchronization in a single-brain recording approach.

This conceptual paper proposes a paradigm which involves a human interacting with a machine endowed with a connectome-based model which is inspired by the HDC paradigm. Since the inter-brain synchronization phenomenon we are interested in is based in frequency, the connectome model would be a model of EEG data as EEG has finer temporal resolution than the other neuroimaging methods. Therefore, the experimental setup would involve a human subject interacting with a machine endowed with an EEG model in real-time. The machine would accept inputs from a sensor and provide outputs to the human subject via a monitor or an robotic effector. This combination of an EEG model with the HDC paradigm would grant us more control over the coordination dynamics and allow us to more systematically study the causal effects of parameter perturbation in the inter-brain dynamics.

2. CONCEPT OF THE HUMAN-MACHINE SYNCHRONIZATION PARADIGM

The paradigm consists of a human subject interacting with a simulated agent, also known as the virtual agent (VA). The human subject is instructed to follow the movement of a visual output on a computer monitor screen. A sensor is used to detect and track the motor movements of the human subject, x. x is then transformed into information which can be used by the agent as inputs to a connectome-based model. The outputs, y from this connectome-based model are transformed into visual outputs on the computer screen. An example of this paradigm using fingerpointing as the imitation task is shown in Fig. 1.

Since we are interested in the neural activity synchronization between the human subject and the VA, neurophysiological recording of the human subject in the form of EEG is carried out during the interaction. Similarly, the model in the VA is used to simulate EEG activity at each time step. There are several different ways of modelling the VA, one of which is by using a connectome-based model. This allows us to look at the degree of neural activity synchronization between the human subject and the VA over time. The EEG simulation of the VA and analysis of inter-brain synchrony can be done online or offline.

3. IMPLEMENTATION OF THE PARADIGM

In this section we describe an ongoing work on how such a paradigm can be realized using a fingerpointing task. As a preliminary work, we have skipped the recording of neurophysiological activity from the human subject in this work.

3.1. Methods

A Leap motion controller (LMC) is used to track the finger motion of the human subject in real-time. LMC (Ultraleap) is a small and portable infrared motion-tracking device which can be used to estimate 3D hand poses using their provided software development kit (SDK). LMC is portable and markerless which is beneficial for the tracking of natural

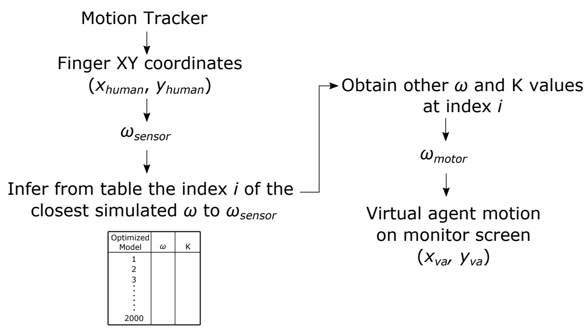

Fig. 2. Procedure for the processing of data from the sensor to the final visual output to the computer monitor.

hand movement [25].

For our current purpose, we are interested in only the finger position data of the human subject. The XY-coordinates (vertical and horizontal dimension) of the finger position estimated by the LMC is recorded at 100 Hz, smoothened with Savitzky-Golay filtering and detrended. The phase angle, θ in each of the dimensions is extracted using Hilbert transform. The instantaneous frequency, ω_{sensor} for each dimension is calculated using Eq. (1).

$$\omega_{sensor}(t) = \frac{\frac{\Theta(t)}{2\pi}}{W} \tag{1}$$

$\Theta(t)$ is unwrapped the phase angle and W is the fixed size of the overlapping time window used to calculate ω. In other words, $\omega_{sensor}(t)$ is calculated using the processed finger position data from $t-W$ to t. At each step, ω_{sensor} is averaged across the two dimensions to give a final instantaneous frequency. We clarify that the frequency described here is defined as the number of taps occurring within the time window W in Hz which is different from the motion velocity.

The final $\omega_{sensor}(t)$ is used to infer from a table containing evolved coupling and natural frequency values from a previous simulation [26]. Briefly, to understand how inter-brain synchrony could occur, in the previous work we have evolved six-node Kuramoto-oscillator models and optimized the models to achieve higher synchronization index values between the two "brain" oscillators. The $\omega_{sensor}(t)$ we have obtained here corresponds to the natural frequency of the sensory oscillator. The model with the closest value of the corresponding sensory oscillator to the currently obtained $\omega_{sensor}(t)$ is referenced, along with all the coupling and natural frequency values for that model. This gives us the coupling and natural frequency values for our VA. Importantly, we obtain the frequency of the motor oscillator, $\omega_{motor}(t)$ and the brain oscillator $\omega_{brain}(t)$ for our current model. This procedure is illustrated in Fig. 2 for clarification.

To close the loop for mutual coupling between the human subject and the VA, the VA provides output in the form of virtual finger movement on a screen. The dynamics of the virtual finger movement is described by a harmonic spring oscillator system Eq. (2) which is adapted from [27].

$$\begin{aligned} \dot{x}_{va} &= x_\omega(t+1) + C(x_{human}(t+1) - x_{va}(t)) \\ \dot{y}_{va} &= y_\omega(t+1) + C(y_{human}(t+1) - y_{va}(t)) \\ \dot{x}_\omega &= -\omega_{motor}(t)x_{va}(t) \\ \dot{y}_\omega &= -\omega_{motor}(t)y_{va}(t) \end{aligned} \tag{2}$$

Note that we have named the variables differently for the purpose of our study, where x_{va} and y_{va} are the X and Y coordinates of the VA respectively. C describes the directional coupling strength from the VA to the human subject. In the first two equations, the first term on the right describes the oscillatory motion of the VA without coupling and the second term serves as an attractive coupling term which pulls the VA output motion to the human subject motion. A higher C value results in motion that very closely follows the human motion, while a lower value generates self-oscillatory motion. The time-delayed form of x_{va} and y_{va} is removed since it is not in our current interests to study the effect of delay on anticipatory synchronization as in the original study[27].

The equations are integrated using the Euler integration method with a time step size $dt = 0.01$. The setup is implemented in MATLAB R2020a[29].

3.2. Preliminary Testing Results

In the current work, we report the preliminary results of our implementation without any neurophysiological recordings. Here, the human subject is tasked with following a dot

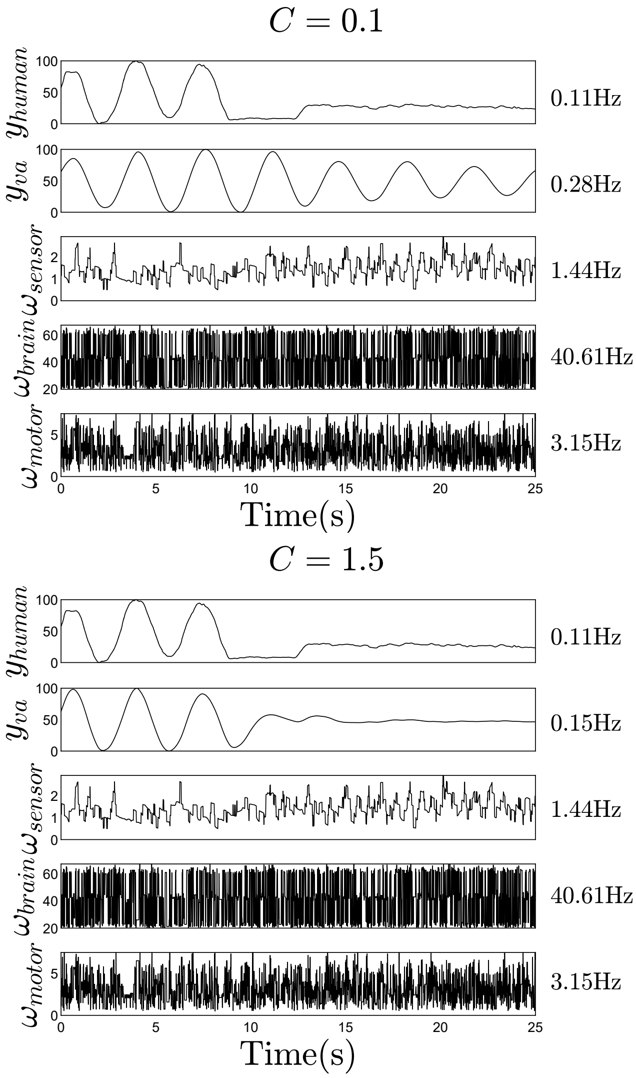

Fig. 3. Example data obtained with the fingertapping implementation, with human-virtual agent(VA) coupling strength $C = 0.1$ and $C = 1.5$. Here the human subject, y_{human} tries to follow the movement of the VA, y_{va}. The VA calculates and extracts its ω from the human finger motion using pre-simulated data. With higher C, the VA follows the human finger motion more closely. The frequency values shown on the right are the overall frequencies of y_{human} and y_{va}, and the mean frequencies of each of the ω values. y_{human} in $C = 1.5$ uses prerecorded data from $C = 0.1$ for reproducibility.

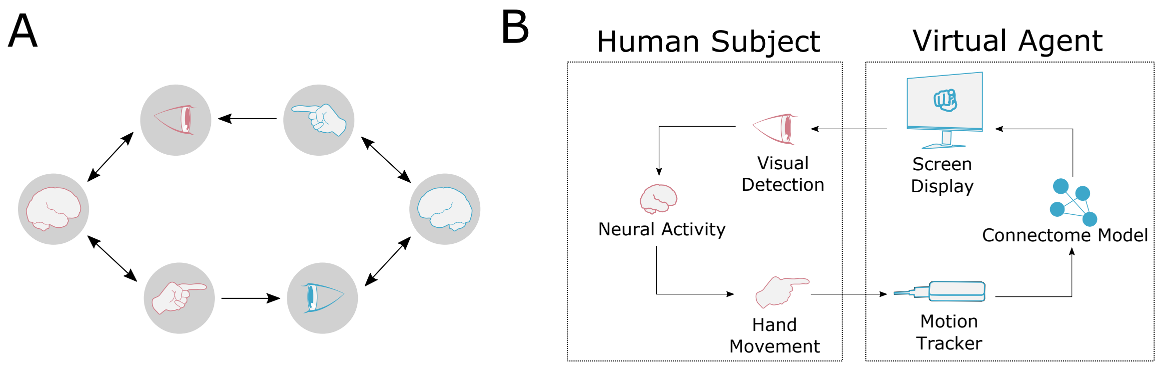

Fig. 4. Comparison between (A) our previous 6-osc simulation model [26] and (B) the current implementation. In (A), each of the nodes represents one Kuramoto oscillator. The fingers and the eyes represent sensorimotor oscillators, while the brain represents neural activity. (B) In the virtual agent(VA), these are replaced with the motion tracker, connectome model and screen display.

on the computer screen using the index finger. We further constrain the task to be only in the Y-dimension, in other words fingertapping motion. However, movement in both dimensions are still being recorded and the VA tracks closely the human finger movement in both dimensions. Fig. 3 shows the raw y_{human}, y_{va} and the VA ω values obtained over 30 s, with the first 5 s removed due to initialization.

Due to the coupling term, y_{human} closely corresponds to y_{va}. With a small C value, y_{va} maintains a stable oscillatory motion using the extracted ω_{motor} at each time step. For example, at around 10 s, even though y_{human} stayed still, y_{va} continued to oscillate. Increasing C to 1.5 increases the coupling from the human to the VA and results in VA motion that tracks the human movement closer.

We also see that ω_{brain} changes over time based on ω_{sensor}. From our previous simulations, ω_{brain} can be interpreted as the frequency at which the VA and the human subject showed the highest synchronization index value given the frequencies of the other sensorimotor oscillators. ω_{brain} has a multimodal distribution with modes at around 24 Hz, 44 Hz and 64 Hz from our previous simulation.

4. DISCUSSION

This conceptual paper presented a human-machine EEG paradigm which is based on the HDC paradigm, along with an example of the implementation and results. As a first step, we have used a model from our previous simulation study [26] to provide model parameters to the VA in real-time. Fig. 4 shows a comparison between our previous model and the current implementation. The VA detects the human finger motion and calculates ω_{sensor} which is then used to extract, from pre-simulated data, the other parameters in the VA.

The current implementation could give us the tools to investigate how inter-brain synchronization frequency dynamically (ω_{brain}) changes over time (See Fig. 3). However, there still lies the main problem of how close does our simulated frequencies and couplings resemble the values recorded in real human-human interaction. Previous hyperscanning experiments involving hand or finger tracking reported inter-brain synchronization in different frequency bands, for example in the alpha-mu (8-12 Hz), beta(13-30 Hz), and gamma(31-48 Hz) bands between the centro-parietal and parieto-occipital regions in a finger imitation task [3], and in the theta (4-7.5 Hz) and beta (12-30 Hz) bands in the centro-parietal and frontoparietal networks in a still finger pointing task [30]. Dumas *et al.* (2020) [31] reported a decrease in mu-alpha (10-13 Hz) power and increase in gamma (30-60 Hz) in the right temporoparietal region in single individuals in a HDC task. In a self-paced dyadic rhythmic finger movement task, it was reported that the phi component (9.2-11.5 Hz) in the centro-parietal region increased in power [11]. In another pilot leader-follower fingerpointing study conducted in our lab (unpublished and full study required for validation, $N = 1$), we found delta (2-3.8 Hz) inter-brain synchronization in the fronto-parietal region, theta (4-7.8 Hz) in the frontal region, alpha (8-12 Hz) in the temporo-parietal region and beta (13-30 Hz) in the parieto-occipital region.

Nonetheless, all of the currently reported results of inter-brain synchronization during hand-motion tasks are time-aggregated results over the whole trial. It would be beneficial to study the changing temporal dynamics of inter-brain synchrony during a fingerpointing task, as the interaction patterns are also changing throughout the interaction. An example of dynamic inter-brain synchrony was recently published in a functional near-infrared spectroscopy (fNIRS) study [32], which segmented inter-brain synchrony using a sliding window approach and characterized the segments into brain dynamic brain states. A similar method could also be applied to a fingerpointing task to allow for comparison with the simulated synchronization frequencies.

Although the purpose of the current paradigm is for the investigation of inter-brain synchrony, it can also be used to improve human-machine,-robot or -computer interaction (HMI, HRI or HCI) by relying on a connectome model that simulates human neural activity, albeit one that is more limited in its range and simplicity of tasks, namely rhythmic coordination. To make the interaction more natural, modifications which would make the VA movements more human-like could be added to the motion equation. For example, a previous study proposed a noise term that randomly triggers a forced exit from synchrony when it reaches a threshold [7], as it is believed that coordination breaking could serve both short- and long-term beneficial functions. Although their motion equations involved velocity instead of position, our model could be modified accordingly. By making the VA output dynamics more natural, this could also support more coordinated activity between the human and the VA, such that they would form a self-organised macroscopic dynamical system as in accordance to the concept of interpersonal synergies [33] and participatory sense-making [8, 9]. These concepts presume that a coordinated interaction does not require the interacting agents to have similar internal models and to mindread each other. Instead, as mentioned in our previous work [26], the control parameter could be low-level processes such as the interaction itself. This macroscopic control parameter could then be studied and compared between human-human and human-machine paradigms or perturbed between different states of interaction [34].

On the other hand, the increased coordination between the human and the VA could support the development of more natural interactions between a human and an interface. For example, the concepts of dynamic interactive artificial intelligence (dAI) [35] and parasitic humanoid (PH) [36], though differing in their implementation, hopes to improve the degrees of freedom of human behavioural interaction through the integration with intelligent interfaces. In addition, dAI proposed the reverse self-organising approach to search for parameter sets that allows coordination, which is similar to the method we used here to infer pre-evolved parameters.

The first step for the proposed paradigm mainly involved finding a minimal method for implementation. The next step involves running an EEG experiment in conjunction with the implementation in hopes that we could identify the dynamic relationship between the neurophysiological and behavioural data, where connectome models could be constrained and pre-evolved. We could also do the opposite in which Kuramoto models could be used to model recorded neurophysiological data. One of the challenges for realizing the paradigm is then to find biologically relevant methods to constrain the couplings between the Kuramoto model and the motor oscillator in the VA.

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