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AI can fool us humans, but not at the psycho-physiological level: a hyperscanning and physiological synchrony study.

F. Dehais[1,2,3], G. Vergotte[1], N. Drougard[1,2], G. Ferraro[1], B. Somon[1,2], C. P. Carvalho Chanel[1,2], and R. N. Roy[1]

***Abstract*— This study aims at investigating the neural and physiological correlates of human-human and human-AI interactions under ecological settings. We designed a scenario in which a ground controller had to guide his/her pilot to reach a location. We also implemented a Controller-Bot and a Pilot-Bot using AI techniques to behave like real human operators. The cooperation between controllers and pilots were either genuine ('Coop scenarios' – four missions), explicitly notified as pilot-Bot and controller-Bot interactions ('No coop scenarios' – two missions), or with no notification that they were actually collaborating with their AI counterparts ('fake coop scenarios' – two missions). Sixteen participants (8 dyads) equipped with EEG and ECG took part in this experiment. Our findings disclosed that Human-Human dyads exhibited similar performance to Human-Bots dyads whether the human participants were aware that they were playing with a bot or not. Our participants declared that they did not realize they were playing with an AI in the fake cooperation condition. These findings indicate that 1) humans can be fooled by AI, and that 2) humans can behave in a natural way with AI. Interestingly enough, our analyses revealed that the cardiac activity of controllers and pilots was more synchronized when they were collaborating together than when they were playing with AI (being aware or not). Similarly, EEG analyses disclosed a higher cerebral efficiency and connectivity between the two brains when teammates were interacting together than when cooperating with AI.**

I. INTRODUCTION

Servicemen are now by far engaged in complex operations involving cooperation with multiple actors and specialists under time-pressure in uncertain and highly dynamic hostile environments. For instance, close air support missions involve Joint Terminal Attack Controllers (JTAC) who guide combat aircraft Pilots from a forward position to identify threats. Efficient communication and synchronization between ground operators, air operators and technology is a key to success. It is expected that AI-based technology (e.g., autonomous robots, decision algorithms) will play a critical role during future operations. The design and the understanding of human-human interactions and humans-AI teaming may benefit from neuroergonomics that promotes the use of mobile sensors to measure brain and behavior in the real world [1], [2]. Such monitoring technology offers promising prospects to account for cooperation by assessing similarity in teammates' (neuro-)physiological responses during interaction.

Montague [3] in 2002 was the first to simultaneously record two participants' brains with fMRIs during interaction tasks. This exciting field of investigation, known as "hyperscanning" (for a comprehensive review see [4]) was extended to electrophysiology (EEG) and portable optical imaging (fNIRS) thus paving the way for social neuroergonomics out of the lab [5]. As an example of everyday-life apllications, hyperscanning has been used to investigate synchronized neural activity of musicians playing together [6], [7] and groups of individuals playing games [8], [9]. Eventually, some studies investigated the neural synchrony of human operators' 'brain at work'. Sciaraffa [10] adapted a simplified flight simulator so that two participants could collaborate like an aircrew, and reported higher connectivity between the two brains when the dyads experienced higher workload than during the baseline. Using a similar setting, classification methods have been used to estimate the level of workload and cooperation of dyads [11], [12]. Lastly, Toppi and collaborators conducted an experiment with aircrews in a full-flight simulator [13] that disclosed an increased interbrain fronto-parietal connectivity during flight phases involving a higher level of cooperation but also a higher level of workload, which may represent a potential confound.

A complementary approach to hyperscanning is to consider physiological synchrony (PS) to investigate the physiological correlates of social interactions. PS is probably the easiest approach to deploy in the field as it requires the use of unobtrusive synchronized physiological devices such as electro-cardiogramm (ECG), respiratory belt or skin conductance sensors [14], [15]. This measure also requires less computational cost to process data than multiple-channel brain imaging techniques. Several studies successfully applied PS to multiplayer video games paradigms or realistic micro-world and disclosed that PS could account for empathy between players [16], intensity of cooperation [17], [18] or even better team performance in a military cleaning room scenario [19]. Taken together, hyperscanning and PS approaches open promising prospects for social neuroergonomics and the design of solutions to assess and improve human-human or human-artificial systems teaming.

[1] ISAE-SUPAERO, Université Fédérale de Toulouse, France. [2] Artificial and Natural Intelligence Toulouse Institute, Université de Toulouse, France.[3] School of Biomedical Engineering, Science Health Systems, Drexel University, Philadelphia, PA, United States `frederic.dehais@isae-supaero.fr`

The present study aims at investigating the cooperation between a military ground controller (JTAC) and a Pilot in the context of close air support. A scenario was designed whereby a JTAC guides his/her Pilot to fly over a location during 8 different missions. During the experiment, teammates were both equipped with EEG and ECG devices. In half of these scenarios the JTAC and Pilot were genuinely cooperating together whereas in the other half, they were respectively playing against a Pilot-Bot and JTAC-Bot, simulated using basic artificial intelligence (AI) techniques. This approach allows to compare participants' cardiac and neurophysiological responses when interacting with another human or an AI, but also to control for potential confounds. Indeed, the design of hyperscanning ecological protocols remains challenging as long higher brain synchrony or PS may account for potential load effects (i.e. dyads are facing high demands at the same time) or task effects (i.e. dyads are doing the same task thus exhibiting similar cerebral activation) rather than real social interaction per se. We first describe the methodological approach and then present and discuss the results of this study conducted with 16 participants (8 dyads).

II. Material and Method

A. Participants

Sixteen participants (i.e. eight couples), all students or staff members from ISAE-SUAPERO (3 women, mean age 29 years) completed the experiment. Eight of them were qualified to fly on DR400 aircrafts and thus ensuring the role of pilots in the dyad. After providing written informed consent, they were instructed to complete task training. Total duration of a subject's session (informed consent approval, sensors set-up, practice task, and real task) was about 2 hours. This work was approved by the Institutional Review Board (IRB) of the Comité d'Ethique de Recherche de l'Université de Toulouse (IRB: 00011835-2019-05-28-149).

B. Experimental set-up

A JTAC user-interface was implemented and was composed of two main parts. The left part of the user interface was a 2D tactical map that displayed the position of the Pilot on the city of Toulouse and surrounding environment. It included various buildings (e.g., castles, supermarkets), rivers, lakes, roads that the JTAC could use as way-points to guide the Pilot until the final location indicated by a black flag on the user interface. The right part of the user interface was dedicated to communication purposes. It allowed the JTAC to compose the instructions to be sent to the Pilot by clicking on different icons, drop-down menus and buttons (eg. "Do you see the castle on your left" or "fly from the castle for 20 s until the lake"). These instructions were sent via a local network to the Pilot using a 10-inch tactile tablet. The reception of each message was notified with an auditory warning to avoid any misses while the Pilot was focused on flying the aircraft. Then the Pilot had to click on one of the following possible responses "Yes visual", "No / No visual", "Reword lost" or "OK Copy" to indicate to the JTAC whether he/she understood the instructions or not. These reply-messages were then notified to the JTAC with an auditory warning. JTAC and Pilots were equipped with in-ear headphones. The aerofly fs2 software was used to simulate the DR400 aircraft, displayed on three 19-inch screens. Pilots had a joystick to control the roll, pitch, yaw and thrust of the simulator. Lastly, a JTAC-Bot and Pilot-Bot were implemented using basic AI techniques. These two artificial agents were programmed to behave like real JTACs or real Pilots (i.e., piloting the plane or guiding the pilot according to their role, and sending communications).

C. Scenarios

Teammates had to perform a total of eight missions of equal difficulty in less than ten minutes. The aim of each mission was for the JTAC to drive the Pilot into identifying and flying over a specific target within the allotted time, using text messages to communicate. If the Pilot had enough time to fly over the target, the mission was considered as achieved. If not, the mission was considered as not achieved. Three types of cooperation conditions were designed, according to the type of interaction between Pilots and JTAC:

- **Coop**: Pilot and JTAC are genuinely cooperating (4 missions);
- **Fake Coop**: Pilot and JTAC are not told that they are respectively cooperating with a JTAC-Bot and Pilot-Bot (2 missions);
- **No Coop**: Pilot and JTAC are told that they are respectively cooperating with a JTAC-Bot and Pilot-Bot (2 missions).

The order of the eight scenarios was counterbalanced across teams to control for training and fatigue effects.

In order to ensure a more realistic cooperation in the 'Fake coop' and 'No coop' conditions, sent messages and corresponding warnings (from the JTAC to Pilot-Bot or from the Pilot to JTAC-Bot) were synchronized. For instance, a message from the JTAC to the Pilot-Bot was not sent until the Pilot was actually responding to the JTAC-Bot.

D. Protocol

The two participants were comfortably seated on a chair but had no visual contact with each other thanks to a partition (see fig 1). They were not allowed to talk until the end of the experiment. They were required to read and sign the informed consent as well as to fill a questionnaire that included demographic data, flight experience, potential social link between the two participants (e.g. friends, colleagues, etc) and the Karolinska Sleepiness Scale (KSS [20]). Participants were then equipped with the EEG and ECG recording devices. After the JTAC and Pilot successfully completed a training session, the experiment *per se* could start. From this point on, the following pattern was repeated 8 times: 1) a 1-min baseline during which the participants were asked to relax while focusing on a cross on a white screen, 2) a mission of maximum 10 minutes.

Fig. 1: Experimental setup: the Pilot (left) is flying the aircraft and exchanges instructions via a tablet with the JTAC (right) who is in charge of supervising the aircraft trajectory and gives instructions to the Pilot via the user interface.

E. Behavioral measures

The mean time to reach the final goal (maximum 10 min) was computed as a marker of performance and analysed with a one-way ANOVA with the experimental condition (coop vs. fake coop vs. no coop) as within subject factor.

F. Cardiac activity

1) Frequency domain analyses

Cardiac activity was recorded for each participant with two active Ag-AgCl electrodes placed under the right clavicle and the left mid-axillary line, and digitized with two BioSemi ActiveTwo (BioSemi, Amsterdam – one for each participant) at 512 Hz. Raw signals were band pass filtered (5^{th} order Butterworth, $[1-30]$Hz). For each scenario, three frequency domain HRV metrics were extracted: the Low Frequency Power (0.04 to 0.15 Hz) as a measure of sympathetic nervous system activity, the High Frequency Power (0.15 to 0.4 Hz) and the Power ratio (Low Frequency / High Frequency) using the Lomb periodogram method as suggested by the literature [21].

Mean frequency measures were computed for each condition (coop, false coop and no coop) and each participant (Pilot and JTAC), and were analyzed separately for Pilots and JTACs with a one-way ANOVA with the cooperation condition as within-subject factor.

2) Physiological synchrony

Similarly to [16], we computed the Wavelet Detrended Cross-Correlation (WDCC) at Lag 0 to quantify the degree of synchronization between ECG time-series to assess the degree of physiological synchrony between the Pilot and JTAC within each couple.

Mean WDCC values at Lag 0 were computed for each condition (coop, false coop, no coop) and each dyad (Pilot-JTAC synchrony), and analyzed with a one-way ANOVA with the cooperation condition as within-subject factor.

G. Cerebral activity

1) Data Processing

EEG data were recorded continuously at 512 Hz using 2 BioSemi Active2 systems (BioSemi, Amsterdam) with 64 active Ag-AgCl scalp electrodes positioned according to the International 10/20 system, and band-pass filtered between $[0–104] Hz$. During the experiment, electrode offsets were kept under 20 mV as recommended by the manufacturer to ensure high signal quality. Preprocessing was performed using EEGLAB (V14.1.2 [22]) and MATLAB (The Mathwork Inc., v.2019a). Data were first re-referenced offline to the algebraic average of all electrodes using the Prep pipeline function [23], high-pass filtered (1 Hz), and noisy portions of data were removed using the artifact subspace reconstruction (ASR) algorithm [24] with the clean_asr function (default settings). Individualized frequency bands were computed to determine the frequency windows for delta, theta, alpha, beta and gamma bands for each participant. To do so, we computed the peak alpha frequency and shifted the other frequency band accordingly (see [25].

2) Hyperscanning metrics

As the hyperscanning approach is based on the assumption that two or more brains are inter-connected during cooperation, we computed the functional connectivity of pre-processed EEG time-series between participants as well as for each participant on four frequency bands of interest (α, θ, β, δ and γ). First, we computed the covariance, characterizing the simultaneous variations of two signals x and y and described as a "measure of joint variability" : :

$$COV(x, y) = E(x - E(x)) \times E(y - E(y)) \qquad (1)$$

x and y represent the signals from two different EEG channels (e.g. channel 1 of the Pilot and channel 1 of the JTAC) and E represents the expected value.

As a complementary measure we computed the Global Efficiency [26] using the brain connectivity toolbox [27]. First, we thresholded each matrix for each frequency band keeping the ten highest covariance links and then binarized the matrices based on this threshold. We computed the Global Efficiency which is the average inverse shortest path length of the network and is defined as:

$$E^w = \frac{1}{n} \sum_{i \in N} E_i = \frac{1}{n} \sum_{i \in N} \frac{\sum_{j \in N, j \neq i} d_{ij}^{-1}}{n-1}. \qquad (2)$$

Where N is the total number of nodes (electrodes in our case), d_{ij} is the shortest path length between node i and j and E_i is the efficiency of node i.

The average Global Efficiency was computed for each condition (Coop, False Coop and No Coop) for each dyad and each frequency band, and analysed separately through a one-way ANOVA for each frequency band with the cooperation level as within subject factor.

III. Results

A. Subjective and behavioral results

A one-way ANOVA disclosed no significant effect of the cooperation condition on the mean time to reach the final goal ($F(2, 27) = 0.02,\ p = 0.98$).

B. Cardiac activity

1) Heart rate variability

The one-way ANOVA highlighted no significant impact of the cooperative condition on heart rate variability metrics. Indeed, there was (i) no significant difference on the Low Frequency variables for the Pilot ($F(2, 23) = 0.47, p = 0.63$) and the JTAC ($F(2, 30) = 0.24, p = 0.78$); (ii) no significant effect on the High Frequency for the Pilot ($F(2, 23) = 0.35, p = 0.71$) nor for the JTAC ($F(2, 30) = 0.01, p = 0.99$); (iii) and no significant effect on the Power Ratio (LF/HF) for the Pilot ($F(2, 23) = 0.36, p = 0.70$) and for the JTAC ($F(2, 30) = 0.61, p = 0.55$). In short, the cardiac activity measures of Pilots and JTACs were similar when interacting with a human or with a bot.

2) Heart Beat synchronization between JTAC and Pilot

The ANOVA revealed a significant effect of the cooperation condition on the WDCC at Lag 0 ($F(2, 23) = 5.2517,\ p = 0.005$). Post-hoc analyses showed an increased WDCC in the coop condition compared to false coop ($p = 0.O05$) and no coop ($p = 0.03$) – see fig IV-B. In short, the JTAC and Pilot were more synchronized at the cardiophysiological level when they were actually interacting together than when they were cooperating with the bots.

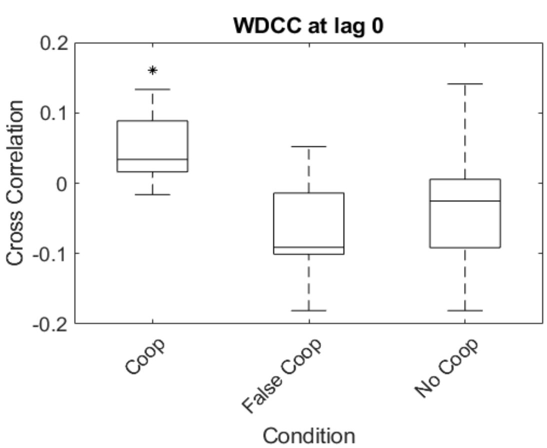

Fig. 2: Physiological synchrony: the windowed detrended cross correlation in the 3 cooperative conditions at lag 0.

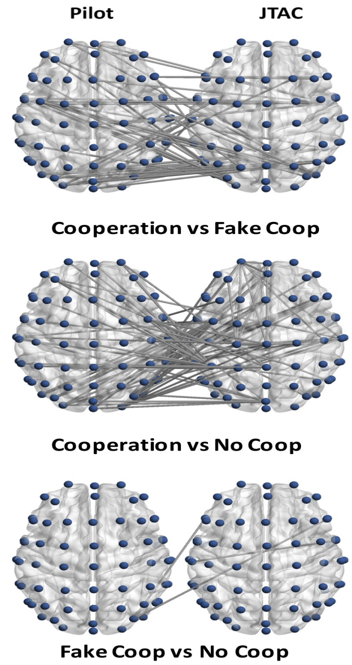

Fig. 3: Double 3D brain representation of the significant inter-individual connections in the alpha frequency band between the Pilot (left) and the JTAC (right) for the 3 experimental conditions.

C. Cerebral activity

Statistical analyses revealed significant differences ($p < 0.05$) for all combinations in the alpha and theta bands. There was a higher number of significant differences for Cooperation vs. False Cooperation (238 significant t-tests) and for Cooperation vs. No Cooperation (1422 significant t-tests) than for False Cooperation vs. No Cooperation (44 significant t-tests) for the theta frequency band; and similar results fort the alpha frequency band (144, 236 and 6 significant t-tests respectively for Cooperation vs. False Cooperation, Cooperation vs. No Cooperation and False Cooperation vs. No Cooperation) (fig. 3).

The one-way ANOVA showed a significant effect of the condition on mean inter-brain global efficiency ($F(2, 35) = 4.30, p = 0.02$). Post-hoc comparisons revealed a higher global efficiency for the Cooperation vs. No Cooperation comparison ($p = 0.05$) but no significant difference between Cooperation and False Cooperation ($p = 0.16$) and between False Cooperation and No Cooperation ($p = 1$) (fig. 4).

IV. Discussion

The objective of the present study was to investigate the cardiac and neurophysiological correlates of cooperation in the context of close air support missions. We designed an experimental scenario whereby a JTAC and Pilot were collaborating together or with bots to reach a target. The two participants were both equipped with a 64-channel EEG and an ECG.

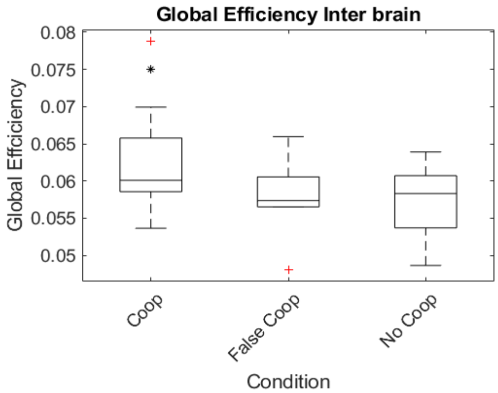

Fig. 4: Boxplot of the global efficiency applied on the alpha frequency correlation matrices.

A. Behavioral and cardiac analyses at the Pilot and JTAC levels

Our behavioral results disclosed that the overall performance (i.e. time to reach the target) was the same in each cooperative condition. Interestingly, we debriefed our participants after the experiment and most of them did not realize that they were playing with a bot in the 'False Coop' condition, meaning that it is possible to fool humans even in an operational setting. This issue is relevant given that humans will be more likely to interact with AI in the battlefield in the near future. The physiological findings at the individual level (i.e. Pilot/JTAC) echoed with the behavioral findings since they did not reveal differences in HRV across the different cooperative condition. Since HRV is thought to reflect catabolic activity to support the mobilization of cerebral resources [28], these latter results seem to indicate that the interaction with a human teammate or a bot induced similar levels of mental workload.

B. Physiological synchrony

One of the main objective of this study was to investigate physiological markers that account for collaboration. The WDCC analyses revealed that our participants exhibited more physiological synchrony when interacting together than when cooperating with bots whether they were aware of it (No coop) or not (False Coop). This result seems to reflect that our participants managed to sense when they were cooperating with their human counterpart but with no apparent effect on behavior. The findings reported in this study, together with others [16], [17], [29], [30], [31], [32], [33], [19], raise the issue of the mechanisms that underlie cardiac synchronization between teammates. Some hypotheses have been put forward such as a the 'chameleon effect' [34], [35] and a 'shared metabolic demand through matched activity or behavior, conditional and environmental influences and synchronized breathing' [14]. Spontaneous group synchrony has been observed via breathing [36]. However, in the present set up, participants had no visual contact with each other and could only 'imagine' the interaction with their teammate.

C. Electrophysiological measures of hyperscanning

Covariance matrices were computed to quantify the level of connection between each electrode for both participants to investigate inter-brain synchronization similarly to [13]. The analyses indicated higher differences between Cooperation and the two conditions performed with bots (False and No Cooperation) in the theta and alpha frequency bands. Furthermore, there wass little difference between False and No Cooperation. Taken together, these results highlight a difference in our main factor of interest (human-human vs. human-bot interaction) irrespective of whether this leads to an increase or decrease in the strength of functional connectivity links. We also used a method derived from the graph theory (Global Efficiency), previously used for hyperscanning research [13], which reflects the overall functional organization of a network at the macroscopic scale [26]. Our results highlighted a significant increase of inter-brain Global Efficiency in the Cooperation compared to the No Cooperation condition. These findings suggest that human-human cooperation yields a better functional brain reorganization. The literature showed that two brains could synchronize neuronal responses through a common external agent such as performing the same task or listening to the same music inducing a confounding effect in the brain study of cooperation as such [37]. Due to our experimental paradigm not involving the same processes for the two participants, these results tend to highlight an inter-brain difference that would be due to the cooperation effect. Nevertheless, it is well known how inter-subject connectivity patterns might be affected by several factors such as the type of connectivity method [38], the statistical assessment of significant effect as well as the task effect discussed above.

D. Conclusion and perspectives

This study evaluated physiological synchrony and hyperscanning in a well-controlled yet ecological set-up. In our scenarios, participants had a common goal (i.e. finding the target), but did not have visual contact with each other, were operating different user interfaces and were not performing similar tasks that could have increased the likelihood of 'synchronization' between teammates. This is a crucial issue because some studies report evidence of hyperscanning or physiological synchrony mainly because their participants were facing similar and synchronous stimuli. In these latter cases, phased-brain and cardiac responses may just reflect synchrony to the task itself rather than true social connectivity. Taken together our subjective, behavioral and cardiac analyses disclosed that human JTAC-human Pilot dyads performed as well as Human-Bots dyads whether humans were aware that they were playing with AI or not. These findings indicate that the design of our protocol was successful and that 1) humans can be fooled by AI and that 2) humans can behave in a natural way with AI. Interestingly enough, the physiological synchrony and EEG-based hyperscanning analyses led us to identify relevant markers to detect when the JTAC and the Pilot are in cooperation, as well as when there is no cooperation. Future analyses should consider to use Granger-causality approach to estimate the functional connection at the source level between the signals of the pilot and JTAC. Such formalism would help to better understand the neural correlate and the dynamics of cooperation.

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