On the Effect of Swarm Collective Behavior on Human Perception: Towards Brain-Swarm Interfaces

George K. Karavas and Panagiotis Artemiadis

***Abstract*— Swarms of autonomous robots consist of a large number of simple and inexpensive units that use local communication and sensing in order to achieve a common goal. They provide improved robustness and efficiency characteristics over single agent solutions due to their interchangeability and inherent redundancy. Human-Swarm Interaction (HSI) is a relatively new field that has captured the attention of many researchers over the last decade. Efforts have mainly focused on the design of human-swarm control interfaces, neglecting significant aspects like the human perception of the swarm behavior. In this work, we attempt to address this issue by examining the perception and representation of collective behaviors of swarms at the brain level of human supervisors. More specifically, the effect of swarm cohesion on the ElectroEncephaloGraphic (EEG) activity of the human supervisor is investigated. We show that brain activity is correlated to swarm cohesion levels, which refers to spreading in the motion of the swarm agents. Moreover, we show that as the cohesion of the swarm becomes lower, the subjects are less able to discern changes in the direction of its motion. This work provides the first evidence of representation of swarm collective behaviors at the brain level, which can lead to the design of a new generation of brain-swarm control and perception interfaces.**

I. INTRODUCTION

Swarms of autonomous robots provide a very robust and efficient framework for mission execution both in military and civilian applications. In general, a *swarm* can be defined as a large group of simple, inexpensive and interchangeable robots (also referred to as *agents*) that try to fulfill a common goal. This is done by cooperating with each other either implicitly or explicitly based on local sensing and/or local communication. Their main advantage over single-agent methods is their redundancy which provides robustness to system failures and disturbances. If one or more agents cease to operate, the remaining agents are still able to complete the mission.

Human Swarm Interaction (HSI) is a relatively new field that has attracted attention from many researchers over the past decade. It is related to the field of Human Robot Interaction (HRI), but it is also different from it, because, in the case of swarms, the interactions with the user can be much more complicated. Most of the previous works in relation to HSI focus either on the interface between the human operator and the swarm or on the interaction itself. For example, in [1] the authors describe the design of an interface for the iRobot platform, both in the hardware and the software level. Its advantage is that it permits interaction with the agents of the swarm as a group and not by handling each of them individually. In [2], the authors discuss the design and development process of an appropriate human-swarm interface for applications where there are interactions between a swarm of robots and a group of firefighters.

With regard to interaction, in [3], the authors examine two types of control, termed as selection and beacon control. During the first type of interaction, the user selects a group of agents and commands them to perform a task while the rest of them follow a predefined behavior, whereas during the second, a virtual beacon is placed by the user inside the operational space of the agents and they react based on their distance from it. In [4], the authors propose a strategy that uses avatars, i.e. robots that belong to the swarm but are controlled directly by the operator. The user can interact locally with the agents of the swarm and is able to inject knowledge with respect to the swarm's state without centralized control. At the same time, the method is simple and easily scalable. In [5] and [6], the user is interacting with the swarm through hand gestures. In [7], the authors introduce the concept of Neglect Tolerance, which refers to the amount of time that the operator can neglect the swarm before the performance starts to degrade. In [8], the authors examine the strategy during which the operator waits for the swarm to stabilize before issuing a new command. This method is termed as Neglect Benevolence.

Other works on the subject analyze the level of autonomy of the system, i.e. the level of interactions between the swarm and the human operator. Such works can be found in [9] and [10]. Specifically in [10], the authors use Sheridan's ten levels of autonomy in combination with a four stage model of information processing to create autonomy profiles. In each of the four stages, different levels of autonomy can be used, involving the human operator to varying amounts at each step. This approach tries to optimize efficiency by engaging the human operator only when necessary. There are also works that focus on the more theoretical aspect of HSI. For example, in [11], the authors propose metrics inspired from biological swarms for the assessment of human-swarm interactions. Among these propositions, there are also human-related metrics such as trust in the system, situation awareness and vigilance.

Although the aforementioned works provide rigorous analysis and viable solutions for the human-swarm interaction problem, they fail to explicitly take into account the factors related to the human perception of swarm behaviors and the possible implications or constraints that this may impose. Understanding and analyzing human perception is a key ele-

George K. Karavas and Panagiotis Artemiadis are with the School of Engineering for Matter, Transport and Energy, Arizona State University, Tempe, AZ 85287 USA. georgekkaravas@gmail.com, panagiotis.artemiadis@asu.edu

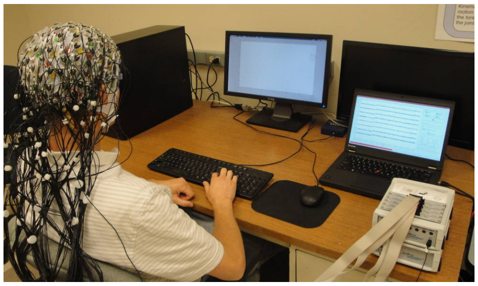

Fig. 1: Subject in front of the monitor wearing the EEG cap and electrodes.

ment when designing human-swarm interfaces or interaction strategies because it may prevent possible caveats due to human inability to interpret correctly specific situations. In this work, we attempt to address this issue by explicitly examining and characterizing the effects of swarm behavior on the human supervisor's brain activity. More specifically, we use non-invasive electroencephalography (EEG) in order to extract Event Related Potentials (ERPs) elicited by changes in a parameter of the swarm's collective behavior, as it travels at constant speed from one edge of a monitor screen to the other. This parameter is the swarm's cohesion which reflects the amount of swarm spreading during its motion. We also measure the reaction times of human supervisors to direction changes of the swarm at different cohesion levels. We hypothesize that (a) subjects have longer reaction times as the cohesion of the swarm gets lower values, i.e. as the spreading becomes more significant and (b) that different cohesion changes elicit different ERP activity at the supervisor's brain. Validation of the hypotheses will for the first time reveal the representation of collective swarm behavior at the supervisor's brain, which can result in the design of a new generation of brain-swarm control and perception interfaces.

The rest of the paper is outlined as follows: Section II describes the experimental setup and procedure for the acquisition and processing of the EEG data. Section III presents and discusses the corresponding results. Finally, Section IV concludes the paper.

II. METHODS

A. Experimental Procedure

The subjects participated in this study were two healthy male adults between the ages of 26 and 35. They did not have any previous mental or brain conditions. After giving informed consent approved by ASU IRB (Protocols: 1309009601, STUDY00001345), the subjects were asked to sit in front of a 20" monitor at a distance of 75-80 cm away from it and observe a simulated swarm of agents flying from one edge of the screen to the other, as shown in Figure 1. Each subject performed one session of 540 trials that lasted 10 to 11 seconds each. For both subjects, the type of trials and their order was the same. A few examples of these trials are given in Figures 2 through 5.

In each trial, the swarm traveled on a straight line starting from a close-packed formation. During its motion and at a

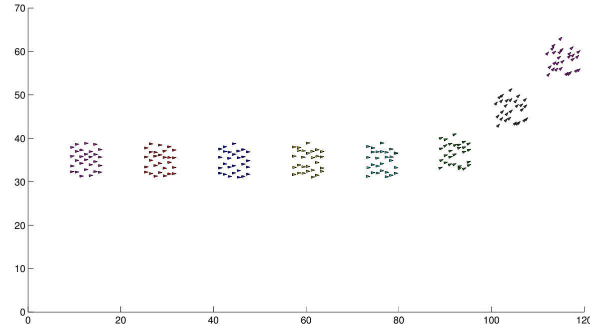

Fig. 2: The swarm moves constantly at high cohesion level until it turns upwards.

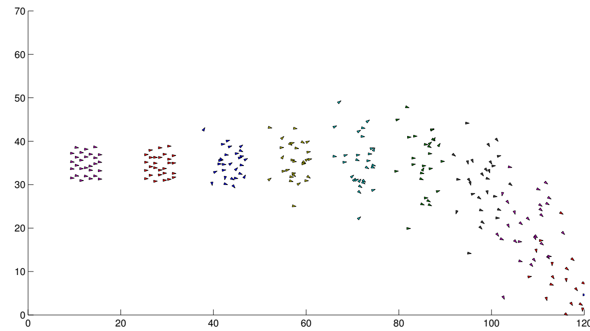

Fig. 3: The swarm changes its cohesion level from high to low and moves downwards.

random time within a window of 20% to 40% of the total screen width, the swarm's cohesion started to change until 10% of the screen width later, when the cohesion reached its final value. This change lasted for approximately 840 ms. Then, at a random time within a window of 60% to 80% of the screen width, the swarm gradually changed its direction towards either the upper or the lower edge of the screen (e.g. see Fig. 2). The subjects were instructed to press a button when this direction change occurred. They were unaware of the cohesion change and they did not have to respond to that. The purpose of the button press action was twofold: a) to provide a metric as to how swarm cohesion levels affect the times when the subjects-supervisors observe direction change in the swarm and b) to keep the subjects engaged in the experiment. The positions where the cohesion change and the direction change occurred guaranteed that there would be no overlaps between ERPs elicited from the two events. The direction towards which the swarm would turn was chosen randomly and irrespectively of the cohesion or the cohesion change.

One of the main contributions of this work is the analysis of the ERP waveforms of the subjects at different levels of swarm cohesion and at cases where the level of cohesion changes during a single trial. In the experiment, *swarm cohesion* is expressed as how strictly parallel are the agents' paths with respect to each other or, in other words, how organized is the swarm while following a prescribed path. A high level of cohesion denotes that the agents move almost on parallel paths, while a low level denotes that the paths can intersect with each other and produce a more random

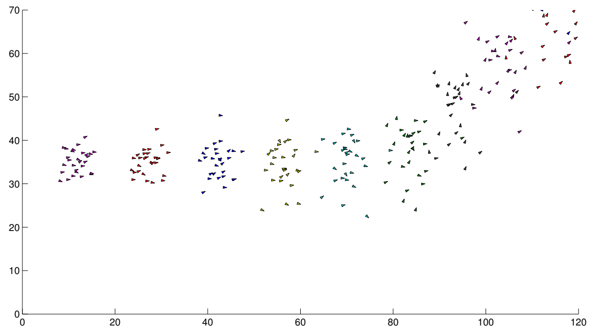

Fig. 4: The swarm changes its cohesion level from medium to high and turns upwards.

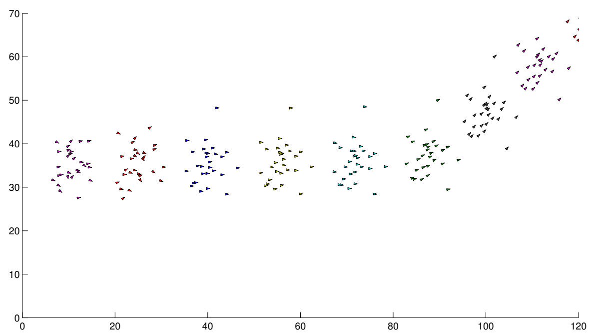

Fig. 5: The swarm changes its cohesion level from high to low and turns upwards.

outspread of the swarm.

In this work, we use three levels of swarm cohesion, namely *high*, *medium* and *low* and we examine the ERP reponses of the subjects to each of these levels and to all possible transitions between them (i.e. high to medium, high to low, low to medium etc.). This creates 9 cases which are listed in Table I.

	Cohesion Levels	
Case #	Start	End
1	high	
2	medium	
3	low	
4	high	medium
5	high	low
6	medium	high
7	medium	low
8	low	high
9	low	medium

TABLE I: Cohesion change cases.

For each of the three cohesion levels, we measure a baseline ERP, when no cohesion change occurs, and we compare it to the ERPs created from changes starting at that particular level. For example, referring to Table I, we compare Cases 4 and 5 where the initial cohesion was *high* but then changed, to Case 1 where the cohesion was kept *high*.

B. Data Acquisition & Conditioning

The EEG data were collected using a BrainProducts ActiCHamp amplifier module and 128 active electrodes. The electrodes were placed on the subjects' scalps based on the International 10-20 system using a BrainProducts ActiCAP cap. The data were recorded at 1000 Hz.

The processing of the EEG data was done using the EEGLAB [12] and ERPLAB [13] packages which are available for the Matlab environment. First, a 6^{th} order lowpass Butterworth filter at 40 Hz followed by a 6^{th} order highpass Butterworth filter at 0.1 Hz were applied to the data in order to remove any high frequency noise and low frequency trends, respectively. A notch filter was also applied in order to suppress any 60 Hz line noise that may have remained after the low-pass filtering. The filtered data were then re-referenced at average reference and epoched at 500ms before and 1.5s after the cohesion change onset. Finally, eye blink and eye movement artifacts were removed from the epoched data using the Independent Component Analysis (ICA) method and the function dipfit of the EEGLAB package. The corresponding results are discussed in the next section.

III. RESULTS

The results of this work consist of two main components: (a) the reaction times of the subjects in response to the direction change of the swarm at each level of cohesion, and (b) the ERP responses corresponding to different levels of swarm cohesion and to different changes among these levels.

The reaction times for both subjects at each level of swarm cohesion are shown in Figure 6. The results validate our initial hypothesis that the relation between swarm cohesion and reaction time is inversely proportional, i.e. it takes more time for subjects to perceive changes in swarm's direction as its cohesion level is reduced. In order to prove that this increase in time is statistically significant, we also provide in Table II the probabilities of the paired t-tests (p-values) that compare reaction times between each pair of cohesion levels for each subject separately. These values are all below 5%, which strongly suggests that there is an increasing trend of reaction times over swarm cohesion.

	Subject 1	**Subject 2**
High vs. Medium	5.34×10^{-4}	8.19×10^{-12}
High vs. Low	1.86×10^{-7}	1.27×10^{-17}
Low vs. Medium	4.2×10^{-3}	2.54×10^{-2}

TABLE II: p-values for reaction time pairs where each pair corresponds to two different cohesion levels.

During the experiment, there were trials where the cohesion level did not change. This created ERP responses that were treated as baseline for that cohesion level. Then, any changes from that level to others created new ERP signals that were compared to the baseline. For example, we examine ERP signals related to a change from the high to the medium

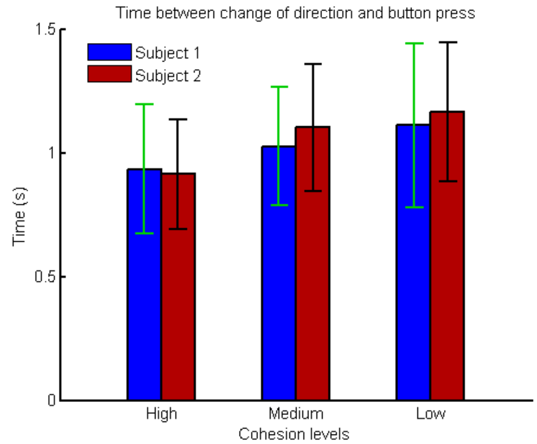

Fig. 6: Supervisors' reaction times (mean and standard deviation) for different levels of swarm cohesion.

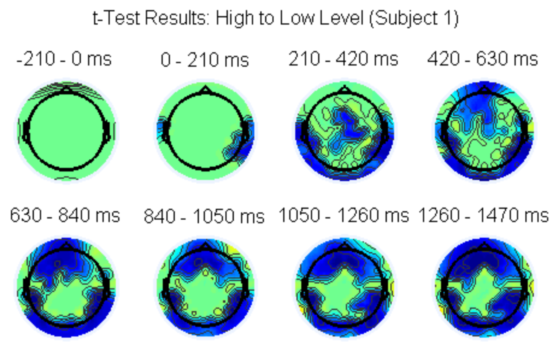

Fig. 7: t-test values for a high-to-low cohesion change over a scalp map (Subject 1).

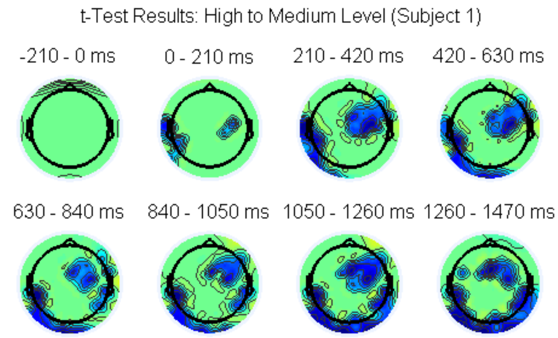

Fig. 8: t-test values for a high-to-medium cohesion change over a scalp map (Subject 1).

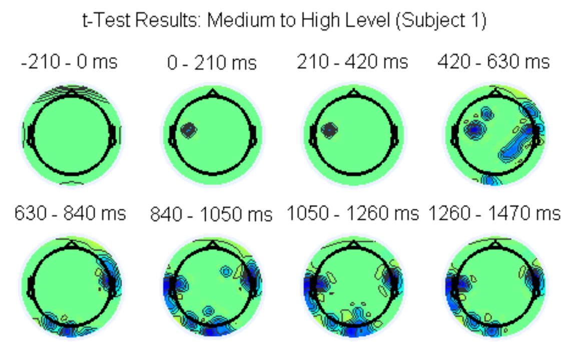

Fig. 9: t-test values for a medium-to-high cohesion change over a scalp map (Subject 1).

cohesion level and we compare them to the baseline for the high level. This creates 6 comparison tests (2 for each level). The corresponding results are shown in Figures 7 to 12 for the first subject and Figures 16 to 21 for the second.

In Figures 7 and 8, we show the statistical differences (p-values) between the cohesion changes from high to low level and from high to medium level compared to the baseline for the high level. For a clearer depiction of the results, we only show the regions where the difference between the two ERP signals is significant which are denoted with dark blue color (low p-values). In our case, significance is denoted by any values below 0.3 (30%). This is due to the fact that during the experiment we expect additional mental activities which may interfere with our results. As it can be seen from both figures, there are regions in the scalp map that are differently activated immediately after the stimulus onset (time = 0 ms) and they continue to be activated after the end of the cohesion change at 840 ms. Those regions are mainly located around the visual association and primary visual cortex, while we also see some activation over the premotor area and the primary motor cortex.

In Figures 9 and 10, we show the corresponding graphs for the medium-to-high and medium-to-low cohesion changes. Here, the differences from the baseline of medium cohesion are less significant and they have a delay with respect to the stimulus onset. The significance persists after the end of the stimulus in this case as well.

Figures 11 and 12, show the corresponding cases for the low baseline, where we see no significant activation in Figure 12. In Figure 11 though, we see an activation for the low-to-high case at a point far later than the end of the cohesion change. Finally, in Figures 13 through 15, we show the brain activations related to each cohesion level and the corresponding cohesion changes for the first subject. One general remark would be that we observe greater activations for greater cohesion changes.

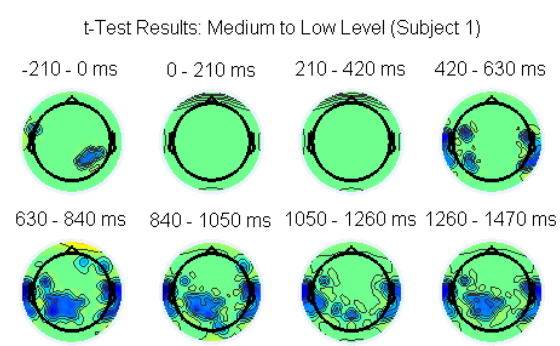

Fig. 10: t-test values for a medium-to-low cohesion change over a scalp map (Subject 1).

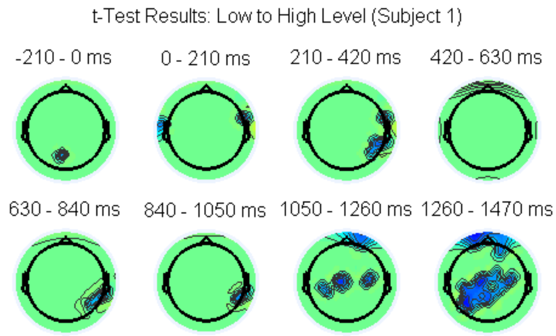

Fig. 11: t-test values for a low-to-high cohesion change over a scalp map (Subject 1).

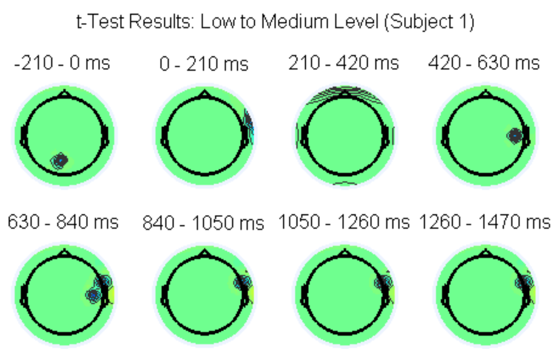

Fig. 12: t-test values for a low-to-medium cohesion change over a scalp map (Subject 1).

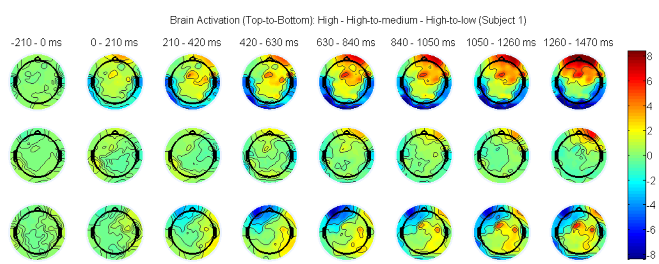

Fig. 13: ERP activations for cases where the starting cohesion level is *high*. The first row denotes no cohesion change, while the last two correspond to the high-to-medium and high-to-low changes, respectively.

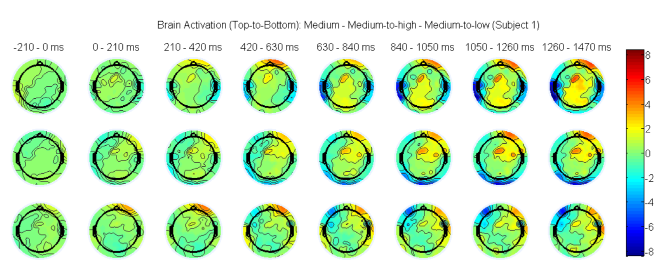

Fig. 14: ERP activations for cases where the starting cohesion level is *medium*. The first row denotes no cohesion change, while the last two correspond to the medium-to-high and medium-to-low changes, respectively.

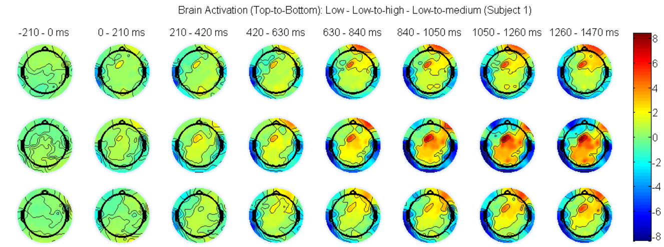

Fig. 15: ERP activations for cases where the starting cohesion level is *low*. The first row denotes no cohesion change, while the last two correspond to the low-to-high and low-to-medium changes, respectively.

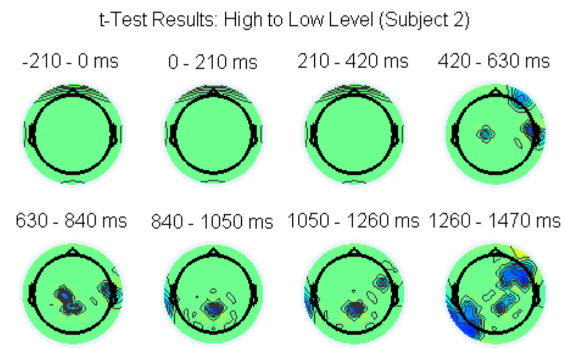

Fig. 16: t-test values for a high-to-low cohesion change over a scalp map (Subject 2).

The corresponding t-test graphs for the second subject are shown in Figures 16 to 21. In these figures, the statistical difference between each cohesion change and the baseline does not have the same patterns and is not as significant as in the case of the first subject. It is though present, which implies that our initial hypothesis about brain activation and swarm cohesion changes is still valid.

IV. CONCLUSIONS

As stated in the introduction, human perception of swarm behaviors in human-swarm interactions is a key element to design successful and efficient interfaces and interaction strategies for supervisory control of swarms. Nevertheless,

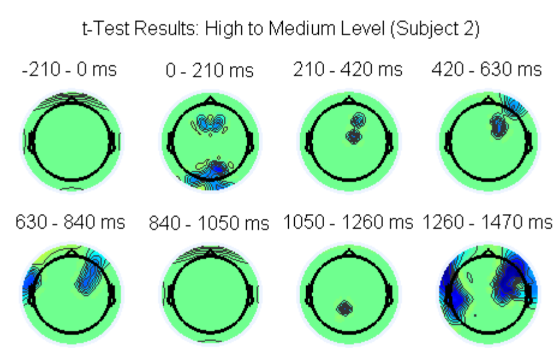

Fig. 17: t-test values for a high-to-medium cohesion change over a scalp map (Subject 2).

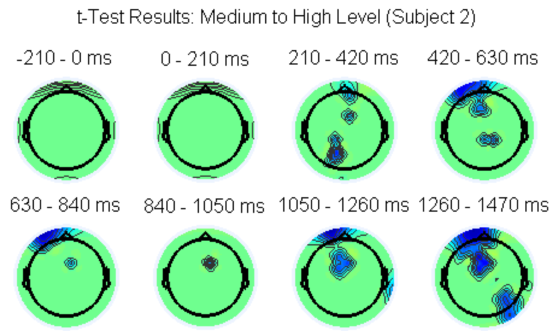

Fig. 18: t-test values for a medium-to-high cohesion change over a scalp map (Subject 2).

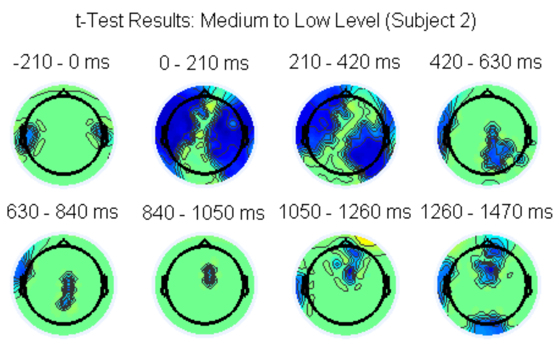

Fig. 19: t-test values for a medium-to-low cohesion change over a scalp map (Subject 2).

Fig. 20: t-test values for a low-to-high cohesion change over a scalp map (Subject 2).

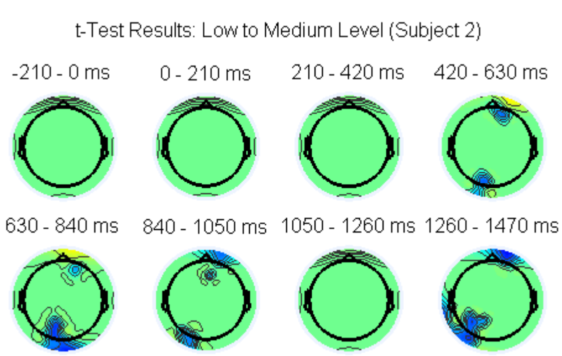

Fig. 21: t-test values for a low-to-medium cohesion change over a scalp map (Subject 2).

this is not an issue that has been extensively studied in the literature. In order to fill this gap, we use EEG to monitor brain activity on human supervisors in relation to a change on a specific swarm behavior, namely swarm cohesion. To the authors' knowledge, this is the first work that addresses human perception in such an explicit manner. We presented experimental results from two healthy individuals that support our initial hypotheses about (a) the correlation between swarm cohesion and brain activity and (b) the inverse relation between levels of cohesion and the discerning of changes in the direction of the swarm. This work provides the first evidence of representation of swarm collective behaviors at the brain level, which can lead to the design of a new generation of brain-swarm control and perception interfaces.

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