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Using Physiological Measurements to Analyze the Tactical Decisions in Human Swarm Teams

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***Abstract*—Human-Swarm interaction has attracted a lot of attention for their applications in areas such as exploration, rescue, surveillance, and interplanetary exploration. When humans assume a supervisory or tactician role in managing the robot swarm, the humans' (physiological) state significantly affects the mission performance. In this work, we explore the physiological correlates with the user's tactical decisions in a simulated search and rescue mission. The mission consists of supervising three groups of unmanned aerial vehicles and three groups of unmanned ground vehicles to search for a target building. The mission complexity is increased by introducing static adversarial teams.Due to the adversarial team's presence, the user should employ different tactics to search for a target. While the user interacts with the swarm, brain activity in forms of electroencephalogram (EEG) and eye movements are recorded. 20 participants, with prior experience in playing real-time strategy games, took part in the study. A linear mixed effect model is used to study the correlated physiological features and tactical decisions. Six features are extracted from the physiological data: engagement level, mental workload, Fz-Pz coherence, Fz-O1 coherence, pupil size, and the number of gaze fixations. The results show that mental engagement and Fz-O1 coherence are the important factors in predicting the tactical decisions. Specifically, Fz-O1 coherence in Beta (22.5-30 Hz) and Gamma (38-42 Hz) band is found to be significant.**

I. INTRODUCTION

Swarm systems or agents that can learn while interacting with the world are quickly becoming widespread due to advances in the machine learning domain [1]. One of the main challenges in such an autonomous system is to learn a diverse set of tactics in different scenarios. Simulating and learning such scenarios requires massive training data, and incurs high training costs [2, 3]. Even humans demonstrations, as a mean to speed up the training process, still need to be labeled by experts. For example, a human operator moves a swarm of robots away from a target building in search and rescue situations, the tactical decision might be to avoid the adversarial teams rather than to exclude that building from search. Instinctively such tactical decisions have temporal context over long horizon [4], making it hard to pinpoint an instance that led to a decision. Consequently, experts should label the tactical decisions, but the large quantity of data makes it infeasible demands a framework to learn labeled tactics from a small subset of expert.

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Such a framework can utilize various features from the state space in predicting the label of the unseen data. However, the state space is generally of high dimension and requires a lot of data to learn the abstract model to predict the labels. Instead, in this work, we explore the use of physiological data of the human playing the game to analyze the tactic labels. In our previous human-multi robot interaction research [5], we have shown the feasibility of using the physiological data to estimate the hidden performance measures such as "reaction time" and "target detection". We hypothesize that physiological information may be correlated with tactical decisions on similar lines. Although, our study is focused on identifying psycho-physiological features to predict the tactical decisions, the identified features can also be used to label human's action and even augment human demonstration (action space) in imitation learning to facilitate an effective learning of new tactical decisions for AI. Physiological features, specifically eye-gaze has previously been applied to automated labeling in image annotation [6], video segmentation [7] and enhancing the imitation learning in Atari-games [8].

We constructed a simulation platform that can simulate the swarm behavior through which we can collect different tactical decisions in a target search mission. The simulation platform has a graphical user interface for human subjects to interact with the swarm. It integrates the recording and synchronization of physiological signals such asEEG and eye-tracking with the game. The swarm behavior is highly autonomous to facilitate the human supervisor in providing tactical instructions or tactic input rather than controlling each swarm member. A preliminary analysis of using EEG and eye features correlates with a tactical decision is provided.

II. METHOD AND MATERIALS

A gaming environment with a graphical user interface (GUI) was created to facilitate the human demonstration study. The GUI allowed the subject to play a real-time strategy game by controlling UAV/UGV platoons. The mission was to perform a search and secure mission in the presence of adversarial teams that allowed users to control and supervise robot swarms to complete the mission. During the gameplay, the subject's brain activity and eye movement were recorded using a non-invasive wireless EEG headset and an eye-tracking system. The international review board approved the human subject study (IRB # STUDY00003659) before experimentation. The details of the human subject study, data collection, and data processing methods are provided in the following sections.

A. Human Subject Study Framework

The human subject study framework consists of 3 modules. The first module is the gaming framework, which includes both the game and the user interaction interface. The second module records the physiological data, and the third module is the lab streaming layer for time synchronization. The overall human subject study framework can be seen in (Fig. 1). All three modules run in parallel using open-source library Ray.

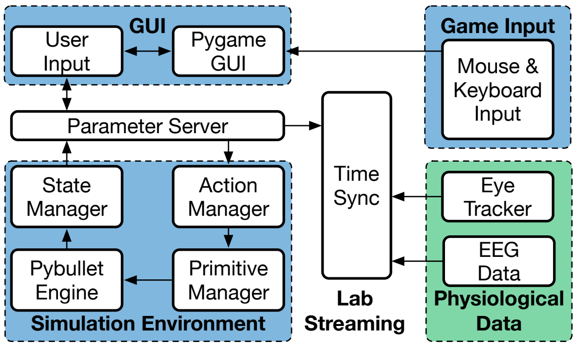

Fig. 1: Overall framework of the human swarm interaction. The three modules are the gaming framework, physiological data, and the lab streaming layer.

The graphical user interface represents the data in the simulation environment in a user-friendly way. The parameter server is the communication between the simulation environment and the GUI, where both components can read and write the information. All of the information in the parameter server is fed directly into the lab streaming layer for time synchronization. The module used for collecting the physiological data consists of two separate components. These components correspond to the two types of physiological data being recorded, eye, and brain activity. The last module of this framework is the lab streaming layer, the ending location for all information. All of the information at every instance is fed into the lab streaming layer for time synchronization. In this module, all the information is stored with a specific time-stamp. These time stamps allow for post-processing alignment of eye data, EEG data, environment data, game data, and user information.

B. Simulation Environment

The simulation environment is where the gaming environment is hosted. This module was created using python's open-source library pybullet. The environment used for the game (the map) can be seen in 2. All robotic swarms are simulated in pybullet with a high level of autonomy using a set of primary primitives, which include formation control, path planning, and task allocation (from the user). There are 3 UAV platoons and 3 UGV platoons, which can be controlled independently.

C. Graphical User Interface

A graphical user interface was created to reflect the simulation environment using the open-source pygame library. All necessary information to complete the search and secure

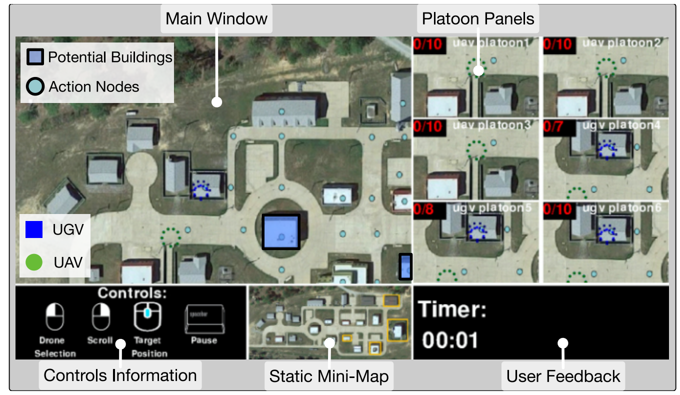

Fig. 2: GUI allows subjects to can control the UxV platoons through the main window. The remaining time, encounter with the adversarial team, and target information is shown in the user feedback panel.

mission from the simulation environment is represented in a user-friendly way. There are five main separated sections in the GUI for the user's convenience. These sections include a 2-dimensional projection of the environment that the users may scroll on to locate the platoons, a zoomed-in real-time image of all the user's platoons. A user feedback panel provides information about enemy attacks, time, and target building. The GUI also shows controls and a mini-map with potential buildings marked (Fig. 2). A new tactical command can be provided through the GUI by pausing the game, choosing the platoon of interest, and selecting a target position. The users may send the platoons anywhere in the environment by clicking on the action nodes Fig. 2. The trajectory generation, obstacle avoidance, and formation control of the platoon will then be handled by the corresponding primitives embedded in the simulation environment.

D. Physiological Measures

To monitor the brain activity, we used the non-invasive B-Alert X24 electroencephalogram headset from Advanced Brain Monitoring©. Signals are recorded from 20 channels with a sampling rate of 256.0 Hz. The sensor locations are O1, O2, P4, POz, P3, Pz, Cz, C3, C4, Fz, F3, F4, T6, T4, F8, Fp1, Fp2, F7, T5, and T3 based on the 10-20 standard location system. A screen-mounted Tobii Pro Nano© eye tracker was used to record the eye gaze location and pupil dimension with a sampling rate of 120 Hz. The eye tracker was calibrated for each subject/session to ensure the eye data's best accuracy.

E. Individual Differences

Individual differences in cognitive abilities and visual search have a significant effect on tactical decision making. Specifically, individual differences in visual search (VS) and multi-object tracking (MOT) have shown to significantly affect the performance and situation awareness of the operators interacting with multi-robot systems [5] and therefore are selected to categorize our participants.

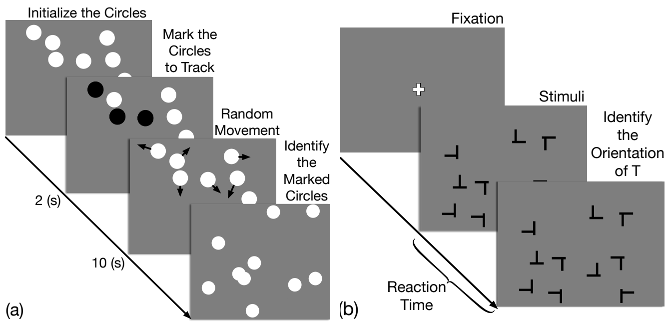

Fig. 3: (a) Multi-object tracking experiment. Participants are required to track the black circles during their random movement and identify them when the movement stops. (b) Visual search experiment. Participants are required to identify the orientation of the 'T' by pressing the arrow key corresponding to the direction of 'T'.

VS and MOT baseline tasks were performed at the beginning of each human subject study. MOT corresponds to a human's ability to maintain spatial awareness of multiple objects as they move. A skilled operator with a high MOT score will be able to track the majority of the target objects as the environment dynamically evolves. MOT was measured by presenting a scene with multiple circles and identifying four specific circles that the user should track. These circles then moved around a space, and the user must select the predefined circle after the environment changes (Fig. 3(a)). VS corresponds to a subject's ability to locate a predefined object in a cluttered environment. It was measured by showing a user an image with one T target letter and multiple distractors (shifted Ls in different orientations). The subjects had four seconds to find the target and select the arrow key corresponding to the stimulus direction "T" as shown in Fig. 3(b). They saw multiple images with different configurations and performed this test multiple times.

F. Participants

20 gamers were recruited from the University at Buffalo student population. All subjects were required to have experience with strategic computer gaming. Participants authenticated their above-average gaming status by participating in a preliminary screening. To familiarize the subjects with the new gaming environment, they were asked to play the human-swarm interaction game on a server in advance, and achieve at least two wins. All subjects had a normal or corrected vision.

G. Experiment

The subjects played two short practice games to refresh their memory, and to get comfortable with the gaming controls. After gaining adequate experience in the testing environment, the individual difference (VS and MOT) assessments were conducted. The subject then played randomized two games consecutively with different environment complexities. The eye tracker is attached to the bottom of the computer monitor using a magnet (Fig. 4) and calibrated before each game. The monitor was mounted to the wall to ensure the keyboard and mouse movements on the table do not affect the eye data.

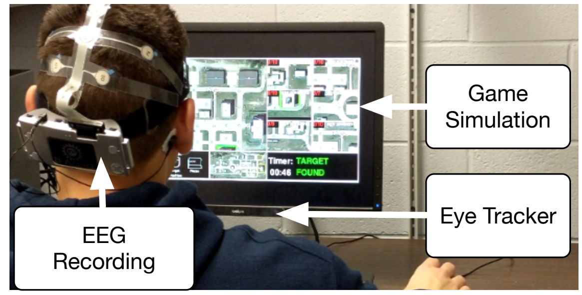

Fig. 4: Experimental setup for physiological monitoring of a user interacting with a swarm of UAVs and UGVs.

Each subject played a search and rescue mission in the presence of adversarial teams. The subject had access to three UAV platoons and three UGV platoons. The UAVs fly in a linear path over the buildings, engage in battle, and notify if the target building is found. The UGVs can perform a path planning algorithm around the buildings, engage in battle, and secure the target. If the user has reached the target with a UGV platoon, the game is won. On the other hand, the user would lose if all the UGVs are lost or if there is a timeout (game-length time was 6 minutes).

The main complexity is an adversarial team that is blocking roads and target buildings. The adversarial team's location will be visualized on the GUI when it is in the field of view of at least one platoon. If the user's platoons encounter an adversarial team, the adversarial team will attack the user's platoon, and both platoons lose drones in a stochastic manner. The battle is complete when there only remains one drone in either platoon. If a platoon is defeated, it will disappear from the map. One trial consisted of two levels of games. The first level is the baseline mission with no adversarial teams, and the second level is with adversarial teams. The levels were randomized throughout the experiment, so the subject does not know which complexities they will be getting each level. All the subjects played only one trial of the game.

III. Data Analysis

A. Feature Extraction

The mission is predominantly searching for information (target search) and efficiently extracting red team position information to avoid blue team casualties. For this reason, we choose two eye features: pupil size and the number of fixations which best represent underlying cognitive activities of the tele-exploration [5]. Pupil size provides a reliable measure of the subject's visual workload and affect, and the number of fixations provides the efficiency of information retrieval [9]. Pupil size is directly obtained as a continuous measurement from the eye tracker. The Z-score of the pupil diameter is calculated for each subject to account for his/her differences. The number of fixations is extracted by counting the number of times the subject's eye gaze remains stationary on an object for at least 50 milliseconds.

EEG signals were band-pass filtered (0.1-70 Hz) and notch filtered at 50 Hz to remove electrical artifacts. Artifacts caused by eye blinks and muscle contractions were removed using independent component analysis with the Picard algorithm in MNE-python [10]. We visually examined 2-D scalp component maps to remove signal sources corresponding to eye movements and non-cognitive activities. After removal, the components were projected back to get an artifact-free EEG signal. Two sets of features are extracted from artifact-free EEG data. The features are extracted from a 2-second window prior to the subject pausing the game and sending a new tactical command. The first set is neuroergonomical features evaluated by B-Alert© software and includes mental engagement and mental workload. To extract this information, we conduct a baseline neuro-cognitive assessment study (Auditory Psycho-Vigilance) and working memory benchmark tasks (mental arithmetic, grid location, and digit-span-task) to individualize the EEG workload and mental engagement classifiers. Additional details on classification methods can be found in [11, 12].

The second set of features are coherence values extracted by comparing the similarity of two electrodes using different frequency bands [13]. In this paper, we calculate the Fz-Pz coherence in the high alpha frequency band and the Fz-O1 coherence in the Beta and Gamma frequency band given by Eq. 1. The high alpha frequency band is from 10-12 Hz, the Beta band is 12-30 Hz, and the gamma frequency band is from 30-80 Hz. We choose these features as they reflect motor planning and visual perception [14, 15]. The game is predominantly visually-oriented, where the subject should search for a target while monitoring the static adversarial team and planning the route towards the target.

$$coh = \frac{|E[Sxy]|}{\sqrt{E[Sxx] * E[Syy]}} \tag{1}$$

Where Sxx, Syy are power spectral densities, and Sxy is cross power spectral density of the channels being used.

B. Tactic Labeling

From the recreated game replay, an expert can label different tactics employed by the subjects. The first observed tactic was *cautious tactic*. Although cautious is a broad term, it incorporates two main behaviors. The first behavior is a basic environmental exploration. This behavior is found when the user sends a platoon to explore a certain area to expose an adversarial team or move them closer to a target building. The second main behavior is a defensive tactic. The defensive tactic happens when an adversarial platoon becomes visible to the user and is in the user's platoon's path. To be a defensive decision, the human must avoid the adversarial by changing the platoon's path to go around the adversarial platoon. The second tactic was an *offensive tactic*. If the human pauses the game, and sends one of there platoons, to directly attack an adversarial team, it is considered an offensive tactic. This is often done to clear the different target building paths or increase enemy casualties. The third observed tactic was the *target search tactic*. This behavior is evident when the human selects a platoon and sends them to a target building to search or secure one of the target buildings. A combination of these three tactics contributes to the human subject's gameplay. All the tactical decisions were labeled by the human expert who watched the recreated games.

C. Statistical Analysis

To study the physiological correlation with tactical decisions, we have used linear mixed models (LMM). It is an extension of the general linear model and considers both fixed and random effects. LMM formulation is given by equation 2 where the $\boldsymbol{B}$ are the fixed effect coefficients, and $\boldsymbol{u}$ are random effect coefficients and $\boldsymbol{X}$, $\boldsymbol{Z}$ are model matrices for fixed and random effects respectively.

$$\mathbf{y} = \boldsymbol{X}\boldsymbol{B} + \boldsymbol{Z}\boldsymbol{u} + \varepsilon \tag{2}$$

LMM allows the response variable, $\mathbf{y}$, to have different distribution rather than Gaussian. In our study, we can consider individual differences (mot and vs) score as random effects. This consideration allows us to study the effect of individual performance level (reflected in VS and MOT score). Moreover, VS and MOT random-effects group different subjects with the same score (VS & MOT) as a single group, which compensates for varying number of tactical decisions under different subjects. We constructed two LMMs with physiological feature as observations and expert labeled actions as outcomes. These models provide the relative importance of different features in predicting user tactics: cautious, offensive, and target search tactics. The first model uses cautious tactics and target search tactics as output, and the second model used cautious tactics and offensive tactics. For both the models, the cautious tactic is used as a reference. In both the models, the random effect can be varied between the VS score and MOT score.

IV. RESULTS

To categorize the subjects based on their VS and MOT scores, we study the effect of these individual differences on normalized completion time (performance measure) in the baseline mission. Note that the target locations are randomized between the subjects, so different subjects can get different target buildings (Fig. 2) placed at different locations of the map. Consequently, considering only the completion time might bias the statistical analysis. Hence, we normalize the completion time by the distance to the target building.

Fig.5 illustrates a negative trend between normalized completion time with respect to the MOT score and a positive trend with respect to the VS score. Thus individual difference influences the gameplay, and hence they are further used along the physiological features to analyze the user tactics.

In terms of physiological features, we considered four features from brain activity: engagement level, mental workload, Fz-O1 (beta and gamma), and Fz-Pz (higher alpha) coherence and two features from eye-tracking: pupil size (PS), number

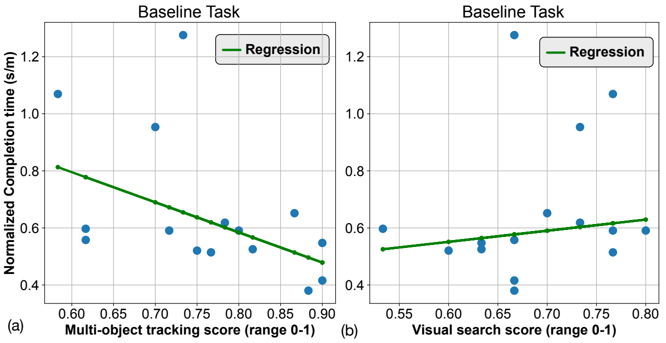

Fig. 5: (a) The trends in the normalized completion time with respect to (a) MOT and (b) VS scores.

of fixations, all extracted from a 2-sec window before sending a new tactical command marked by pausing the game.

Table I shows the LMM results for the target search tactic with VS and MOT score as a random effect. Two factors, namely: mental engagement and Fz-O1 coherence, have a significant effect ($p < 0.05$) in estimating the target search tactic. However, other factors did not have significant results. Thus, using individual difference scores (VS/MOT), engagement level, and Fz-O1 coherence target searching tactic can be estimated.

Table II shows the LMM results for the offensive tactic. In this model, when MOT is used as a random effect, Fz-O1 coherence has a significant effect ($p < 0.05$). On the flip side, with VS random effect, Fz-Pz and Fz-O1 coherence have a significant effect ($p < 0.05$). All the other factors were not significant in predicting the offensive tactic. In both the models, the common features selected are Fz-O1 coherence in Gamma (38-40 Hz) frequency range. The site Fz and O1 are predominantly associated with motor planning and visual perception [14]. Fig. 6 shows the distribution of Fz-O1 coherence under different tactics. Clearly, in Target Search and Offensive tactics, the coherence is less when compared

TABLE I: LMM results for prediction of target search tactics.

Random Effect	Type	Observations	Estimate	CI	p
VS	**EEG**	**Engagement**	**-0.37**	**[-0.60 -0.15]**	**<0.05**
		Mental Workload	-0.23	[-0.73 0.27]	0.374
	Eye	Pupil Size	-0.08	[-0.25 0.09]	0.352
		Fixations	0.01	[-0.01 0.03]	0.477
	Coherence	Fz-Pz High Alpha	-0.08	[-0.50 0.35]	0.719
		Fz-O1 Gamma	**-0.44**	**[-0.81 -0.06]**	**<0.05**
		Fz-O1 Beta	**-0.54**	**[-0.97 -0.11]**	**<0.05**
MOT	**EEG**	**Engagement**	**-0.31**	**[-0.55 -0.06]**	**<0.05**
		Mental Workload	-0.23	[-0.79 0.34]	0.434
	Eye	Pupil Size	-0.06	[-0.27 0.14]	0.55
		Fixations	0	[-0.02 0.03]	0.698
	Coherence	Fz-Pz High Alpha	-0.14	[-0.59 0.30]	0.53
		Fz-O1 Gamma	**-0.43**	**[-0.86 0]**	**<0.05**
		Fz-O1 Beta	**-0.53**	**[-1.04 -0.02]**	**<0.05**

TABLE II: LMM results for prediction of offensive tactics.

Random Effect	Type	Observations	Estimate	CI	p
VS	EEG	Engagement	-0.11	[-0.35 0.13]	0.356
		Mental Workload	-0.24	[-0.75 0.27]	0.351
	Eye	Pupil Size	-0.04	[-0.21 0.13]	0.62
		Fixations	0.01	[-0.01 0.04]	0.216
	Coherence	**Fz-Pz High Alpha**	**0.44**	**[0.02 0.86]**	**<0.05**
		Fz-O1 Gamma	**-0.44**	**[-0.81 -0.06]**	**<0.05**
		Fz-O1 Beta	**-0.62**	**[-1.04 -0.20]**	**<0.05**
MOT	EEG	Engagement	-0.03	[-0.28 0.22]	0.834
		Mental Workload	-0.01	[-0.57 0.56]	0.985
	Eye	Pupil Size	-0.04	[-0.23 0.16]	0.715
		Fixations	0.01	[-0.01 0.03]	0.325
	Coherence	Fz-Pz High Alpha	0.38	[-0.05 0.81]	0.081
		Fz-O1 Gamma	**-0.61**	**[-1.01 -0.21]**	**<0.05**
		Fz-O1 Beta	**-0.69**	**[-1.17 -0.22]**	**<0.05**

to cautious tactics. This is also reflected in the negative correlation coefficient in the Table I and II.

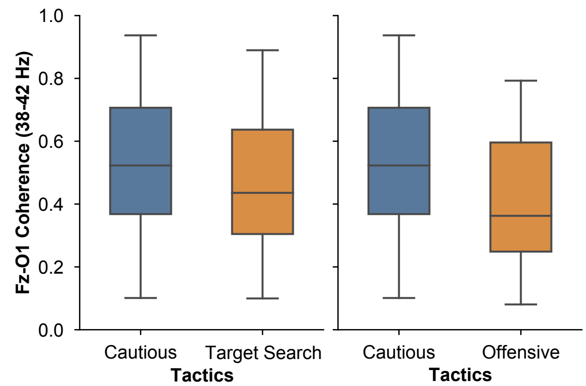

Fig. 6: Distribution of Fz-O1 gamma coherence with VS and MOT as random effect.

The power spectral-topo maps (Fig. 7) of a subject between different tactics and the coherence values show predominant activity near the occipital region of the brain, which is associated with visual perception. Concretely, the above model shows that the features extracted from physiological measurements (EEG) can be used to analyze the tactical decisions taken by a subject. Also, these models are particularly important during imitation learning, where the instances of information gathering and decision-making need to be identified to properly guide the learning framework towards better actions.

V. CONCLUSION

This paper presented the design and preliminary results of a human swarm interaction framework to analyze the tactical decision using physiological data in a target search mission. Brain activity and eye movements were recorded while participants supervised multiple robot swarms as they completed the mission. The complexity of the mission is

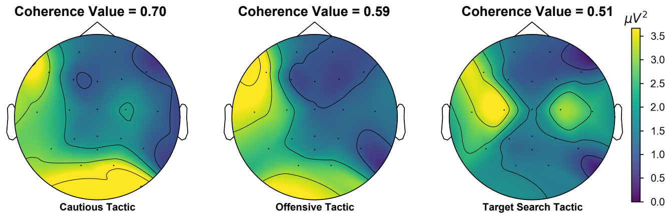

Fig. 7: Coherence values and power spectral density over the scalp in the Gamma (38-42 Hz) frequency range.

increased by introducing static adversarial teams which users can attack.

Qualitative analysis of human games revealed distinctive tactics across different subjects. There were three sets of tactics: offensive, cautious, and target finding. Since individual cognitive difference among subjects is inevitable, we used two tasks: multi-object tracking (MOT) and visual search (VS) to capture the individual difference. Analysis of individual differences revealed that the time taken to complete the mission is inversely proportional to the MOT skill level (measured as MOT score). Thus MOT and VS scores are considered for further analysis. From physiological data, six features were extracted for further analysis. The six features are engagement level, mental workload, Fz-Pz, Fz-O1 coherence, pupil size, and the number of fixations. These features are analyzed at instances when the user executed different tactics. A linear mixed-effect model was used to study whether the tactical decisions are correlated with physiological features. In this model VS and MOT were used as a random effect. Two features: engagement level and Fz-O1 coherence had a significant effect ($p<0.05$) in target search and offensive tactic. Other features were not significantly different under different tactics. In our future research, we intend to use this framework to investigate human physiological data augmentation with swarm interaction to facilitate an interactive imitation learning for discovering new tactics.

It should be noted that even though the linear mixed models have enough power to signify the importance of different physiological features, increasing the number of subjects can further bolster the study outcomes. In terms of tactics, the offensive tactic was less used by the subjects. Consequently, the number of data labeled with offensive tactics was less compared to cautious and target search tactics; hence, the presented model might be biased. However, the bias can be decreased by collecting more trials and new subject data.

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