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A Hybrid BMI for Control of Robotic Swarms: Preliminary Results

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Abstract— **Human Swarm Interaction (HSI) is a new field which relates to the effective control of robotic swarms by human operators. The iterature has shown that the control of swarms can become quite complicated. On the other hand, Brain Machine Interfaces (BMI) can offer intuitive control in a plethora of applications where other interfaces alone (e.g. joysticks) are inadequate or impractical, e.g. for people with motor disabilities. There are multiple types of BMI, but most of them rely on the analysis of ElectroEncephaloGraphic (EEG) signals. The authors have previously shown that swarm behaviors elicit specific brain activity on human subjects that observe them. Motivated by this result, in this work, we present preliminary results of a hybrid BMI that combines information from the brain and an external device. An algorithm for extracting information from the frequency domain of EEG signals that allows integration with the manual task of using a joystick is presented. The hybrid interface shows high accuracy and robustness when used as a brain-robot interface. Moreover, it allows for continuous control variables extracted from the EEG signals. Finally, its efficacy is proven across multiple subjects, while its performance is also demonstrated in the real-time control of a swarm of quadrotors.**

I. INTRODUCTION

A Human Swarm Interface (HSI) is a system where one or more human operators interact with a swarm of robots in order to complete a specific task. Over the years many approaches have been proposed. Some of them consider the entire operation cycle of the swarm from programming and deploying to charging [1]. Others focused on user input and proposed methods that rely on gestures [2] or EMG devices [3], while joysticks can also be used [4]. These methods though may be complicated and not intuitive for the user.

Recently, we showed that swarm collective behaviors elicit specific brain activity in human subjects that observe them [5]. Motivated by this result, we decided to use the brain as an additional input and explore the possibilities of a hybrid system combining brain signals with input from external devices. We posit that such a system may inspire a new kind of interface which could provide intuitive control strategies for the users by translating their thoughts directly into computer commands with minimum delay and without the need of complicated interaction strategies, while also allowing quantitative feedback for the user's performance based on the brain activity. In this work, we focus on the user input rather than the feedback.

Brain Machine Interfaces (BMI) can offer intuitive control in a plethora of applications where other interfaces alone (e.g. joysticks) are inadequate or impractical, e.g. for people with motor disabilities. Most of them rely on the analysis of ElectroEncephaloGraphic (EEG) signals and they have been applied in many different applications, such as controlling the position of a cursor on a screen in 2D [6] and 3D space [7] or driving a mobile robot through a maze-like environment while avoiding collisions based on on-board sensing [8]. In these cases, the output is either based on the modulation of frequency bands that are specifically chosen for each user [6], [7] or on machine learning techniques [9] that properly differentiate between different brain states and, thus, correctly identify the users' intent. Another flavor of BMI is hybrid BMI systems [10]. For example in [11], the authors combine Event Related Desynchronization / Synchronization (ERD/ERS) based signals [12] with P300 potentials. Alternatively, hybrid BMI may combine EEG signals with different types of biosignals such as electromyograms (EMG) [13], electrooculograms (EOG) [14], or with assistive technologies (AT) [15], such as wheelchairs, mice or keyboards. The goal of such systems is either to enhance the accuracy of the brain state classification or provide a type of "brain switch" that can help users complete more complicated tasks.

In this work, we propose a hybrid BMI system which combines EEG signals and joystick input. The goal is to provide a platform that will allow efficient control of robotic swarms while remaining intuitive for the user. As a preliminary step to this goal, we start by exploiting the ERD/ERS phenomena that take place during actual or imagined limb movement via combination of Principal Component Analysis (PCA) with Hidden Markov Models (HMMs). Detection of ERD/ERS has been proven to be a robust method for controlling robotic platforms such as prostheses [16] or quadrotors [17] and to provide features that are more or less common across various users. On the other hand, HMMs can deal effectively with the non-stationarity of brain signals. The resulting system is easy to use and requires minimum training. Moreover, its EEG related output is a continuous variable that not only controls the direction of the associated Degree of Freedom (DOF) but also its rate of change. We present results that prove the feasibility of our platform for multiple subjects. We also apply this methodology on the control of a swarm of quadrotors showing both the system's capability for control of actual robotic platforms and the feasibility of controlling robotic swarm behaviors using EEG signals. In particular, we control the swarm density using the brain recordings. To the authors' knowledge, this is the first time that such a hybrid system is proposed and applied to a highly dynamic platform with success, and we believe that this work will motivate further research on hybrid BMI, Brain Swarm Interfaces

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Fig. 1: The subject wears an EEG electrode cap and looks at a monitor which shows the task that must be executed.

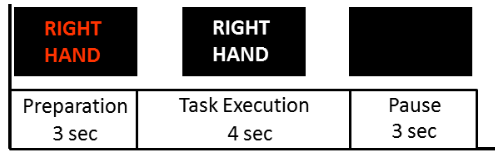


Fig. 2: Stages of the data collection phase.

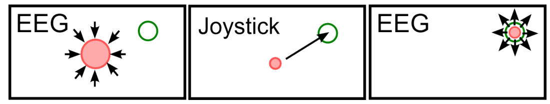


Fig. 3: Stages of the control phase (virtual environment).

(BSI) and Human Swarm Interfaces (HSI) in general.

The rest of the paper is organized as follows. Section II presents the methods and algorithms developed in this work. Section III presents and analyzes the results of the validation experiments, while Section IV concludes the paper.

II. MATERIALS & METHODS

A. Experimental Procedure

In order to assess the performance of our hybrid BMI and show its viability for controlling a swarm of quadrotors, we performed two separate experiments. In the first experiment, five subjects (S1-5, all right-handed males between the ages of 22 and 27) were asked to control the position and size of a two-dimensional object in a virtual environment. The experimental setup is shown in Fig. 1. The experimental protocol was approved by the ASU IRB (Protocols: 1309009601, STUDY00001345). The experiment consisted of three phases, namely a data collection phase, a model training phase and a control phase. During the data collection phase, the subjects were instructed to relax their muscles, stay still and stare at a computer monitor in front of them which provided instructions. They were also given a game controller to hold with their right hand. At the beginning of each trial, instructions were shown on the screen as text. The text was either "Right Hand", "Left Hand" or "Rest". In the first case, the subjects were asked to randomly move the right joystick of the controller using their *right hand*. In the second case, they had to imagine the kinesthetic sensation of closing their *left hand* to a fist, while in the last case, they were instructed to remain still and focus on their breathing or their nose (*volitional rest* [17]). At each trial, the text appeared at first in red color for 3 seconds to prepare the subjects for the task, then it became white for 4 seconds in order to inform them to execute the corresponding action repeatedly over that period of time and after that there was a pause of 3 seconds followed by the next trial (Fig. 2). The subjects were instructed to initiate the corresponding task as soon the text on the screen changed from red to white. Each subject completed 20 trials per each task, i.e. 60 trials in total, randomized between the three different tasks. During each trial, the subjects were instructed to avoid eye blinks as much as possible. During the model training phase, the data recorded during the previous step were passed through an algorithm to detect the frequencies where the ERD/ERS phenomena were more distinct. The same data were also used to train the models that would classify the corresponding brain states. During the control phase, the subjects were manipulating the size and position of a circular disk in order to fit it perfectly into a hollow circle of smaller radius and different position. Ideally, they would descrease the disk's size using a "Left Hand" task, move it into the target circle using the joystick and increase its size again by performing a "Rest" task (Fig. 3). Once the disk fit the circle perfectly, the trial was deemed successful and the next trial began after a 5-second pause. Each subject completed two sessions of 40 trials each (80 trials in total), with a 10-20 minutes pause in between. All sessions were performed on a single day and lasted approximately 30 to 40 minutes each, depending on completion times. In each trial, the users had to complete the task in 60 seconds. If they could not, the trial was deemed unsuccessful and they proceeded to the next one. In a session, the 40 trials would be randomized with respect to the position of the circle, its size and the size of the disk. The same exact sequence of 40 trials was used in both sessions (and across users) in order to properly compare the performance of the system across the two sessions and to provide more training time to the subjects. In the second experiment, a user was controlling a swarm of quadrotors in a linear formation. The experiment comprised the same exact three phases as the first one. During control, the subject had to decrease the distance between the quadrotors using a "Left Hand" task, pass them through a rectangular hoop that represented a narrow passage using the joystick and, after that, change the quadrotor distance back to its original value by performing a "Rest" task.

B. Data Acquisition and Signal Conditioning

The EEG signals were recorded at 500 Hz using the BrainProducts ActiCHamp amplifier system with 64 electrodes placed according to the 10/20 International system [18]. A 5th order Butterworth bandpass filter between 1 and 40 Hz was applied to the data in order to remove low-frequency trends and line noise. In order to accommodate for the volume conduction effects that are typical in scalp EEG measurements [19], a large Laplacian filter was applied to each of the channels of interest. The filter was applied based on its difference approximation, where for each channel we subtracted the mean of its 4 next-nearest neighbors from the

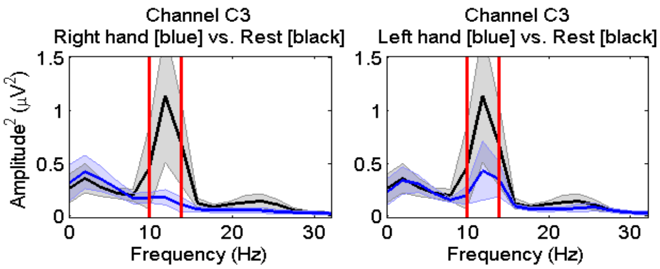


Fig. 4: Frequency band detection for Subject S4 and channel C3. The red lines denote the frequency band of interest.

original signal.

In this work, the analysis was focused on channels C3, Cz, C4, FC3, CP3, C1, FCz, CPz, C2, FC4, and CP4 (sensorimotor cortex). The same preprocessing procedure was followed both during the off-line analysis in the training phase and during the on-line processing for the control phase. The only difference was that in the latter an electrooculogram (EOG) artifact removal algorithm [20] was also applied before the large Laplacian referencing in order to eliminate any artifacts from eye blinks and eye movements.

C. Feature Extraction

After preprocessing, a Fast Fourier Transform (FFT) was applied to the data in order to extract the spectral features of the signals. The FFT was applied to a window of 256 datapoints sliding every 25 datapoints (or 50 ms) after a Hanning window of the same length was applied to the data.

For each channel, a dedicated algorithm selected automatically the frequency band where the ERD/ERS phenomena due to limb movement imagination ("Left Hand" task) or actual limb movement ("Right Hand" task/joystick) were more distinct. Specifically, it was searching for a reduction of the FFT spectrum with respect to the "Rest" task in the alpha (α) band (7-15Hz) and/or an increase of the spectrum in the beta (β) band (15-30Hz). To this end, the algorithm computed separately for each task the average of each FFT coefficient across time for each trial corresponding to the task and, then, the grand mean across all trials of the same task. Next, the "Right Hand" and "Left Hand" tasks were each compared to the "Rest" task in order to identify the frequencies at each channel in which the highest deviation from the "Rest" task occurred. The frequency coefficients of interest included the coefficient with the highest deviation and the coefficients before and after that as shown in Fig. 4.

In order to further guarantee good differentiation among the tasks, a Principal Component Analysis (PCA) [21] was also applied to the selected FFT features. In detail, the FFT features for all three tasks ("Right Hand", "Left Hand", "Rest") were used as input to the PCA and only those Principal Components (PCs) that would describe 90% or above of the data variance were selected. This resulted in 4 to 5 components for each subject. Finally, these PCs were applied to the data to extract the final features. These were then collected in data sequences which were used for the training of the machine learning models.

D. Hidden Markov Models (HMM) methodology

The features extracted previously were classified into the 3 available tasks using Hidden Markov Models (HMM) [22]. Any HMM can be defined by its state transition matrix A, its observations probability model B and the initial state probability π [22]. In this work, the probability distribution of the observations B, related to the previously extracted features, was modeled as multiple Gaussian mixtures [23]. For each of the three tasks a separate HMM was trained. They all had the same number of members in the Gaussian mixtures and the same number of hidden states.

Each HMM was trained based on feature vector sequences corresponding to one task. The signals of the data collection phase were used to extract feature vectors. The resulting feature set was divided into a training and a validation set. The HMM sequences were extracted from the training set by sliding a 20-point window (corresponding to data of 1s) on the set point-by-point. The parameters of the models were estimated iteratively by using the Baum-Welch algorithm [22]. The number of members in the Gaussian mixtures as well as the number of hidden states for the HMM were different for each subject. Their choice was made by training separate models for different pairs of these variables and checking their classification accuracy on the validation set.

During the control phase, a sequence of feature vectors was fed into each of the models, a log-likelihood value was computed for each of them using the Forward algorithm [22] and the data were classified according to the maximum of these likelihood values.

E. System output generation

The system combined the power of the EEG signals, the classification decision on the brain state and the joystick input into a command vector; each of its elements regulated a specific DOF of the robotic platform. Concretely, at iteration k, the activation parameter v_k was calculated as follows:

$$v_k = (\bar{F}_{CP3,Re} - F_{CP3,k}) + (\bar{F}_{CP4,Re} - F_{CP4,k}) \qquad (1)$$

where $F_{CP3,k}$, $F_{CP4,k}$ represent the spectral power of the frequency band of interest (see also Section II) at channels CP3 and CP4, and $\bar{F}_{CP3,Re}$, $\bar{F}_{CP4,Re}$ represent the mean of the spectral power at the same channels during the "Rest" task as recorded during the data collection phase. The value v_k was then passed through an exponential filter:

$$\tilde{v}_k = (1-\alpha)v_k + \alpha\tilde{v}_{k-1} \qquad (2)$$

where α is a smoothing constant. Finally, a thresholding procedure was applied to $\tilde{v}_k$ in order to ensure that any misclassification would not have any adverse effect during the control phase. There were two thresholds, a *high* t_H and a *low* t_L. They were computed separately for each subject:

$$t_H = p \cdot [\bar{F}_{CP3,Re} + \bar{F}_{CP4,Re} - \min(F_{CP3,LH}) - \min(F_{CP4,LH})] \qquad (3)$$

$$t_L = \sqrt{\mathrm{Var}(F_{CP3,Re}) + \mathrm{Var}(F_{CP4,Re})} \qquad (4)$$

where p is a weighting factor and $\bar{F}_{CP3,Re}$, $\bar{F}_{CP4,Re}$ are the mean of the spectral power at CP3, CP4 during the "Rest" task as in (1). The statistics Var() and $\min()$ were applied to the activations of the data collection phase and denote the variance and the minimum values of the data, respectively.

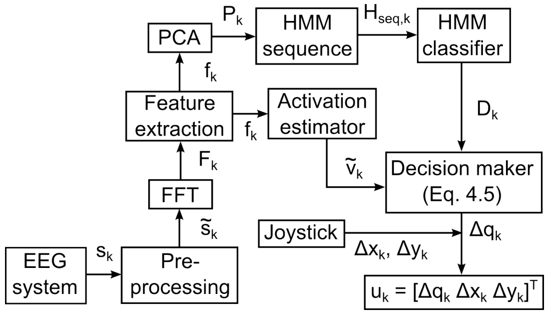


Fig. 5: System output computation during control phase. s_k is the raw EEG signal, $\tilde{s}_k$ is the preprocessed signal, F_k are the FFT coefficients, while f_k refers to the spectral features extracted from F_k. P_k refers to the PCA features and $H_{seq,k}$ is the HMM sequence. Finally, $\tilde{v}_k$ is the activation parameter, D_k is the classification decision, Δq_k refers to the EEG command, Δx_k, Δy_k refer to the joystick input.

The subscripts LH and Re refer to the "Left Hand" and "Rest" tasks, respectively.

A value Δq_k was then computed at each iteration k based on the relation of $\tilde{v}_k$ to t_L and t_H and the classification decision D_k. The decision D_k could take three values, namely $D_k = 0$ ("Right Hand" task), $D_k = 1$ ("Left Hand" task) and $D_k = 2$ ("Rest" task). Based on that:

$$\Delta q_k = \begin{cases} 0 & \text{if } t_L < \tilde{v}_k < t_H \vee D_k = 0 \\ -(\tilde{v}_k - t_H) & \text{if } \tilde{v}_k > t_H \wedge D_k = 1 \\ -(\tilde{v}_k - t_L) & \text{if } \tilde{v}_k < t_L \wedge D_k = 2 \end{cases} \tag{5}$$

The final command vector $u_k = [\Delta q_k, \Delta x_k, \Delta y_k]^T$ consisted of the EEG command Δq_k and the joystick input $c_k = [\Delta x_k, \Delta y_k]$, which were continuous functions of time. In the first experiment, Δq_k controlled the size of the solid disk, while Δx_k and Δy_k controlled its position on the screen. In the second experiment, Δq_k controlled the agent distance and Δx_k and Δy_k controlled the swarm position along an axis normal to the line formation and along its height, respectively. During the "Right Hand" task ($D_k = 0$), the size of the disk or the agent distance would not change ($\Delta q_k = 0$). A diagram of the procedure is shown in Fig. 5. In all experiments and subjects, the smoothing constant $\alpha = 0.9418$ and the weighting factor $p = 0.85$ were used. Their values were chosen during preliminary tests based on reports from the subjects on the performance of the system.

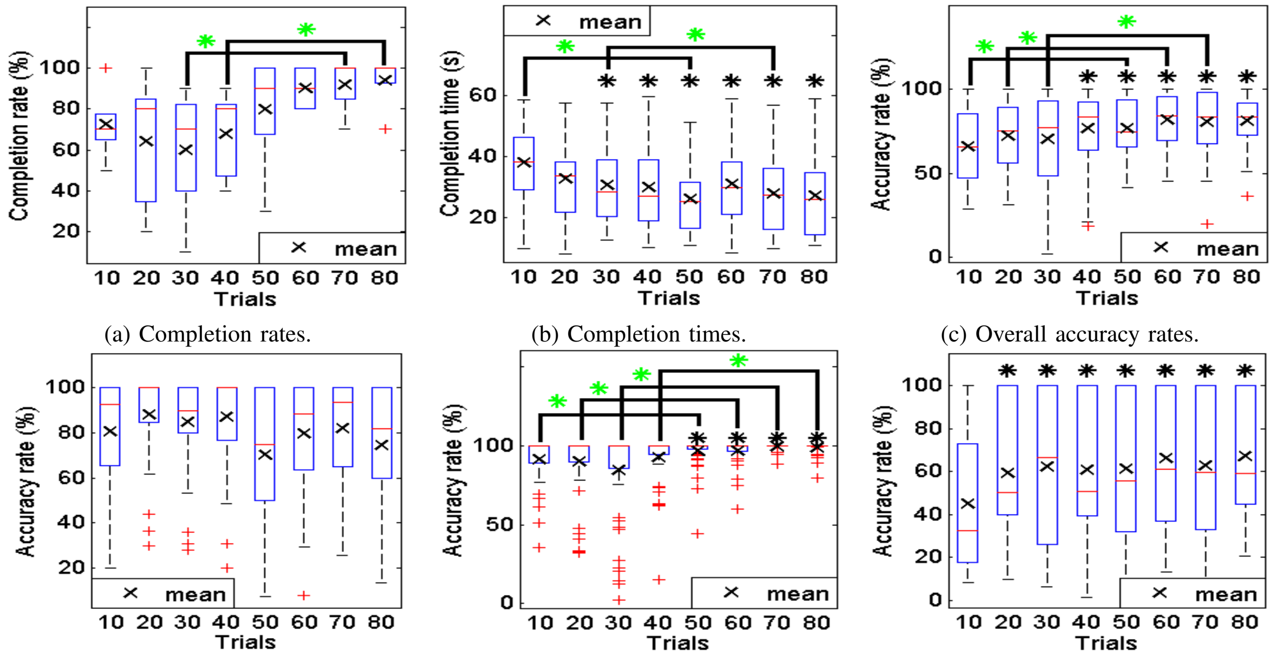
F. EEG output to Quadrotor Control

In the second experiment, the user was controlling a swarm of quadrotors, initially alined at a certain distance. A dedicated planning algorithm, whose details are out of the scope of this paper, took into account the position of the agents and the desired change in their distance Δq_k together with the joystick input Δx_k, Δy_k and provided the new reference positions for the quadrotors. A 4-camera optical motion capture system (Bonita, Vicon Inc) was used for the tracking of the vehicles. Subsequently, a high-level controller [24] used these desired positions in order to calculate the desired roll, pitch and yaw angles and the appropriate thrust input which would move the vehicles to their destination. They were sent via Bluetooth to the quadrotors where an on-board controller on each of them translated these values into motor commands. More details about the control strategy can be found in [25].

III. RESULTS

A. Virtual Environment Experiment

For the assessment of our algorithm we used three different metrics, namely completion rate, completion time and accuracy. Completion rate refers to the amount of trials that the subject was able to complete successfully, and it is presented as a percentage of completed trials across every 10 trials of the experiment. In Fig. 6a, we show that the completion rates increase, reaching 100% as the subjects become accustomed to the system. We also show improvement for corresponding trials between the two sessions (green asterisks) based on a left-tailed paired t-test. Fig. 6b shows completion times, which represent the time it took the users to complete the task in seconds. Only trials which the subjects were able to complete successfully are taken into account. Based on a right-tailed paired t-test, we show a statistically significant decrease across the experiment when compared to its beginning (black asterisks). We show similar results when comparing trials 1-10 with 41-50 and 21-30 with 61-70 (green asterisks) using the same test. The metric of accuracy in this work is defined as the ratio of correct state transitions of the solid circle (i.e. size increase, size decrease, cursor movement) over all state transitions. Regarding the size of the disk, the transition was correct if the users were decreasing its size when it was outside the target and were increasing it when it was inside. Regarding the position, the transition was correct if the size did not change. We chose to study the accuracy rate of our system and not the misclassification rate because the subjects were free to complete the task in a self-paced way and, thus, the desired brain states were not known a priori. The overall accuracy rates are presented in Fig. 6c, while the corresponding accuracy rates for each brain state separately are shown in Fig. 6d - 6f. The overall accuracy over all trials is above 60% on average. At the same time, there is an increase in the accuracy rates as the subjects interact more with the system (Fig. 6c), as shown by a left-tailed paired t-test. Finally, examining the accuracy rates of the individual brain states leads to the following remarks. First, there is no statistical difference across the trials that correspond to the "Right Hand" task (Fig. 6d). This is expected since moving the joystick does not require any thought process from the users and they do not have to modulate explicitly any type of brain signals to perform that task. Thus, no training is involved and the activations should not change. On the other hand, there are statistically significant differences for both the "Left Hand" (Fig. 6e) and the "Rest" task (Fig. 6f) as indicated by left-tailed paired t-tests. Based on the previous results, we can safely postulate that the system can be used successfully by multiple users while achieving high performance and accuracy rates with



(a) Completion rates. (b) Completion times. (c) Overall accuracy rates.

(d) “Right Hand” task accuracy. (e) “Left Hand” task accuracy. (f) “Rest” task accuracy.

Fig. 6: Completion rates, completion times and accuracy rates across all subjects. The $\times$ represents the mean value of the shown metric. *’s mark a box as statistically different from the first box at the 5% significance level. A * marks boxes as statistically different at the same significance level when comparing a group of trials (box) of session 1 with the same group of session 2 (Section II), e.g. when comparing trials 1-10 to trials 41-50, trials 11-20 to trials 51-60 and so on.

minimum training (the entire control phase lasted on average less than an hour). It is important to note that the accuracy rates for most users at the first 10 trials are still high enough to permit the completion of the task several times.

B. Control of a Swarm of Quadrotors

In the second experiment, a subject was controlling a team of 3 quadrotors using the proposed hybrid BMI system. In Fig. 7, we show snapshots of the experiment, where the user changes the formation of the quadrotors, passes them through the hoop and then returns them in their original formation. A video of the experiment is included in [26]. In Fig. 8, we show how the elements Δq and Δy of the command vector u affect the position of the quadrotors in the line formation and their height, respectively, in a cumulative way. The position and height of the quadrotors are expressed in meters with respect to the global frame provided by the Vicon system. In this figure, we also show the phases of the experiment. The subject was able to change the control input seamlessly from joystick to EEG signals and back with minimum error and without the vehicles changing their relative distance while passing through the hoop. This was a real-time demonstration of controlling a swarm of quadrotors using our proposed hybrid BMI using both EEG activations and joystick inputs.

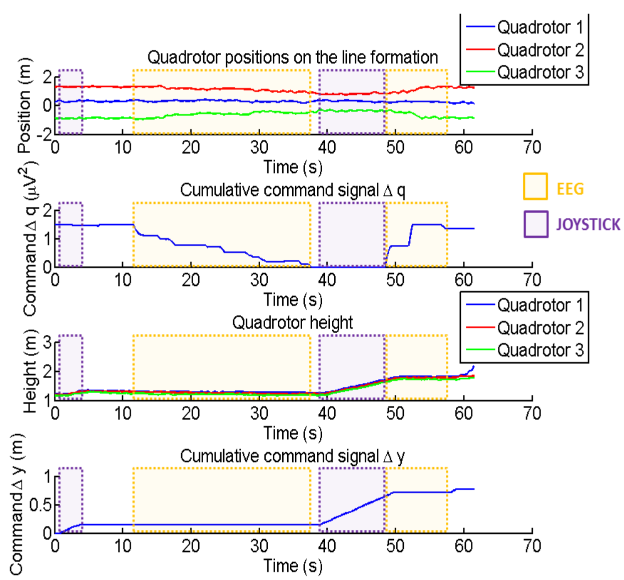


Fig. 8: Position of the 3 quadrotors and EEG and joystick input during the second experiment against time.

IV. CONCLUSIONS

In this work, we proposed a hybrid BMI approach that combined the brain signals produced by the ERD/ERS phenomena during imagined or actual limb movement with input from a joystick controller. The resulting system was simple to use and we provided experimental data that showed the efficiency of our algorithm and the fact that the users needed very little training before they could use the system with high accuracy. In addition, we applied this methodology successfully on the real-time control of a swarm of quadrotors. More specifically, the user was able to control a parameter related to the overall behavior of the swarm,

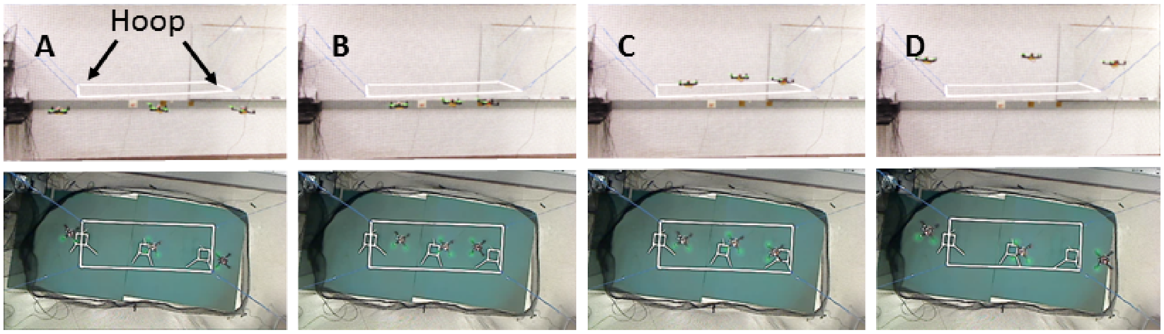


Fig. 7: Snapshots of the quadrotors passing through the rectangular hoop during the second experiment. The top row shows a side view of the motion of the swarm, while the bottom row shows the top view of the quadrotors. A: Initial formation, B: Change of formation, C: Passing the quadrotors through the hoop, D: Returning to initial formation. Video at [26].

namely its density, by using brain signals, while at the same time the user was controlling its position using the joystick. In all experimental paradigms, the control of the system was self-paced, seamless and the user was able to perform the corresponding task without any reported difficulty.

In the future, we will investigate different types of mental imagery for the control of swarm behaviors such as visual and speech imagery. In addition, we will implement a training protocol which will be adaptive to the user in order to make the training process easier for the subjects.

ACKNOWLEDGMENT

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