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14. ABSTRACT The goal of this project is to acquire high performance Electroencephalogram (EEG) systems that enable real-time measurement of human brain activities at high spatial-temporal resolution in both laboratory and real-life environments. Our long-term vision is to develop a strong research and education center on brain machine interaction (BMI) at the University of Texas at San Antonio (UTSA). By acquiring this system, we will significantly advance the ability of the UTSA faculty to conduct research and education in the area of BMI. We proposed to acquire two state-of-the-art Biocom Active Type EEG device to enable real-time measurement of brain					
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Report Title

Final Report: Acquisition of High Resolution Electroencephalogram Systems for Advancing Brain - Machine Interaction Research

ABSTRACT

The goal of this project is to acquire high performance Electroencephalogram (EEG) systems that enable real-time measurement of human brain activities at high spatial-temporal resolution in both laboratory and real-life environments. Our long-term vision is to develop a strong research and education center on brain machine interaction (BMI) at the University of Texas at San Antonio (UTSA). By acquiring this system, we will significantly advance the ability of the UTSA faculty to conduct research and education in the area of BMI. We proposed to acquire two state-of-the-art Biosemi Active Two EEG device to enable real-time measurement of brain wave with highest possible resolution at a laboratory environment, and 2) additional dry electrode, wearable wireless EEG caps to measure brain activities in real life environment and for educational use. The proposed acquisition will be the first inclusion of high performance EEG systems at UTSA and offer key instruments essential for BMI and brain research and education. They will be an important addition to research and educational capability at UTSA and help advance the research and development of BMI and brain research in San Antonio.

Enter List of papers submitted or published that acknowledge ARO support from the start of the project to the date of this printing. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

Received

Paper

TOTAL:

Number of Papers published in peer-reviewed journals:

(b) Papers published in non-peer-reviewed journals (N/A for none)

Received

Paper

TOTAL:

Number of Papers published in non peer-reviewed journals:

(c) Presentations

1. Mao, Z., Lawhern, V., Meriño, L., Ball, K. Deng, Li, Lance, B.J., Robbins, K. & Huang, Y. (2014) Deep stack network applied on RSVP data. UTSA College of Sciences Research Conference, San Antonio, TX, Oct 3, 2014.
2. Mao, Z. et al. (2014). Detection of target events in rapid serial visual presentation by deep learning, UTSA College of Sciences Research Conference, the University of Texas at San Antonio, Oct. 7, 2014.
3. Mao, Z. et al, Detection of target events in rapid serial visual presentation by deep learning. CANCTA All Hands meeting, ARL Aberdeen, MD, Nov. 20-21, 2014

Number of Presentations: 3.00

Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

<u>Received</u>	<u>Paper</u>
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TOTAL:

Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Peer-Reviewed Conference Proceeding publications (other than abstracts):

<u>Received</u>	<u>Paper</u>
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- | | | |
|------------|------|---|
| 12/21/2015 | 2.00 | Vernon Lawhern, Lenis Mauricio Merino, Kenneth Ball, Li Deng, Brent J. Lance, Kay Robbins, Yufei Huang, Zijong Mao. Classification of non-time-locked rapid serial visual presentation events for brain-computer interaction using deep learning, 2014 IEEE China Summit & International Conference on Signal and Information Processing (ChinaSIP). 08-JUL-14, Xi'an, China. : , |
| 12/21/2015 | 3.00 | Mehdi Hajinoroozi, Tzyy-Ping Jung, Chin-Teng Lin, Yufei Huang. Feature extraction with deep belief networks for driver's cognitive states prediction from EEG data, 2015 IEEE China Summit and International Conference on Signal and Information Processing (ChinaSIP). 11-JUL-15, Chengdu, China. : , |
| 12/21/2015 | 4.00 | Mehdi Hajinoroozi , Zijong Mao , Yufei Huang . Prediction of Driver's Drowsy and Alert States From EEG Signals with Deep Learning, IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive Processing. 12-DEC-15, . : , |

TOTAL: 3

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts):

(d) Manuscripts

<u>Received</u>	<u>Paper</u>
12/20/2015	1.00 Jinqi Li, Zhiguo Jiang, Jia-Hong Gao, Crystal G. Franklin, Yufei Huang, Jack L. Lancaster, Guang H. Yue, Wan X. Yao. Aging interferes central control mechanism for eccentric muscle contraction, Frontiers in aging neuroscience (05 2014)
TOTAL:	1

Number of Manuscripts:

Books

<u>Received</u>	<u>Book</u>
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TOTAL:

<u>Received</u>	<u>Book Chapter</u>
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TOTAL:

Patents Submitted

Patents Awarded

Awards

2nd Place, UTSA Center for Innovation and Technology Entrepreneurship competition, April, 2015

3rd Place, EE Technology Symposium, UTSA, April, 2015

Graduate Students

<u>NAME</u>	<u>PERCENT SUPPORTED</u>	Discipline
Lenis Mauricio Meriño	0.00	
Zijing Mao	0.00	
Mehdi Hajinoroozi	0.00	
FTE Equivalent:	0.00	
Total Number:	3	

Names of Post Doctorates

<u>NAME</u>	<u>PERCENT SUPPORTED</u>
FTE Equivalent:	
Total Number:	

Names of Faculty Supported

<u>NAME</u>	<u>PERCENT SUPPORTED</u>	National Academy Member
Yufei Huang	0.00	
Daniel Pack	0.00	
Yusheng Feng	0.00	
Kay Robbins	0.00	
Nicole Wicha	0.00	
Wan Xiang Yao	0.00	
FTE Equivalent:	0.00	
Total Number:	6	

Names of Under Graduate students supported

<u>NAME</u>	<u>PERCENT SUPPORTED</u>	Discipline
Garrett Hall	0.00	Electrical Engineering
Ken Poulin	0.00	Electrical Engineering
Rikki Pilgrim	0.00	Electrical Engineering
Sultan Alotaibi	0.00	Electrical Engineering
Christopher Herzing	0.00	Electrical Engineering
Jonathan Jardine	0.00	Electrical Engineering
FTE Equivalent:	0.00	
Total Number:	6	

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

The number of undergraduates funded by this agreement who graduated during this period: 5.00

The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:..... 5.00

The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:..... 1.00

Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale):..... 1.00

Number of graduating undergraduates funded by a DoD funded Center of Excellence grant for Education, Research and Engineering:..... 0.00

The number of undergraduates funded by your agreement who graduated during this period and intend to work for the Department of Defense 0.00

The number of undergraduates funded by your agreement who graduated during this period and will receive scholarships or fellowships for further studies in science, mathematics, engineering or technology fields:..... 0.00

Names of Personnel receiving masters degrees

NAME

Total Number:

Names of personnel receiving PHDs

NAME

Total Number:

Names of other research staff

NAME

PERCENT SUPPORTED

FTE Equivalent:

Total Number:

Sub Contractors (DD882)

Inventions (DD882)

Scientific Progress

1. List of Appendixes, Illustrations and Tables (if applicable)

Figure 1 Illustration of the proposed human-UAV cooperative decision system, where UAVs are controlled actively (through a thought-based command) and passively (through sensing the cognitive states) by soldiers' thoughts detected by EEG sensors placed in their helmet.

Figure 2 The acquired Active Two 256-channel Biosemi systems and the EEG lab established at UTSA

Figure 3 Block diagram of the proposed SSVEP-based brain-controlled UAV system.

Figure 4 Illustration in the SSVEP BCI system that implements 6 commands. (A) the arrangement of the flickering and the frequencies. (B) Illustration of a participant looking at flickering visual stimulus in the real system.

Figure 5 The locations of the 12 electrodes used in this system.

Figure 6 Power spectrum for a 10Hz (left) and 15Hz (right) trial. Different curves correspond to different channels. Significant peaks at 10Hz (left) and 15Hz (right) and their respective harmonics can be clearly seen.

Figure 7 Average error rates of the experiment involving 40 participants, each conducted 3 trials.

Figure 8 Screenshots of real demonstration of brain-control quad-copter flight missions.

Figure 9 . A The general DSN architecture with three stacking modules (dotted blue boxes). Note input (V) and output (Y_{n-1}) are concatenated to form the input the 2nd and third module. B. The detailed architecture of a DSN module, which is a simplified MLP that includes a single layer RBM followed by a linear classification layer. C. The detailed architecture of the proposed DSNTF module, which includes a set of weights (with superscript "A") trained from other subjects and another set (with superscript "O") trained specifically for the SOI.

2. Statement of the problem studied

One key objective of the project in this reporting period is to acquire high performance EEG Biosemi systems. In addition to our effort in acquiring the EEG systems, we have also been working on two proposed projects in the area of brain computer interface (BCI).

2.1 Acquisition of high performance EEG systems

The goal of this project is to acquire high performance Electroencephalogram (EEG) systems that enable real-time measurement of human brain activities at high spatial-temporal resolution in both laboratory and real-life environments. The specific aims are to enable 1) multi-subject capability; 2) real-time measurement of brain wave with highest possible resolution at a laboratory environment; 3) real-time measurement of brain activity in real life environments. In addition, we also intend to acquire additional EEG devices suitable for classroom and research-based educational purpose. We propose to acquire 1) the most advanced Biosemi Active Two EEG device to enable real-time measurement of brain wave with highest possible resolution at a laboratory environment, and 2) dry electrode, wearable wireless EEG caps to measure brain activities in real life environment and for educational use. For this reporting period, we focused on the acquisition of Biosemi Active Two EEG devices.

2.2 Controlling a Simulated Quad-copter using a SSVEP-based Brain-Computer Interface

Our long term goal is to develop and demonstrate core technologies to control cooperative small unmanned aerial vehicles (SUAVs) to complete simple missions using brain waves of a soldier (Fig. 1). There has been substantial amount of technical advances made over the past two decades in the area of autonomous unmanned vehicles. The miniaturization of computational, sensory, and communicational components have accelerated the pace of the recent advancement. Most of previous works dealt with a variety of user interface issues for control stations. What has not been studied in depth is ways for soldiers to interact directly with SUAVs. However, successful SUAV mission executions rely heavily on the ability to sense critical information of a mission situation from different complimentary sensor resources. While these sensors have proven to provide information that can lead to improved decision making, soldiers' comprehension of complex environments, including the collective sensor information, and their cognitive decisions are often the most valuable, enabling effective and efficient execution of complex SUAV missions. Integrating soldiers into the cooperative decision making of SUAVs is imperative. Furthermore, due to pervasive threats from enemies that employ unconventional tactics, it would be highly desirable to have an integrated, human-SUAV, sociotechnical system, where SUAVs possess the ability to sense the potential risks from soldiers' high level cognitive commands and act accordingly to avert the risks.

The ultimate goal of this project is to design a BCI system to control a group of UAVs to perform a simple cooperative mission, such as a simple search mission and an Intelligence Collection, Surveillance, and Reconnaissance (ISR) mission by only using brain waves of a human. The goal for this reporting period is to design a BCI system based on the Steady-State visually Evoked Potentials (SSVEP) method to interface with a Quad-copter simulator to control the takeoff (which also hovers) and landing using brain wave.

2.3 A deep neural-network system for cross-subject and cross-experiment prediction of image rapid serial visual presentation events

We propose to study in the project a particular BCI system that uses brain signals to detect rare target images within a large collection of non-target images. Such BCI-based systems can significantly increase the speed of target image identification in large image databases over manual procedures. Data collection for training such BCI systems is commonly carried out under a rapid serial visual presentation (RSVP) paradigm, where test subjects are asked to identify a target image from a continuous burst of image clips presented at a high rate. The EEG recordings or their power spectrums within 300-1000ms immediately following the onset of target and non-target images are collected and a classifier capable of predicting the presence of target images based on EEG responses is trained using this data.

The prediction of target images using the trained classifier can be categorized as a within-subject, cross-subject, or cross-experiment task, depending upon, if the prediction data come from the same subject, different subjects, or different RSVP experiment as the training data source, respectively. So far, a number of classifiers including logistic regression, linear discriminant analysis (LDA), support vector machines (SVM) and hierarchical discriminant component analysis (HDCA) have been proposed in the literature. Although some of these classifiers have been shown to achieve high accuracy for within-subject prediction, all of them suffer significant performance degradation when applied for a cross-subject or cross-experiment task. This degradation can be largely attributed to the increased differences in brain activities across subjects and experiments. As demonstrated in the literature, the target event related potential (ERP) can change in both magnitude and timing with subject and experiment. To improve the prediction performance, new methods that can extract robust EEG features across subjects and experiments and can adapt to the changes of subjects and experiments need to be developed. Moreover, it would be of significant practical interest to develop a prediction system that can integrate existing data from other subjects with that from the subject of interest to improve the prediction performance. However, given the potential differences in brain activities across subjects and experiments, it is unclear if and how data from other subjects/experiments can be transferred to improve the target prediction. In this project, we investigated deep learning (DL) classifiers for cross-subject and cross-experiment prediction of RSVP target events and we also proposed a novel deep transfer learning algorithms that can integrate data from other subjects for improved target prediction. Deep learning is a new family of learning methods with a multiple-layered architecture that have been shown to offer superb representation of complex data. DL has gained great interest in recent years due to its ability to outperform other classification methods in several machine learning competitions and in a variety of applications including image classification and speech recognition. Its application in EEG-based BCI data analysis is still at a very early stage. We have previously shown on a small dataset that deep learning algorithms achieved about 5% performance gain over other exiting algorithms for within-subject RSVP target prediction. However, more studies need to be conducted to confirm the improvement of DL classifier for within-subject prediction based on relative small training data because the superior performance of DL in other applications is almost always achieved as a result of enormous training data (e.g. millions of training images). Furthermore, if and how DL can improve cross-subject or cross-experiment prediction based on limited training samples has not been explored.

3. Summary of the most important results

We first summarize in the following important results for each of the 3 tasks stated in section “Statement of the problem studied”. We will then discuss the outcome of outreach and educational efforts.

3.1 Acquisition of high performance EEG systems

We have purchased two (2) 256-channel Biosemi Active Two EEG devices. This biopotential measurement system has 256 active electrodes and 24-bit resolution. It is the most advanced Biosemi EEG system that offers to measure brain activity at the highest possible spatial and temporal resolution. Each system includes an ActiveTwo Base System that includes A/D Box, 2 battery Units, battery Charger, USB 2.0 Interface, Interface Cable, and acquisition Software, an amplifier/converter module, an auxiliary 8-channel input box, 256 sensors, and 3 head cap with different size. In addition, we have acquired one 64-channel, one 32-channel, and two 16-channel Cognionics dry sensor headsets. We have also set up a 110 ft² EEG room for storing the EEG systems and conducting experiments (Fig. 2).

3.2 Controlling a Simulated Quad-copter using a SSVEP-based Brain-Computer Interface

The main objective of this project is to control a simple Unmanned Aerial Vehicle (UAV) using the brain activity, specifically using a Brain-Computer Interface (BCI) system. The overall block diagram of the designed system can be found in Fig. 3. The main BCI element is a Steady-State Evoked Potentials (SSVEP) system that functions to induce a specific pattern in brain signals associated with a particular command (e.g. turning left). The command associated signals are detected by the Canonical Correlation Analysis (CCA) algorithm and sent to the control unit or Robot Operating System (ROS) of a quad-copter (the UAV), which will execute the specific command.

3.2.1 Introduction to SSVEP

Several approaches have been developed for BCI and they make it possible to control an electronic device using the subject's neural activity. The approach chosen for this project is called Steady-State Evoked Potentials (SSVEP). In brief, the main principle behind this approach is that when the subject observes a visual stimulus that flickers at a certain frequency f , the neural activity generated in the visual cortex registers (among other activities) a sinusoidal-like signal whose frequency is also f . This fact makes it possible to design a BCI system that codes stimulus frequencies as commands to be sent to the output device. By accurately recognizing the frequency of the visual stimulus the subject is looking at, the coded command can be detected.

SSVEP belongs to the REACTIVE type of BCI, which means the subject is not concentrated in giving direct orders with his mind. The design of an SSVEP experiment is usually quick, simple and inexpensive. SSVEP is a very active research topic within the BCI field and several detections algorithms have been tested and diverse kind of applications have been built. Important factors that need to be carefully considered when designing a SSVEP system are listed in the following:

- The visual stimulus: shape, size, brightness, color, etc. are factors that influence the SSVEP performance; using flickering images as source of stimulus has been documented.
- Focal distance, concentration level, fatigue and other mental and physical states also affect the SSVEP performance.
- The visual stimulus are usually presented using arrays of LEDs, TVs or computer monitor. When using TV or computer monitors, the refresh rate of the screen has to be taken in consideration to correctly reproduce the flickering frequencies.
- Frequencies ranging as low as 6Hz to high as 90Hz have been successfully used for SSVEP.
- Minimum training is required for an SSVEP experiment.

3.2.2 The proposed SSVEP experiment

The objective of the experiment is to capture the sine-like signal using EEG, which is elicited when the subject watches the SSVEP visual stimulus. An illustration of our SSVEP experiment is shown in Fig. 4. The detailed design of the experiment can be summarized as follows:

- A 24 inches computer monitor is placed in front of the subject, approximately 30 – 50 cm focal distance. The visual stimulus corresponding to two flickering squares are located on the left and right borders of the screen at a central high. Each square is approximately 5 cm length per side.
- Participant is wearing an EEG cap with 12 electrodes (Fig. 5). Several different arrangements of sensors on the scalp have been used in the literature. In our case, the 12 channels are spread throughout several locations around the scalp in a symmetric fashion, emphasizing particularly the area of visual cortex. The sampling rate of the system is 512Hz.
- Visual stimulus has six flickering with 6.0Hz, 7.5Hz, 8.57Hz, 10Hz, 10.9Hz and 13.3 Hz (Fig. 4-(A)).
- Participant starts in neutral position, looking at the fixation mark. An arrow indicator displays for 7 seconds, directing participant to a specific flicker. After 7 seconds, the arrow disappears and the fixation mark appears for 7 seconds. This arrow rotates clockwise with the 7 second intervals. This rotation occurs 3 times during a trial for a total of 18 views of the various flickers. After viewing 18 flickers the trial finishes and the flickers disappears, participant has 40 seconds to rest before the next cycle begins
- Presentation program was implemented in MATLAB using the Psychophysics Toolbox (PTB) for the low-level communications with the computer monitor through OpenGL.
- The lab-streaming layer (LSL) library was used to stream the EEG recordings from BioSemi hardware and combined with the SSVEP presentation data (event labels, timing, etc.).

3.2.3 EEG acquisition and preprocessing

EEG signals were recorded using a Biosemi Active Two System. As mentioned before, 12 electrodes were used on the standard adult-size 256 electrodes cap. The SSVEP presentation program and the EEG recording were performed on the same computer. For the experiment, EEG data were recorded using the built-in Labview-based Biosemi acquisition software. The data pre-processing was conducted using MATLAB and the EEGLAB toolbox. After signal was correctly loaded and trimmed (initial seconds of PTB initialization), the following operations were carried out for pre-processing:

- Downsampling to 128 Hz
- FIR band-pass filter with frequencies 1Hz to 60Hz
- Averaged re-referencing

- Baseline removal

After these steps of preprocessing, the power spectrum was generated to verify if there was frequency spikes at the stimulus frequency and their harmonics as suggested by the SSVEP theory. An example of a 10Hz and 15Hz frequency response for a single trial can be seen in Fig. 6.

3.2.4 Detection of SSVEP frequencies with Canonical Correlation Analysis

We investigated the Canonical Correlation Analysis (CCA) algorithms for automatic detection of the SSVEP frequencies and evaluated its performance for our experiment. In a nutshell, the CCA algorithm performs correlations between a sinusoidal signal and its harmonics with the predefined frequency (e.g. 10Hz or 15Hz) and EEG recording from different channels and then finds a linear transformation that maximizes the combination of the correlations or the CCA correlation. The frequency that associated with the largest CCA correlation is detected as the stimulus frequency.

3.2.5 Investigate the performance of the SSVEP system.

To evaluate the performance of the designed SSVEP system, we conducted experiments of 40 subjects, each performed 3 trials that last for about 15 seconds. Specifically, the participant was asked to sit still in trial 1 and 2 but allowed to talk and move in trial 3. Data were spitted into a 3-second length epochs, where each epoch contains only a single stimulus. A total of 192 epochs were obtained from all the recorded data for each participant in each trial. CCA was applied to each epoch and the detection frequency was compared with the true frequency of the flickering. An error is record if the predicted and the true frequencies did not agree. We obtain an average error rate of 0.0996, 0.1466 and 0.2936 for trial 1, 2 and 3, respective (Fig 7). We observed that the average error rate is low in trial 1 & 2 but increases significantly in trial 3. We performed T-test to test the differences between the trials. The test determines that there is no significant differences between the error rate of trial 1 & 2 ($p < 0.05$) but shows a significant difference between the error rates between trail 1 & 3 or 2 & 3. Since the difference between trial 1 (or 2) & 3 is the allowed movement of the participant, we conclude that movement during SSVEP experiment significantly impairs the detection performance.

3.2.6 Execution of the brain-controlled quadcopter flight operations

As the final step, we connected the SSVEP BCI system with the real quadcopter and performed two types of flight mission. The first mission involves one quadcopter and six low level commends are executed, which includes "Move Forward", "Move Backward", "Move Right", "Move Left", "Move Up", and "Move Down". Using these commends, we successfully demonstrated the direct execution of these commends and the square formation. The second mission includes controlling two drones to execution high level commands including "Scatter" (two drones move away from each other) and "Gather" (two drones move closer to each other), which we were able to successfully implemented as well.

3.3 Deep learning methods for cross-subject and cross-experiment prediction of image rapid serial visual presentation events

We investigated the performance of Deep Stacking Network (DSN) and deep neural network (DNN), two most popular deep learning algorithms, for cross-subject and cross-experiment prediction of RSVP targets. In addition, we also proposed a new deep transfer learning algorithm, where we augment the training data of a subject of interest (SOI) with data from other subjects.

3.3.1 A new transfer learning deep stacking network algorithm

The goal of transfer learning is to augment the training data of a subject of interest (SOI) with data from other subjects from either the same of different experiment. However, simply augmenting data from other subject might not help improve the performance for SOI. Especially, the training data from other subject can be of much larger size than that from SOI. In this case, the discriminant features of SOI can be significantly skewed by virtue of the enormous data size from other subjects. This could be beneficial when data from other subject carries more discriminant information but it could equally be detrimental when target event related brain activities from other subjects are not as discriminant. Therefore, it is desirable to develop an algorithm that can transfer only the useful, discriminant information of other subject to SOI. We propose a novel DSN architecture for transfer learning or DSNTF (Fig. 9). The uniqueness of DSNTF is that it is essentially an augmentation of a SOI DSN with a cross-subject DSN. To train this DSNTF, we first train a cross-subject DSN suing data from other subjects. Then, the SOI DSN is trained using only data from SOI. However, before training, the hidden units in each module are expanded by including those from the trained cross-subject DSN, where the corresponding RBM weights for the cross-subject hidden units are also retained. The training thus involves learning the weights for the SOI hidden units as well as updating the weights for cross-subject hidden units using the subject-specific data. Because the training of each DSNTF module should maximize the classification performance, weight updating for cross-subject hidden units functions to transfer the discriminant information learned from other

subjects about the target event to the individualized DSN designed for the subject of interest. As a result, this new architecture integrates subject-specific knowledge and cross-subjects knowledge about the target event to produce a prediction that not only emphasizes individual characteristics in brain activity but also reflects the subject-wide consensus that defines the global brain activity underlying the target event. Because the cross-subject hidden units bring the global, potentially more robust features into the classification, this new architecture is likely immune to data noise in outlier samples, thus making the individualized prediction more robust. At the same time, when cross-subject hidden units are less discriminant, the updating process should function to discount these cross-subject hidden units, thus maintaining a performance close to that of the within-subject.

3.3.2 DL algorithms showed significant improvement over existing algorithms.

We evaluated the performance of DSN and DNN for within-subject target classification for two RSVP datasets, the static motion and the Cognitive Technology Threat Warning System (CT2WS). The static motion experiment include presentation of images of enemy soldiers/combatants (target) versus the background image (non-target). In the CT2WS experiment, target images include moving people and vehicle animations, whereas the non-targets are other types of animation. For both experiments, the images were presented at 2Hz (one image presented every 500ms) and brain signals were recorded with 64-channel Biosemi EEG systems at a sampling rate of 512 Hz. There were a total of 16 and 15 subjects in the static motion and CT2WS experiment, respectively. For both experiments, DNN and DSN both had very similar Area Under the ROC, or Az performance and DNN reported an Az score of 94.5% for the static motion RSVP experiment. When compared with the state-of-the-art HDCA method, the two DL algorithms reported > 6% improvements in Az scores for both experiments. Taken together, this result demonstrated good performance and a clear improvement achieved by DL algorithms for within-subject target prediction.

3.3.3 DL classifiers are more robust for cross-subject and cross-experiment predictions.

We investigated how robust DL algorithms when used to predict the target event for a test subject different from those for training. We first evaluated their cross-subjects performance, where the test subject and training subjects are from the same experiment. As expected, both HDCA and LDA deteriorated significantly relative to their within-subject performance, where the Az scores of HDCA dropped for more than 10% from 0.87 to 0.74 for the static motion and 0.8 to 0.7 for the CT2WS. In contrast, both DNN and DSN demonstrated a much robust performance, suffered only 4.7% and 2.1% performance degradation for the static motion and 0.8 to 0.7 for the CT2WS, respectively.

We then examined if this more robust performance can still be observed for cross-experiment prediction, which is a more difficult task than cross-subject prediction because the test subject is from an experiment different from the training subject. For this test, we trained the classifiers using all subject data from the static motion RSVP experiment and then evaluated their performance for each subjects from the CT2WS experiment. As expected, the performance of all tested classifiers including DNN and DSN degraded more than cross-subject performance. However, the two DL algorithms registered a less degradation in performance than either HDCA or LDA (~12% for DL from 0.86 to 0.76 vs. ~16% for HDCA from 0.8 to 0.67 and 28% for LDA from 0.74 to 0.58). Taken together, the results indicated that DL algorithms are more robust for both cross-subject and cross-experiment predictions.

3.3.4 The proposed transfer learning DSN improves over the within-subject prediction performance

We investigated if the proposed transfer learning schemes can improve the within-subject performance by integrating additional data from other subjects either from the same experiment or different experiment. For the within-experiment transfer learning, similar procedure as the within-subject test was followed except that the within-subject training data is augmented also by data from other subjects of the same experiment. Surprisingly, directly augmenting the training data from other subjects appeared to harm rather than improve the within-subject performance. This result suggests that there exist differences in the learned discriminant EEG features for different subjects and many discriminant EEG features for other subjects would not be discriminant for the subject of interest. As a result, including data from other subjects might add more non-discriminant features and subsequently degrade the performance. However, the fact that DNN with data augmentation (DNDA) and DSN with data augmentation (DSNDA) only suffered a slight drop in performance suggests once again that the discriminant features learnt by the DL algorithms are more robust cross subjects. In contrast, the performance of HDCA and LDA deteriorated much closer to their corresponding cross-subject performance. This observation could suggest that the discriminant EEG features learnt by HDCA and LDA cross subjects are potentially very different. The learnt discriminant features became similar to those by cross-subject training, hence the performance, because after data augmentation there were much more data samples from cross subjects than subject of interest.

On the contrary, we noticed that the proposed transfer learning DSN did achieved improvement over the within-subject DSN. This result substantiated our original motivation for proposing the transfer learning architecture. Indeed, this TF architecture enables to transfer these cross-subjects discriminant features that are only beneficial to the subject of interest. The result that DSNTF achieved almost the same performance as within-subject DSN for the CT2WS experiment also demonstrated that when the cross-subjects data appear very different, this architecture seems to allow potentially no features transferred.

We further validated this result about transfer learning by augmenting data of subjects from different experiments. HDCA and

LDA suffered more significant deterioration because of the impact of additional cross-experimental differences. As expected, DSNDA and DNNDA only have small drops in performance. Overall, DSNTF still reported the best performance which is only 1% lower than that of within-subject DSN. This result confirmed that the conceived advantages of the proposed transfer learning DSN.

3.4 Education and outreach activities

Overall, we have involved 2 PhD students, one MS student, and 2 undergraduate students in conducting research that are related to this project.

We hosted Kristine Diaz, a female, Hispanic undergraduate student from the Alamo College to implement a SSVEP based BCI system from July-Aug, 2014. Kristine Diaz was selected through the Alamo College Summer Research Program, a National Science Foundation funded program. Ms. Diaz has participated in the SSVEP experiments both as a test subject and in helping out with the experiments. She has also involved in data collection, preprocessing, and analysis. She has reported her research experience and results from this project in a poster presented the final research conference of the program.

We have also recruited Jonathan David Upchurch and Garrett Hall, two UTSA electrical engineering undergraduate students and Air Force veterans, to work on the brain-controlled UAV project. Both of them have been helping conducting SSVEP experiments and research the dry sensor EEG systems.

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Technology Transfer

Final Report

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Scientific Progress and Accomplishments

1. List of Appendixes, Illustrations and Tables (if applicable)

Figure 1 *Illustration of the proposed human-UAV cooperative decision system, where UAVs are controlled actively (through a thought-based commend) and passively (through sensing the cognitive states) by soldiers' thoughts detected by EEG sensors placed in their helmet.*

Figure 2 *The acquired Active Two 256-channel Biosemi systems and the EEG lab established at UTSA*

Figure 3 *Block diagram of the proposed SSVEP-based brain-controlled UAV system.*

Figure 4 *Illustration in the SSVEP BCI system that implements 6 commends. (A) the arrangement of the flickering and the frequencies. (B) Illustration of a participant looking at flickering visual stimulus in the real system.*

Figure 5 *The locations of the 12 electrodes used in this system.*

Figure 6 *Power spectrum for a 10Hz (left) and 15Hz (right) trial. Different curves correspond to different channels. Significant peaks at 10Hz (left) and 15Hz (right) and their respective harmonics can be clearly seen.*

Figure 7 *Average error rates of the experiment involving 40 participants, each conducted 3 trials.*

Figure 8 *Screenshots of real demonstration of brain-control quad-copter flight missions.*

Figure 9 . **A** *The general DSN architecture with three stacking modules (dotted blue boxes). Note input (V) and output (Y_{n-1}) are concatenated to form the input the 2nd and third module. **B.** *The detailed architecture of a DSN module, which is a simplified MLP that includes a single layer RBM followed by a linear classification layer. **C.** *The detailed architecture of the proposed DSN_{TF} module, which includes a set of weights (with superscript "A") trained from other subjects and another set (with superscript "O") trained specifically for the SOI.***

2. Statement of the problem studied

One key objective of the project in this reporting period is to acquire high performance EEG Biosemi systems. In addition to our effort in acquiring the EEG systems, we have also been working on two proposed projects in the area of brain computer interface (BCI).

2.1 Acquisition of high performance EEG systems

The **goal** of this project is to acquire high performance Electroencephalogram (EEG) systems that enable real-time measurement of human brain activities at high spatial-temporal resolution in both laboratory and real-life environments. The specific aims are to enable 1) multi-subject capability; 2) real-time measurement of brain wave with highest possible resolution at a laboratory environment; 3) real-time measurement of brain activity in real life environments. In addition, we also intend to acquire additional EEG devices suitable for classroom and research-based educational purpose. We propose to acquire 1) the most advanced Biosemi Active Two EEG device to enable real-time measurement of brain wave with highest possible resolution at a laboratory environment, and 2) dry electrode, wearable wireless EEG caps to measure brain activities in real life environment and for educational use. For this reporting period, we focused on the acquisition of Biosemi Active Two EEG devices.

2.2 Controlling a Simulated Quad-copter using a SSVEP-based Brain-Computer Interface

Our long term goal is to develop and demonstrate core technologies to control cooperative small unmanned aerial vehicles (SUAVs) to complete simple missions using brain waves of a soldier (Fig. 1). There has been substantial amount of technical advances made over the past two decades in the area of autonomous unmanned vehicles. The miniaturization of computational, sensory, and communicational components have accelerated the pace of the recent advancement. Most of previous works dealt with a variety of user interface issues for control stations. What has not been studied in depth is ways for soldiers to interact directly with SUAVs. However, successful SUAV mission executions rely heavily on the ability to sense critical information of a mission situation from different complimentary sensor resources. While these sensors have proven to provide information that can lead to improved decision making, soldiers' comprehension of complex environments, including the collective sensor information, and their cognitive decisions are often the most valuable, enabling effective and efficient execution of complex SUAV missions. Integrating soldiers into the cooperative decision making of SUAVs is imperative. Furthermore, due to pervasive threats from enemies that employ unconventional tactics, it would be highly desirable to have an integrated, human-SUAV, sociotechnical system, where SUAVs possess the ability to sense the potential risks from soldiers' high level cognitive commands and act accordingly to avert the risks.

The ultimate goal of this project is to design a BCI system to control a group of SUAVs to perform a simple cooperative mission, such as a simple search mission and an Intelligence Collection, Surveillance, and Reconnaissance (ISR) mission by only using brain waves of a human. The goal for this reporting period is to design a BCI system based on the Steady-State visually Evoked Potentials (SSVEP) method to interface with a Quad-copter simulator to control the takeoff (which also hovers) and landing using brain wave.

2.3 A deep neural-network system for cross-subject and cross-experiment prediction of image rapid serial visual presentation events

We propose to study in the project a particular BCI system that uses brain signals to detect rare target images within a large collection of non-target images. Such BCI-based systems can significantly increase the speed of target image identification in large image databases over manual procedures. Data collection for training such BCI systems is commonly carried out under a rapid serial visual presentation (RSVP) paradigm, where test subjects are asked to identify a target image from a continuous burst of image clips presented at a high rate. The EEG recordings or their power spectrums within 300-1000ms immediately following the onset of target and non-target images are collected and a classifier capable of predicting the presence of target images based on EEG responses is trained using this data.

The prediction of target images using the trained classifier can be categorized as a within-subject, cross-subject, or cross-experiment task, depending upon, if the prediction data come from the same subject, different subjects, or different RSVP experiment as the training data source, respectively. So far, a number of classifiers including logistic regression, linear discriminant analysis (LDA), support vector machines (SVM) and hierarchical discriminant component analysis (HDCA) have been proposed in the literature. Although some of these classifiers have been shown to achieve high accuracy for within-subject prediction, all of them suffer significant performance degradation when applied for a cross-subject or cross-experiment task. This degradation can be largely attributed to the increased differences in brain activities across subjects and experiments. As demonstrated in the literature, the target event related potential (ERP) can change in both magnitude and timing with subject and experiment. To improve the prediction performance, new methods that can extract robust EEG features across subjects and experiments and can adapt to the changes of subjects and experiments need to be developed. Moreover, it would be of significant practical interest to develop a prediction system that can integrate existing data from other subjects with that from the subject of interest to improve the prediction performance. However, given the potential differences in brain activities across subjects and experiments, it is unclear if and how data from other subjects/experiments can be transferred to improve the target prediction. In this project, we investigated deep learning (DL) classifiers for cross-subject and cross-experiment prediction of RSVP target events and we also proposed a novel deep transfer learning algorithms that can integrate data from other subjects for improved target prediction. Deep learning is a new family of learning methods with a multiple-layered architecture that have been shown to offer superb representation of complex data. DL has gained great interest in recent years due to its ability to outperform other classification methods in several machine learning competitions and in a variety of applications including image classification and speech recognition. Its application in EEG-based BCI data analysis is still at a very early stage. We have previously shown on a small dataset that deep learning algorithms achieved about 5% performance gain over other exiting algorithms for within-subject RSVP target prediction. However, more studies need to be conducted to confirm the improvement of DL classifier for within-subject prediction based on relative small training data because the superior performance of DL in other applications is almost always achieved as a result of enormous training data (e.g. millions of training images). Furthermore, if and how DL can improve cross-subject or cross-experiment prediction based on limited training samples has not been explored.

3. Summary of the most important results

We first summarize in the following important results for each of the 3 tasks stated in section “Statement of the problem studied”. We will then discuss the outcome of outreach and educational efforts.

3.1 Acquisition of high performance EEG systems

We have purchased two (2) 256-channel Biosemi Active Two EEG devices. This biopotential measurement system has 256 active electrodes and 24-bit resolution. It is the most advanced Biosemi EEG system that offers to measure brain activity at the highest possible spatial and temporal resolution. Each system includes an ActiveTwo Base System that includes A/D Box, 2 battery Units, battery Charger, USB 2.0 Interface, Interface Cable, and acquisition Software, an amplifier/converter module, an auxiliary 8-channel input box, 256 sensors, and 3 head cap with different size. In addition, we have acquired one 64-channel, one 32-channel, and two 16-channel Cognionics dry sensor headsets. We have also set up a 110 ft² EEG room for storing the EEG systems and conducting experiments (Fig. 2).

3.2 Controlling a Simulated Quad-copter using a SSVEP-based Brain-Computer Interface

The main objective of this project is to control a simple Unmanned Aerial Vehicle (UAV) using the brain activity, specifically using a Brain-Computer Interface (BCI) system. The overall block diagram of the designed system can be found in Fig. 3. The main BCI element is a Steady-State Evoked Potentials (SSVEP) system that functions to induce a specific pattern in brain signals associated with a particular command (e.g. turning left). The command associated signals are detected by the Canonical Correlation Analysis (CCA) algorithm and sent to the control unit or Robot Operating System (ROS) of a quad-copter (the UAV), which will execute the specific command.

3.2.1 Introduction to SSVEP

Several approaches have been developed for BCI and they make it possible to control an electronic device using the subject's neural activity. The approach chosen for this project is called Steady-State Evoked Potentials (SSVEP). In brief, the main principle behind this approach is that when the subject observes a visual stimulus that flickers at a certain frequency f , the neural activity generated in the visual cortex registers (among other activities) a sinusoidal-like signal whose frequency is also f . This fact makes it possible to design a BCI system that codes stimulus frequencies as commands to be sent to the output device. By accurately recognizing the frequency of the visual stimulus the subject is looking at, the coded command can be detected.

SSVEP belongs to the REACTIVE type of BCI, which means the subject is not concentrated in giving direct orders with his mind. The design of an SSVEP experiment is usually quick, simple and inexpensive. SSVEP is a very active research topic within the BCI field and several detections

algorithms have been tested and diverse kind of applications have been built. Important factors that need to be carefully considered when designing a SSVEP system are listed in the following:

- The visual stimulus: shape, size, brightness, color, etc. are factors that influence the SSVEP performance; using flickering images as source of stimulus has been documented.
- Focal distance, concentration level, fatigue and other mental and physical states also affect the SSVEP performance.
- The visual stimulus are usually presented using arrays of LEDs, TVs or computer monitor. When using TV or computer monitors, the refresh rate of the screen has to be taken in consideration to correctly reproduce the flickering frequencies.
- Frequencies ranging as low as 6Hz to high as 90Hz have been successfully used for SSVEP.
- Minimum training is required for an SSVEP experiment.

3.2.2 The proposed SSVEP experiment

The objective of the experiment is to capture the sine-like signal using EEG, which is elicited when the subject watches the SSVEP visual stimulus. An illustration of our SSVEP experiment is shown in Fig. 4. The detailed design of the experiment can be summarized as follows:

- A 24 inches computer monitor is placed in front of the subject, approximately 30 – 50 cm focal distance. The visual stimulus corresponding to two flickering squares are located on the left and right borders of the screen at a central high. Each square is approximately 5 cm length per side.
- Participant is wearing an EEG cap with 12 electrodes (Fig. 5). Several different arrangements of sensors on the scalp have been used in the literature. In our case, the 12 channels are spread throughout several locations around the scalp in a symmetric fashion, emphasizing particularly the area of visual cortex. The sampling rate of the system is 512Hz.
- Visual stimulus has six flickering with 6.0Hz, 7.5Hz, 8.57Hz, 10Hz, 10.9Hz and 13.3 Hz (Fig. 4-(A)).
- Participant starts in neutral position, looking at the fixation mark. An arrow indicator displays for 7 seconds, directing participant to a specific flicker. After 7 seconds, the arrow disappears and the fixation mark appears for 7 seconds. This arrow rotates clockwise with the 7 second intervals. This rotation occurs 3 times during a trial for a total of 18 views of the various flickers. After viewing 18 flickers the trial finishes and the flickers disappears, participant has 40 seconds to rest before the next cycle begins
- Presentation program was implemented in MATLAB using the Psychophysics Toolbox (PTB) for the low-level communications with the computer monitor through OpenGL.
- The lab-streaming layer (LSL) library was used to stream the EEG recordings from BioSemi hardware and combined with the SSVEP presentation data (event labels, timing, etc.).

3.2.3 EEG acquisition and preprocessing

EEG signals were recorded using a Biosemi Active Two System. As mentioned before, 12 electrodes were used on the standard adult-size 256 electrodes cap. The SSVEP presentation

program and the EEG recording were performed on the same computer. For the experiment, EEG data were recorded using the built-in Labview-based Biosemi acquisition software.

The data pre-processing was conducted using MATLAB and the EEGLAB toolbox. After signal was correctly loaded and trimmed (initial seconds of PTB initialization), the following operations were carried out for pre-processing:

- Downsampling to 128 Hz
- FIR band-pass filter with frequencies 1Hz to 60Hz
- Averaged re-referencing
- Baseline removal

After these steps of preprocessing, the power spectrum was generated to verify if there was frequency spikes at the stimulus frequency and their harmonics as suggested by the SSVEP theory. An example of a 10Hz and 15Hz frequency response for a single trial can be seen in Fig. 6.

3.2.4 **Detection of SSVEP frequencies with** Canonical Correlation Analysis

We investigated the Canonical Correlation Analysis (CCA) algorithms for automatic detection of the SSVEP frequencies and evaluated its performance for our experiment. In a nutshell, the CCA algorithm performs correlations between a sinusoidal signal and its harmonics with the predefined frequency (e.g. 10Hz or 15Hz) and EEG recording from different channels and then finds a linear transformation that maximizes the combination of the correlations or the CCA correlation. The frequency that associated with the largest CCA correlation is detected as the stimulus frequency.

3.2.5 Investigate the performance of the SSVEP system.

To evaluate the performance of the designed SSVEP system, we conducted experiments of 40 subjects, each performed 3 trials that last for about 15 seconds. Specifically, the participant was asked to sit still in trial 1 and 2 but allowed to talk and move in trial 3. Data were spitted into a 3-second length epochs, where each epoch contains only a single stimulus. A total of 192 epochs were obtained from all the recorded data for each participant in each trial. CCA was applied to each epoch and the detection frequency was compared with the true frequency of the flickering. An error is record if the predicted and the true frequencies did not agree. We obtain an average error rate of 0.0996, 0.1466 and 0.2936 for trial 1, 2 and 3, respective (Fig 7). We observed that the average error rate is low in trial 1 &2 but increases significantly in trial 3. We performed T-test to test the differences between the trials. The test determines that there is no significant differences between the error rate of trial 1 &2 ($p < 0.05$) but shows a significant difference between the error rates between trail 1 &3 or 2 & 3. Since the difference between trial 1 (or 2) & 3 is the allowed movement of the participant, we conclude that movement during SSVEP experiment significantly impairs the detection performance.

3.2.6 Execution of the brain-controlled quadcopter flight operations

As the final step, we connected the SSVEP BCI system with the real quadcopter and performed two types of flight mission. The first mission involves one quadcopter and six low level commands are executed, which includes “Move Forward”, “Move Backward”, “Move Right”, “Move Left”, “Move Up”, and “Move Down”. Using these commands, we successfully demonstrated the direct execution of these commands and the square formation. The second mission includes controlling two drones to execution high level commands including “Scatter” (two drones move away from each other) and “Gather” (two drones move closer to each other), which we were able to successfully implemented as well.

3.3 Deep learning methods for cross-subject and cross-experiment prediction of image rapid serial visual presentation events

We investigated the performance of Deep Stacking Network (DSN) and deep neural network (DNN), two most popular deep learning algorithms, for cross-subject and cross-experiment prediction of RSVP targets. In addition, we also proposed a new deep transfer learning algorithm, where we augment the training data of a subject of interest (SOI) with data from other subjects.

3.3.1 A new transfer learning deep stacking network algorithm

The goal of transfer learning is to augment the training data of a subject of interest (SOI) with data from other subjects from either the same or different experiment. However, simply augmenting data from other subject might not help improve the performance for SOI. Especially, the training data from other subject can be of much larger size than that from SOI. In this case, the discriminant features of SOI can be significantly skewed by virtue of the enormous data size from other subjects. This could be beneficial when data from other subject carries more discriminant information but it could equally be detrimental when target event related brain activities from other subjects are not as discriminant. Therefore, it is desirable to develop an algorithm that can transfer only the useful, discriminant information of other subject to SOI. We propose a novel DSN architecture for transfer learning or DSN_{TF} (Fig. 9). The uniqueness of DSN_{TF} is that it is essentially an augmentation of a SOI DSN with a cross-subject DSN. To train this DSN_{TF} , we first train a cross-subject DSN using data from other subjects. Then, the SOI DSN is trained using only data from SOI. However, before training, the hidden units in each module are expanded by including those from the trained cross-subject DSN, where the corresponding RBM weights for the cross-subject hidden units are also retained. The training thus involves learning the weights for the SOI hidden units as well as updating the weights for cross-subject hidden units using the subject-specific data. Because the training of each DSN_{TF} module should maximize the classification performance, weight updating for cross-subject hidden units functions to transfer the discriminant information learned from other subjects about the target event to the individualized DSN designed for the subject of interest. As a result, this new architecture integrates subject-specific knowledge and cross-subjects knowledge about the target event to produce a prediction that not only emphasizes individual characteristics in brain activity but also reflects the subject-wide consensus that defines the global brain activity.

underlying the target event. Because the cross-subject hidden units bring the global, potentially more robust features into the classification, this new architecture is likely immune to data noise in outlier samples, thus making the individualized prediction more robust. At the same time, when cross-subject hidden units are less discriminant, the updating process should function to discount these cross-subject hidden units, thus maintaining a performance close to that of the within-subject.

3.3.2 DL algorithms showed significant improvement over existing algorithms.

We evaluated the performance of DSN and DNN for within-subject target classification for two RSVP datasets, the static motion and the Cognitive Technology Threat Warning System (CT2WS). The static motion experiment includes presentation of images of enemy soldiers/combatants (target) versus the background image (non-target). In the CT2WS experiment, target images include moving people and vehicle animations, whereas the non-targets are other types of animation. For both experiments, the images were presented at 2Hz (one image presented every 500ms) and brain signals were recorded with 64-channel Biosemi EEG systems at a sampling rate of 512 Hz. There were a total of 16 and 15 subjects in the static motion and CT2WS experiment, respectively. For both experiments, DNN and DSN both had very similar Area Under the ROC, or Az performance and DNN reported an Az score of 94.5% for the static motion RSVP experiment. When compared with the state-of-the-art HDCA method, the two DL algorithms reported > 6% improvements in Az scores for both experiments. Taken together, this result demonstrated good performance and a clear improvement achieved by DL algorithms for within-subject target prediction.

3.3.3 DL classifiers are more robust for cross-subject and cross-experiment predictions.

We investigated how robust DL algorithms when used to predict the target event for a test subject different from those for training. We first evaluated their cross-subjects performance, where the test subject and training subjects are from the same experiment. As expected, both HDCA and LDA deteriorated significantly relative to their within-subject performance, where the Az scores of HDCA dropped for more than 10% from 0.87 to 0.74 for the static motion and 0.8 to 0.7 for the CT2WS. In contrast, both DNN and DSN demonstrated a much robust performance, suffered only 4.7% and 2.1% performance degradation for the static motion and 0.8 to 0.7 for the CT2WS, respectively.

We then examined if this more robust performance can still be observed for cross-experiment prediction, which is a more difficult task than cross-subject prediction because the test subject is from an experiment different from the training subject. For this test, we trained the classifiers using all subject data from the static motion RSVP experiment and then evaluated their performance for each subjects from the CT2WS experiment. As expected, the performance of all tested classifiers including DNN and DSN degraded more than cross-subject performance. However, the two DL algorithms registered a less degradation in performance than either HDCA or LDA (~12% for DL from 0.86 to 0.76 vs. ~16% for HDCA from 0.8 to 0.67 and 28% for LDA from 0.74 to 0.58). Taken together, the results indicated that DL algorithms are more robust for both cross-subject and cross-experiment predictions.

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Figures

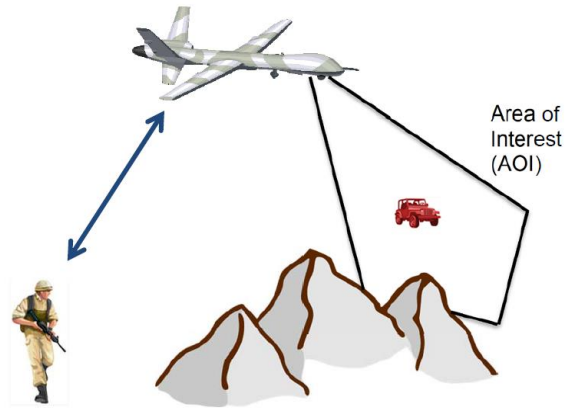


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Figure 2 The acquired Active Two 256-channel Biosemi systems and the EEG lab established at

Design elements – SSVEP-Based BCI

Visual stimulus: flickering squares

- Choose size, position, frequency
- Each flicker encodes a command on target device

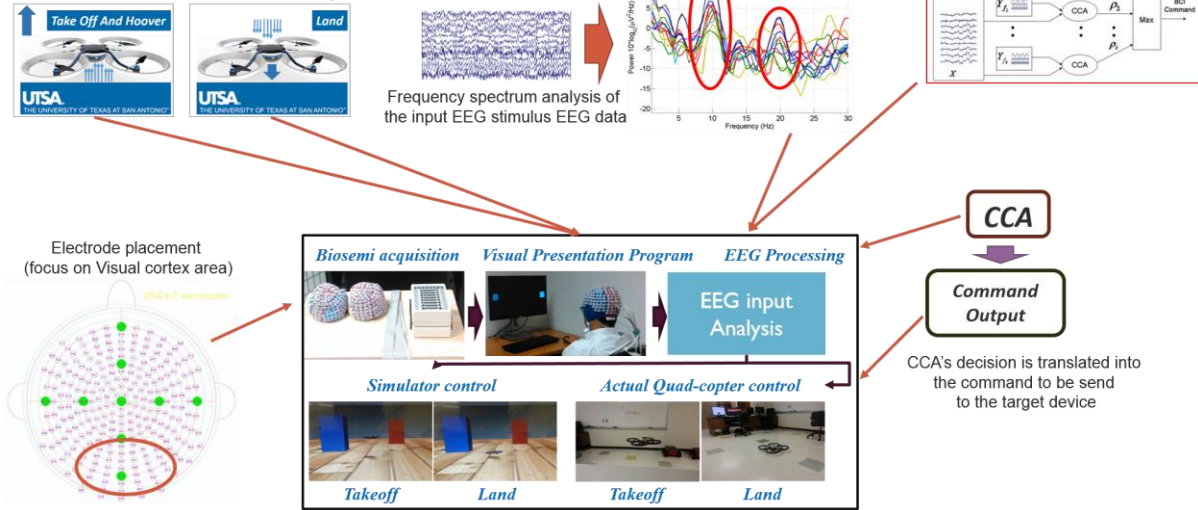
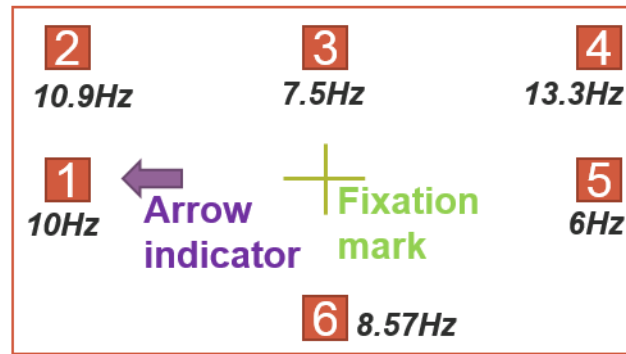
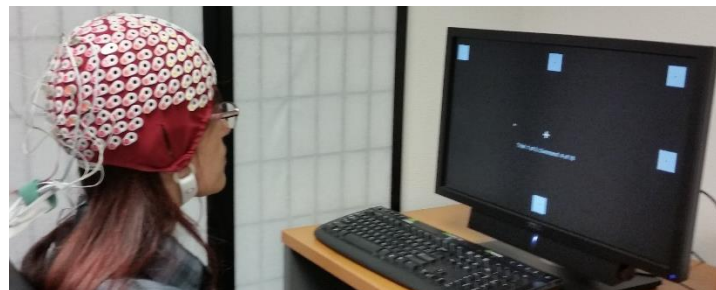


Figure 3 Block diagram of the proposed SSVEP-based brain-controlled UAV system.



(A)



(B)

Figure 4 Illustration in the SSVEP BCI system that implements 6 commands. (A) the arrangement of the flickering and the frequencies. (B) Illustration of a participant looking at flickering visual stimulus in the real system.

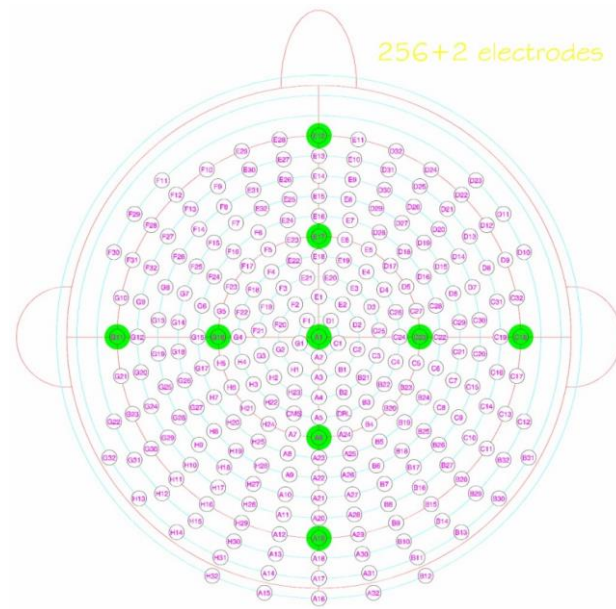


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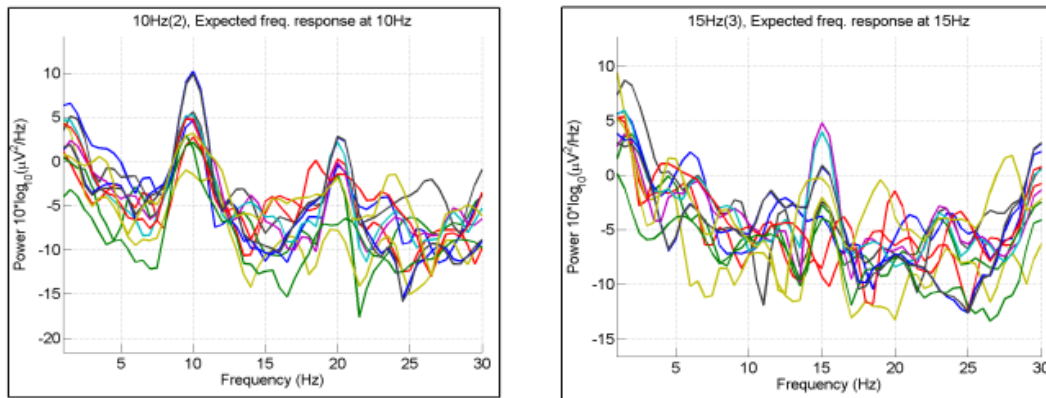


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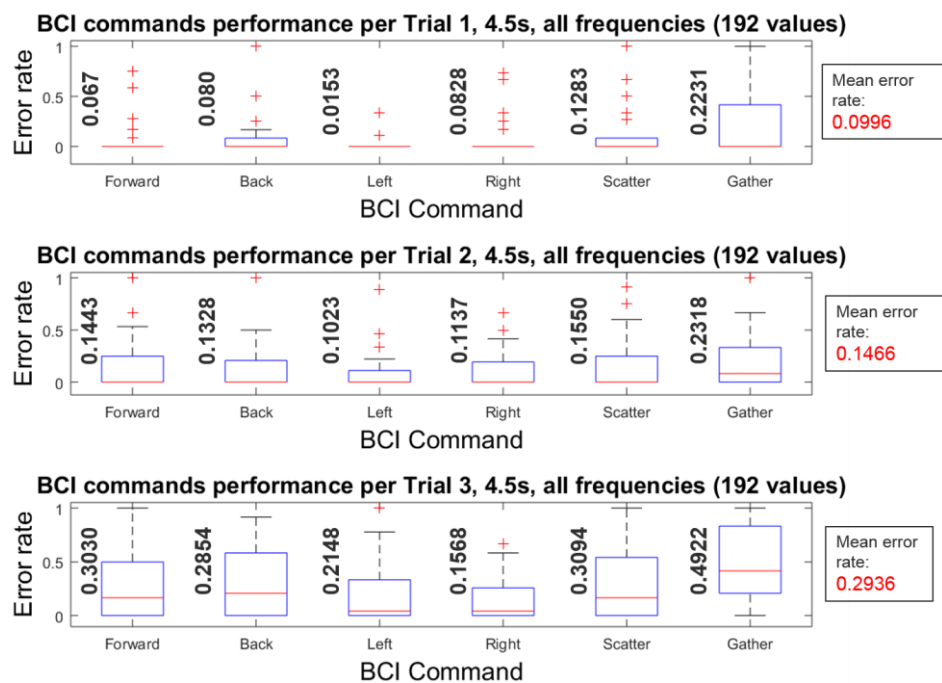


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Figure 8 Screenshots of real demonstration of brain-control quad-copter flight missions.

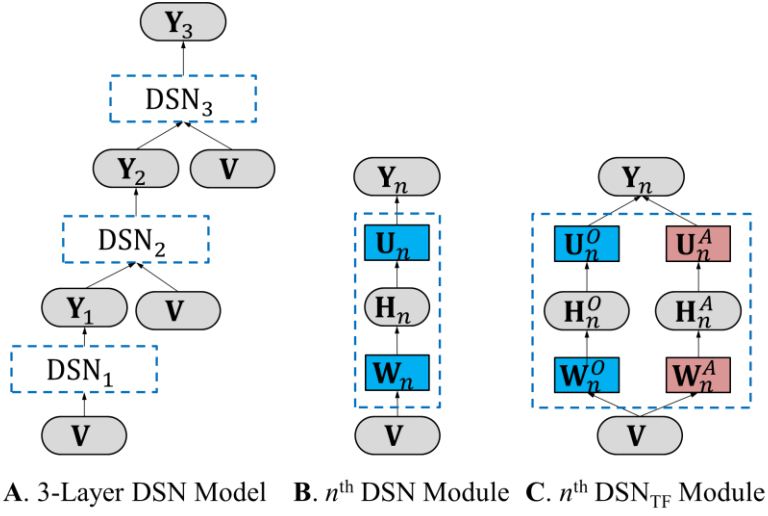


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