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14. ABSTRACT
Brain-machine interfaces (BMIs) have traditionally been designed with paralyzed or locked-in patients in mind with subjects exerting no motor control. However, applicability of BMIs could be significantly expanded if BMIs could be designed for use by able-bodied individuals such as soldiers during normal physical activity. Our ARO-sponsored research systematically investigated this possibility using non-invasive electroencephalographic (EEG) BMIs.

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Report Title

Final Report: Simultaneous BMI and Manual Control in Able-Bodied Subjects

ABSTRACT

Brain-machine interfaces (BMIs) have traditionally been designed with paralyzed or locked-in patients in mind with subjects exerting no motor control. However, applicability of BMIs could be significantly expanded if BMIs could be designed for use by able-bodied individuals such as soldiers during normal physical activity. Our ARO-sponsored research systematically investigated this possibility using non-invasive electroencephalographic (EEG) BMIs.

Our project pursued the following 3 goals:
1. Simultaneous BMI and manual control in virtual environments: We explored virtual reality games in which able-bodied subjects controlled cursors or their own movement using motor imagery while simultaneously using a manual device (keyboard or joystick) to control movement direction or other virtual objects. We measured two aspects of performance: (1) degree of overlap between brain-based and manual control attainable by a subject, and (2) the time course of adaptation in the brain as the subject learns the task.
2. BMI in the presence of force feedback: We explored force feedback in the virtual reality task to move one step closer to real-world applications. A force-feedback joystick was used to test whether subjects can control their own movement or a virtual object using the BMI while simultaneously controlling other properties using the joystick with varying amounts of force feedback from the virtual environment.
3. Co-adaptive BMI for real-world operations. To enable the transition from laboratory to the field, we explored the application of our methods to designing co-adaptive simultaneous BMI and physical control. Feasibility studies were conducted to evaluate the adaptive and augmentative capabilities of these systems in the presence of nonstationarities and noise expected when deployed in the field.

Our results pave the way for the use of BMIs to augment the sensorimotor capabilities of soldiers in the field, contributing to ARO's mission of improving warfighter performance with cutting-edge technology.

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
09/30/2013	15.00	T. Blakely, K. J. Miller, K. E. Weaver, L. A. Johnson, J. D. Olson, E. E. Fetz, R. P. N. Rao, J. G. Ojemann, J. D. Wander. Distributed cortical adaptation during learning of a brain-computer interface task, Proceedings of the National Academy of Sciences, (06 2013): 0. doi: 10.1073/pnas.1221127110
09/30/2013	11.00	Kai J Miller, Christopher J Honey, Dora Hermes, Rajesh PN Rao, Marcel denNijs, Jeffrey G Ojemann. Broadband changes in the cortical surface potential track activation of functionally diverse neuronal populations, NeuroImage, (09 2013): 0. doi: 10.1016/j.neuroimage.2013.08.070
09/30/2013	13.00	Felix Darvas, Rajesh P. N. Rao, Micheal Murias. Localized High Gamma Motor Oscillations Respond to Perceived Biologic Motion, Journal of Clinical Neurophysiology, (06 2013): 0. doi: 10.1097/WNP.0b013e3182872f40
11/03/2012	7.00	Reinhold Scherer, Josef Faller, David Balderas, Elisabeth V. C. Friedrich, Markus Pröll, Brendan Allison, Gernot Müller-Putz. Brain–computer interfacing: more than the sum of its parts, Soft Computing, (07 2012): 0. doi: 10.1007/s00500-012-0895-4

TOTAL: **4**

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

Number of Presentations: 0.00

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

Received	Paper

TOTAL:

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

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

Received		Paper
06/12/2016	10.00	Matthew Bryan, Griffin Nicoll, Vibinash Thomas, Mike Chung, Joshua R. Smith, Rajesh P. N. Rao. Automatic extraction of command hierarchies for adaptive brain-robot interfacing, ICRA 2012. 14-MAY-12, Saint Paul, MN. : ,
06/12/2016	14.00	Willy Cheung, Devapratim Sarma, Reinhold Scherer, Rajesh P. N. Rao. Simultaneous brain-computer interfacing and motor control: Expanding the reach of non-invasive BCIs, 2012 34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 27-AUG-12, San Diego, CA, USA. : ,

TOTAL: **2**

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

(d) Manuscripts

Received		Paper
06/10/2016	2.00	Vibinash Thomasy, Mike Chung└, Joshua R. Smithy, Rajesh P. N. Rao└, Griffin Nicolly, Matthew Bryan└. Automatic Extraction of Command Hierarchies for Adaptive Brain-Robot Interfacing, ( )
TOTAL:		**1**

Number of Manuscripts:

Books

Received		Book
11/03/2012	9.00	Rajesh P. N. Rao. Brain-Computer Interfacing: An Introduction, New York: Cambridge University Press, (02 2013)
TOTAL:		**1**

Received	Book Chapter
TOTAL:	

Patents Submitted

Patents Awarded

Awards

Matthew Bryan (student): Computing Research Association's Outstanding Undergraduate Researcher of the Year (2013)
Rajesh Rao (PI): Fulbright Scholar Award (2014)

Graduate Students

NAME	PERCENT_SUPPORTED	Discipline
Dev Sarma	0.40	
Tiffany Youngquist	0.50	
Jeremiah Wander	0.10	
FTE Equivalent:	**1.00**	
Total Number:	**3**	

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Names of Faculty Supported

NAME	PERCENT_SUPPORTED	National Academy Member
Rajesh Rao	0.10	
FTE Equivalent:	**0.10**	
Total Number:	**1**	

Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED	Discipline
Michael Chung	0.50	
Matthew Bryan	1.00	
Joseph Wu	0.50	
FTE Equivalent:	**2.00**	
Total Number:	**3**	

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: 3.00

The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:...... 3.00

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):...... 3.00

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:...... 1.00

Names of Personnel receiving masters degrees

NAME

Total Number:

Names of personnel receiving PHDs

NAME
Jeremiah Wander

Total Number: **1**

Names of other research staff

NAME	PERCENT_SUPPORTED

FTE Equivalent:
Total Number:

Sub Contractors (DD882)

Inventions (DD882)

Scientific Progress

Statement of the problem studied

Considerable progress has been made in brain-machine interfacing over the past few years: humans and animals have been shown to be capable of controlling cursors, spellers, prosthetic arms, and mobile robotic devices directly through brain signals [1-15]. Almost all of this research has focused on the goal of restoring communication and motor control in paralyzed and disabled individuals.

In contrast, our ARO-sponsored project investigates whether able-bodied subjects can operate a brain-machine interface (BMI) while at the same time being engaged in physical activity. The ability to operate a BMI while at the same time manipulating objects with both hands could, for example, significantly augment human capabilities and expand of the realm of applications of BMI technology.

Our approach has focused on non-invasive brain-machine interfacing based on electroencephalography (EEG). The specific BMIs we have developed are based on the detection of oscillatory sensorimotor EEG activity induced by motor imagery, i.e., imagining the movement of specific body parts such as a hand or a finger. Several neurological and imaging studies have suggested that motor execution and motor imagery may share similar neural areas [16,17,18]. This raises the possibility that parallel execution of motor commands and motor imagery might be limited. However, many subjects experience the phenomenon of abstraction, wherein, after sufficient practice with a BMI, the subject reports no longer using explicit motor imagery but instead reports directly controlling the object [16]. This phenomenon is similar to the abstraction of other motor skills in humans involving parallel execution of multiple motor programs, such as being able to walk while talking on the phone. These differences between imagery and movement-related activation could be exploited for simultaneous BMI and manual control.

Summary of the most important results
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1. Simultaneous BMI and manual control

In results presented at the IEEE Engineering in Medicine and Biology conference [19], we demonstrated for the first time that able-bodied human subjects can control a cursor in two dimensions by simultaneously using BMI and manual control.

Subjects performed a set of BMI-only blocks and a set of BMI + manual control blocks. In BMI-only blocks, either the top or bottom target was shown. The subject used motor imagery to move the cursor up, and rested (no motor imagery) to move the cursor down. During the simultaneous BCI + manual control blocks, one of the corner targets was shown. The subject used imagery to move the cursor up or down, and a joystick to control left and right cursor movement.

In the performance of 3 subjects on the MI-only and MI+manual control task, most notable was the difference in the simultaneous motor imagery BCI (MI) + joystick condition from the first day to the second. For subjects B and C, their first day was heavily biased toward the top targets (“MI + joystick” in Table 1), indicating active interference from ipsilateral motor control of the joystick. However, on the second day, subjects appear to have learned to overcome this interference from joystick control, balancing the top versus bottom target hits and exhibiting a much higher degree of purposeful control. It is important to note that chance performance in this task is not 50% (up/down) or 25% (four corners task). This is because in the task, a subject had 140 possible movement steps (including along diagonals), with 62 consecutive steps from the origin needed to hit the up or down target. Assuming arbitrary random walk, the likelihood of hitting either the up or down target in the time allotted (6 secs) is extremely low.

The results from our project suggest that subjects are able to learn to use motor imagery to control one degree of freedom while using a joystick to control the other. In other experiments, we have also explored simultaneous control in more realistic scenarios where the subject is not only moving through an environment but also using manual control to operate handheld devices.

Our results are to our knowledge the first rigorous scientific investigation of the extent to which healthy human subjects can engage in physical activity while simultaneously exerting control on objects using a brain-machine interface. Past BMI research has focused almost exclusively on BMI in the absence of physical movements because the targeted applications were clinical and aimed at helping paralyzed patients. Our ARO research opens the door to potential use of BMIs by healthy individuals during normal day-to-day activities, thereby vastly increasing the range of applications of BMI technology.

2. Learning and Adaptation in BMIs

In a paper published in the Proceedings of the National Academy of Sciences [20], we have explored how the brain adapts

when learning to use a BMI. Seven subjects were implanted with electrocorticography (ECoG) electrodes and had multiple opportunities to practice a 1D BCI task. As subjects became proficient, strong initial task-related activation was followed by lessening of activation in prefrontal cortex, premotor cortex, and posterior parietal cortex, areas that have previously been implicated in the cognitive phase of motor sequence learning and abstract task learning. These results demonstrate that, although the use of a BCI only requires modulation of a local population of neurons, a distributed network of cortical areas is involved in the acquisition of BCI proficiency.

3. Probabilistic co-adaptive brain-computer interfacing

In a paper published in the Journal of Neural Engineering [21], we introduced a new approach to brain–computer interfacing based on partially observable Markov decision processes (POMDPs). POMDPs provide a principled approach to handling uncertainty and achieving co-adaptation in the following manner: (1) Bayesian inference is used to compute posterior probability distributions ('beliefs') over brain and environment state, and (2) actions are selected based on entire belief distributions in order to maximize total expected reward; by employing methods from reinforcement learning, the POMDP's reward function can be updated over time to allow for co-adaptive behaviour. We illustrated our approach using a simple non-invasive BCI which optimized the speed–accuracy trade-off for individual subjects based on the signal-to-noise characteristics of their brain signals. We additionally demonstrated that the POMDP BCI can automatically detect changes in the user's control strategy and can co-adaptively switch control strategies on-the-fly to maximize expected reward. Significance. Our results suggest that the framework of POMDPs offers a promising approach for designing BCIs that can handle uncertainty in neural signals and co-adapt with the user on an ongoing basis. The fact that the POMDP BCI maintains a probability distribution over the user's brain state allows a much more powerful form of decision making than traditional BCI approaches, which have typically been based on the output of classifiers or regression techniques. Furthermore, the co-adaptation of the system allows the BCI to make online improvements to its behaviour, adjusting itself automatically to the user's changing circumstances.

Relevance to ARO

Our research is most closely related to the following two goals of the ARO Life Sciences Research Program (Neurophysiology and Cognitive Neurosciences): 1) non-invasive methods of monitoring cognitive states and processes during normal activity, and 2) mind-machine interfaces for optimizing auditory, visual and/or somatosensory display and control systems based on physiological or psychological states.

Our research paves the way for co-adaptive brain-based control of virtual and physical devices during ongoing physical activity, an outcome of considerable relevance to the Army's mission. Being able to operate a BMI in the field could significantly augment a soldier's normal physical and mental capabilities by enhancing perception, allowing non-verbal communication, and attaining a higher bandwidth of control over the immediate environment.

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Technology Transfer