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Information Conveyed Through Brain-Control: Cursor Versus Robot

Dawn M. Taylor, Stephen I. Helms Tillery, and Andrew B. Schwartz

***Abstract*—Microwire electrode arrays were implanted in the motor and premotor cortical areas of rhesus macaques. The recorded activity was used to control the three-dimensional movements of a virtual cursor and of a robotic arm in real time. The goal was to move the cursor or robot to one of eight targets. Average information conveyed about the intended target was calculated from the observed trajectories at 30-ms intervals throughout the movements. Most of the information about intended target was conveyed within the first second of the movement. For the brain-controlled cursor, the instantaneous information transmission rate was at its maximum at the beginning of each movement (averaged 4.8 to 5.5 bits/s depending on the calculation method used). However, this instantaneous rate quickly slowed down as the movement progressed and additional information became redundant. Information was conveyed more slowly through the brain-controlled robot due to the dynamics and noise of the robot system. The brain-controlled cursor data was also used to demonstrate a method for optimizing information transmission rate in the case where repeated cursor movements are used to make long strings of sequential choices such as in a typing task.**

***Index Terms*—Brain–computer interface (BCI), brain–machine interface (BMI), information rates, information theory, neural prosthesis, neurocontrollers, prosthetics, robots, virtual reality.**

I. Introduction

Many types of brain–computer interfaces (BCIs) have been developed for assisting the disabled [1]–[7]. Possible functions include choosing letters to spell words [1]–[4], moving a cursor to select from a menu, and mentally directing the motion of a robot, a wheelchair, or a neuroprosthetic limb [5], [6]. Such diversity of output tasks makes it difficult to compare the performance of one BCI with another. However, letter selection, movement direction, and menu choice can all be quantified into bits—the number of binary digits—or yes-or-no questions needed to specify the action.

Here, we measured the information conveyed with a BCI that uses the firing rates of a population of single cells and multicell clusters recorded from microwire electrode arrays implanted in the motor and premotor cortical areas of rhesus macaques [7]. We compared the information transferred when the cortical signals were used to control a three-dimensional (3-D) virtual cursor versus a six-degree-of-freedom robotic arm (ZeroZebra). In both cases, the task was a 3-D center-out task where the brain-controlled cursor or robot had to move from a center start position to targets that appeared at one of eight corner positions of an imaginary cube. In this analysis, we only evaluated the information conveyed about the intended target and not about the details of the movement trajectory itself. Information about the intended target was calculated at the output end of each system (i.e., the cursor movement and the robot movement) as opposed to the input end (i.e., the information imbedded in the cortical activity itself). Although information may be encoded in many aspects of the cortical activity, some of that information will be lost when using simplistic algorithms to translate cortical activity into 3-D movements. Additional information will be lost when the calculated 3-D movements are further translated into physical movements due to variability and noise in the physical system. Here, we calculate the information about intended target conveyed through the brain-controlled cursor and robot to compare the *functional* information transmission rate through each of these complete systems.

Georgopoulos and Massey [8] have shown that more information about intended target direction can be obtained from neural activity of the motor cortex than from the actual arm movement itself during the initial part of the movement. This suggests that information is naturally lost through the motor system during volitional movement. This also suggests that, if enough motor cortex cells are used, controlling a computer cursor directly from the motor cortex may produce more accurate movements than controlling a cursor by physically moving a mouse. In the Georgopoulos study, motor cortex information was calculated by predicting intended targets from a population vector [9] that combined the simulated activity of up to 253 motor cortex cells. Their results showed that the information conveyed by the population vector exceeded that conveyed by arm movements once the number of cells used in the population vector reach between 40 and 50. Their simulated cell activity was modeled after cells which where recorded one at a time using a movable electrode. These acute electrodes allowed them to optimally place the electrode near each cell body and record large well-isolated waveforms. The recording quality is likely to be lower in chronic cortical implants where arrays of electrodes are fixed in place. With chronic electrodes, the recorded cell waveforms are often poorly isolated or too small in amplitude to be completely separated from the system noise. Therefore, the number of recorded units needed to exceed the information conveyed with actual arm movements is likely to by higher with chronic implants than what the Georgopoulos study suggests. In our study, cursor and robot movements were controlled by the activity of 39 ± 2 cortical units which consisted of a more typical sampling of the quality of recordings seen in fixed chronic implants.

II. Methods

In the first experiment, rhesus macaques controlled the 3-D movements of a cursor in a virtual workspace while both arms were restrained. The animals' cortical activity was translated into cursor movements in real time. Full details of the experimental design and cortical decoding algorithm have been reported elsewhere [7].

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D. M. Taylor was with the Bioengineering Department, Arizona State University, Tempe, AZ 85287 USA. She is now with the Cleveland VA Medical Center, Cleveland Functional Electrical Stimulation Center, Cleveland, OH 44109 USA (e-mail: dxt42@po.cwru.edu).

S. I. H. Tillery is with the Bioengineering Department, Arizona State University, Tempe, AZ 85287 USA (e-mail: Steve.HelmsTillery@asu.edu).

A. B. Schwartz was with the Bioengineering Department, Arizona State University, Tempe, AZ 85287 USA and also with the Neurosciences Institute, La Jolla, CA 92121 USA. He is currently with the Department of Neurobiology, University of Pittsburgh, Pittsburgh, PA 15238 USA (e-mail: abs21@pitt.edu).

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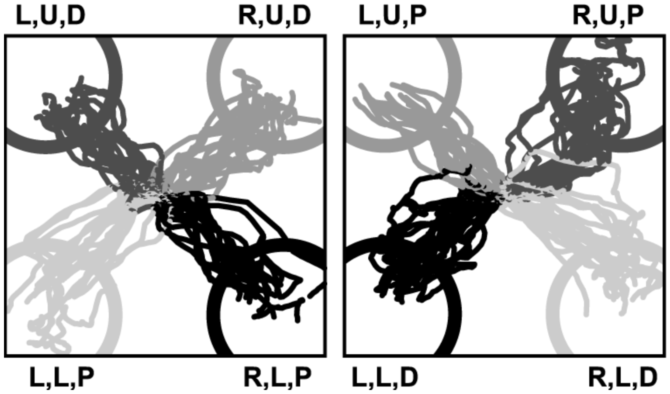

Fig. 1. Examples of brain-controlled cursor trajectories. Trajectories to all eight 3-D targets are plotted in two groups of four for easier viewing. Corner circles indicate target locations. Trajectory shading matches the shading of the intended target. The three letters indicate the 3-D target position in the following order: left-or-right, upper-or-lower, proximal-or-distal.

In a second experiment, a robot was added into the control loop. The animal still viewed the task through the same virtual cursor interface. However, instead of controlling the cursor directly from the brain activity, the robot was controlled directly from the brain activity, and a position sensor on the end of the robot determined the position of the cursor in the monkey's virtual workspace. The monkey did not see the actual brain-controlled robot, but did see the robot's movements via the 3-D virtual cursor.

These series of experiments were designed to evaluate the use of cortical activity for directional control of an upper-limb neural prosthesis. Therefore, the task required that the subjects make trajectories to each target and hold the cursor or robot at the target to get a reward. Although this is appropriate for evaluating the naturalness of the hypothetical prosthetic limb movement, these full trajectories resulted in the transfer of redundant information about the intended targets. Enough information was usually conveyed early on in the trajectory to determine the intended target well before reaching it. In this type of task, with a limited number of discrete goals, a smart controller could predict the intended target early on in the movement and complete the movement for the subject without the need for further information.

Fig. 1 demonstrates this point. Five minutes of brain-controlled cursor trajectories to all eight targets are shown. In this example, all intended targets could be predicted two-thirds of the way into the movement because there was no overlap of the trajectory distributions after that point. Therefore, three bits of information (which of the eight possible targets) were transmitted in the first two-thirds of the movement. The additional trajectory information would not provide any more information about which target the subject was aiming for (although it did provide qualitative information about the form of the trajectories).

To evaluate the target-related information conveyed over the time course of the movements, predictions of intended targets were made at 30-ms intervals along each trajectory recorded from 15 days of brain-controlled cursor data and six days of robot data from one animal (about 15 min/day). At each time interval, the intended target was predicted using two different methods. The first method assumed the closest target was the intended goal. Therefore, classification boundaries were equally spaced between neighboring targets. However, on some days, trajectories to one or more targets showed a consistent curvature or would consistently hit one side of a target over the other. Therefore, shifting the classification boundaries to reflect these consistent deviations should result in greater prediction accuracy. In the second method, target predictions were made by first defining a "typical" movement path for each target, then placing the classification boundaries equal distance between these paths. These "typical" movement paths were calculated as the median of each day's trajectories to each particular target. However, in order to avoid the unfair advantage of including the trajectory that is being classified in the calculation of its own classification boundaries, these boundaries were recalculated for each trajectory with that particular trajectory eliminated from the boundary calculation.

Information theory [10], [11] was used to measure average information conveyed each day at various stages of the movement. For a system with eight possible discrete targets, the average information conveyed about the target can be calculated as

$$I = \sum_{Tp=1}^{8} P(Tp)\left(S[Ta] - S[Ta|Tp]\right) \tag{1}$$

where I is average information conveyed about the intended target, $P(Tp)$ is the probability of predicting target Tp, $S[Ta]$ is the entropy in the distribution of actual targets, and $S[Ta|Tp]$ is the entropy of the conditional distribution of the actual targets, Ta, given the predicted target was Tp.

The two entropy terms are defined as

$$S[Ta] = -\sum_{Ta=1}^{8} P(Ta)\log 2\left(P(Ta)\right) \text{ and} \tag{2}$$

$$S[Ta|Tp] = -\sum_{Ta=1}^{8} P(Ta|Tp)\log 2\left(P(Ta|Tp)\right). \tag{3}$$

Here, $P(Ta)$ is the probability of the actual target being Ta. In the case where all eight targets are equally likely, this would simply be 1/8, and $S[Ta]$ would equal three bits. $P(Ta|Tp)$ is the conditional probability that the actual target was Ta given the target predicted by the observed trajectory was Tp.

This form of the information equation is a weighted average of what is learned about the actual target when each of the eight targets is predicted from the observed trajectories. The entropy term $S[Ta]$ measures the number of bits needed to describe the full range of the possible intended targets Ta. The term $S[Ta|Tp]$ measures the number of bits needed to describe the more limited range of possible values of Ta given that target Tp is predicted. The difference between the two is the information gained about Ta by the prediction of target Tp. The information gain from predicting each specific target Tp is then weighted by the probability of actually getting a prediction of Tp. These values are then summed across all possible targets to get the average information conveyed about the intended targets.

Finally, in addition to movements to the eight corners of a cube, both the brain-controlled cursor and robot were used in a task that required movements from the center to random target positions throughout the workspace, and then back to the center start position. This was done to verify that the control algorithm, which was optimized for the eight-target center-out task, would also allow the subject to make movements to all parts of the workspace and make 180° real-time changes in movement direction.

All experiments were approved and monitored by Arizona State University's Institutional Animal Care and Use Committee. The guidelines put forth by the Association for Assessment and Accreditation of Laboratory Animal Care (AAALAC) and the Society for Neuroscience were followed.

III. Results

Fig. 2 shows the mean and standard deviation (std) across days of the average information conveyed by the brain-controlled cursor and

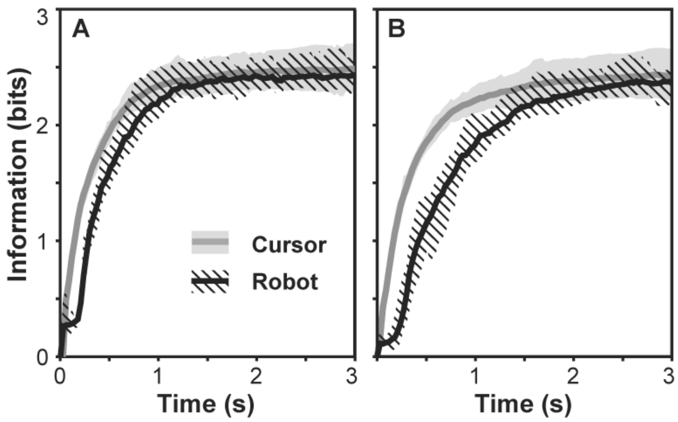

Fig. 2. Average information conveyed about intended target at different stages of the movement. Dark-gray lines (mean) and light-gray areas (std) are from cursor movements (15 days). Black lines (mean) and hatched areas (std) are from robot movements (6 days). Information calculations used classification boundaries based on minimum distance to (a) 'typical' trajectories or to (b) the targets.

robot trajectories at successive time intervals within the movement. The dark-gray lines and light-gray areas reflect information conveyed by the brain-controlled cursor position. The black lines and hatched areas reflect information conveyed by the brain-controlled robot position. For both the robot and cursor movements, using the classification boundaries based on "typical" trajectories [Fig. 2(a)] resulted in a slightly faster gain of information than using classification boundaries evenly spaced between the targets [Fig. 2(b)].

In both the robot and cursor tasks, the total information gained per movement began to saturate around 1–1.5 s into the movement. This demonstrates that most of the information about the intended target was conveyed early on in the movements. Therefore, most information in the later part of each trajectory was redundant and did not provide new information. Each day's average information per movement seldom reached the full 3 b needed to specify which of the eight targets the animal was trying to hit. This is because not all trajectories went to their intended targets. Periodically, the cursor or robot would tend to wander randomly about the workspace. This was most likely due to the animal's occasional inattention to the task since the errors tended to come in blocks and did not show any particular relation to the targets. These blocks were often associated with distracting noises outside the experiment room and/or the animal looking way from the screen. If the target was not hit within 3 s in the cursor task or 4.5 s in the robot task, the cursor or robot would be returned back to the center start position and the next target would appear. The daily average percentage of targets hit was $83 \pm 6\%$ in the cursor task and $92 \pm 4\%$ in the robot task.

For the brain-controlled cursor, the highest information transmission rate, (i.e., the slope of $I(t)$), occurred in the earliest part of the cursor movement. The information gained at this stage was about 1.5 b in 0.275 s (5.5 b/s) when using classification boundaries based on typical trajectories, or 1.5 b in 0.31 s (4.8 b/s) when using classification boundaries based on target distance. The brain-controlled robot had a fairly irregular information transmission rate at the beginning of the movement, but achieved an information transmission rate similar to the cursor once the movement got underway.

In the final tests, where the subject had to move from the center to random 3-D target positions and then return to the center target, the animal was equally successful hitting the new random target positions as it had been hitting the eight well-practiced targets. In addition, the animal readily changed movement directions to return the cursor or robot to the center after hitting an outer target. However, there were qualitative differences in the round-trip trajectories of the cursor versus the robot. Fig. 3 shows examples of these trajectories. The light-gray dots indicate when an outer target was hit. The dark-gray dots indicate when the center target was hit on the return path. Dots are 30 ms apart in time. The robot moved more slowly than the cursor and was allowed more time to complete each movement.

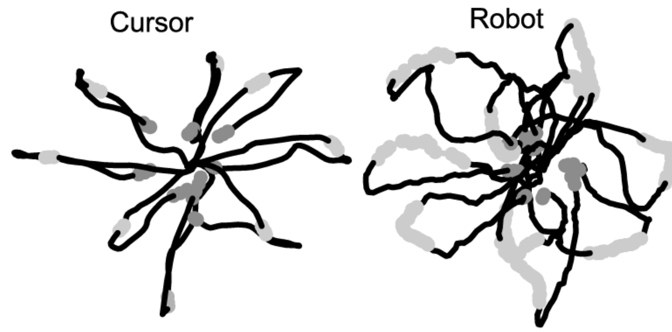

Fig. 3. Examples of robot and cursor trajectories going from the center to the target and back to the center. Light-gray dots indicate when the outer target was hit. Dark-gray dots show when the center target was hit on the return path.

IV. Discussion and Conclusion

In the center-out task, the goal of each movement was simply to get to one of eight possible targets. Reaching the targets could have represented selecting letters or groups of letters in a communication task, selecting options from a menu of environmental controls, or choosing between several predefined hand configurations for controlling stimulation of a paralyzed limb [12]. In this analysis, we were only looking at how much information was transmitted about the intended target. Therefore, the total information could not exceed 3 b because there were only eight targets. However, the initial information transmission rate was 4.8–5.5 b/s for the brain-controlled cursor. It may be possible for a subject to work at this higher information transfer rate in a free-form drawing task which is not defined by a preset number of goals. By identifying this potential information transmission rate and using Fitts' Law [13], one could determine the gain of the system needed to produce the desired accuracy level in free-form brain-controlled movements.

In most BCIs, cursor movement is used to choose between a fixed number of discrete choices. As was shown here, redundant information may be produced if the cursor goal can be predicted fairly accurately before the end of each movement. In BCI tasks where long sequences of selections are made in a row, such as selecting letters in a typing task, shortening duration to minimize redundant information should increase the net information transferred over a longer fixed time period. Shorter duration will allow more selections to be made in a given time period. However, the proportion of those selections that are correct will often also be reduced. In the typing example, cutting movement duration in half could result in typing a two-page letter with five typos in the same amount of time as typing a one page letter with no typos. In spite of the increased percentage of errors, the total information transmitted during that time period will have increased.

A high information transfer rate needs to be balanced against the functional "cost" of this higher percentage of errors (i.e., how important is it to correct the errors and how much time does the correction process take). If the task is to choose between menu options for putting your brain-controlled car into park, reverse, neutral, or drive, then the cost of an incorrect choice could be quite high. In that case, the movement duration should be set long enough to guarantee that all information is received before executing the action. However, if the task is to shoot down alien invaders in a video game where laser direction is under brain-control, then the extra number of incorrect selections (i.e., shooting empty space) at the higher information transmission rate may

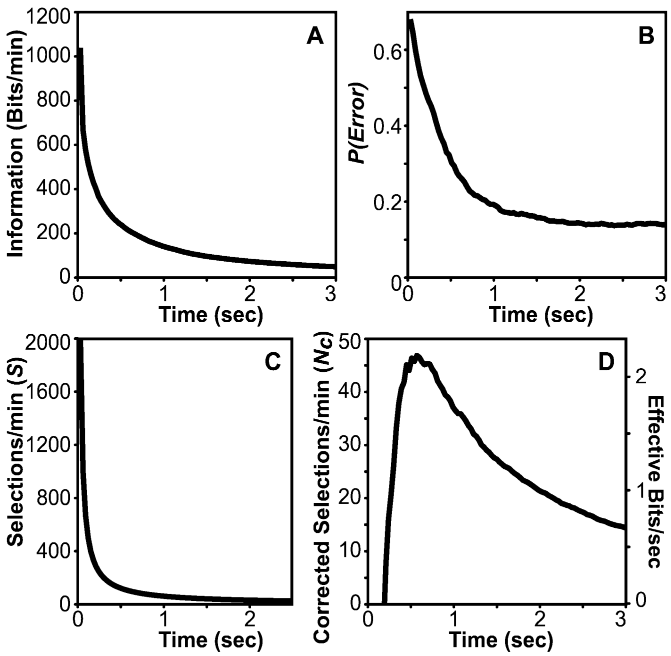

Fig. 4. Movement duration's effect on (a) total information conveyed per minute, (b) proportion of targets incorrectly selected $P(Error)$, (c) number of selections made per minute S, and (d) number of corrected selections made per minute N_c.

have little or no "cost" in the game. Using a shorter duration between firings should still allow more "hits" per unit time giving the player the best chance of saving the earth.

In communication BCIs, where letters or words are selected, the cost of an incorrect selection is simply the extra time it takes to cancel the selection and remake the selection. The process of optimizing movement duration based on functional cost can be demonstrated using the cursor data from the eight-choice task shown in Fig. 2(a) (gray line). Suppose the selection task was to choose between seven choices or a "cancel-previous-selection" option. Then the number of *correct* selections per minute N_c would be approximately

$$N_c = S - (2S \cdot P(\mathrm{Error})) \tag{4}$$

where S is the number of selections per minute, and $P(\mathrm{Error})$ is the probability the selection would be incorrect. $2SP(\mathrm{Error})$ represents the number of movements per minute that did not produce a correct selection. This term is comprised of all incorrect movements, $SP(\mathrm{Error})$, plus an equal number of "cancel-previous-selection" movements. Note, N_c, $P(\mathrm{Error})$, and S, as well as total information, are all functions of movement duration. Fig. 4 plots these functions using the cursor data from the experiment where the intended target was predicted using classification boundaries based on "typical" trajectories. Although the total information transferred is highest at the shortest time durations [Fig. 4(a)], the proportion of incorrect selections is also highest [Fig. 4(b)]. This can be reconciled by understanding that the short duration results in a "noisier" signal, but the speed at which it is sent [number of selections per minute, Fig. 4(c)] more than makes up for the excess noise. The time "cost" of removing the excess noise $-2SP(\mathrm{Error})$ makes the shortest time durations inefficient in spite of the higher information transmission rate. Fig. 4(d) shows N_c, the number of correct selections that could be made per minute once the time to remove the errors is accounted for. In this task, setting movement duration to 0.57 s would be the most efficient way to produce an error-free sequence of choices. At this duration, the subject could make about 47 correct choices per minute with each choice being one of seven options. This is equivalent to correctly typing 47 digits of a base-seven code per minute (equivalent to about 2.2 b/s).

The method shown here is intended to illustrate how to choose a movement duration that will maximize the practical function of a BCI. However, the calculations in this example simply used the proportion of targets missed at each duration. Average information conveyed was never used. Note that the transmission rate of *corrected* bits per second was about 2.2 in this example, where as the actual information transmission rate at the same movement duration was 2.1 b in 0.57 s or 3.7 b/s [see Fig. 2(a)]. This discrepancy can be accounted for by the fact that some of the information is imbedded in the structure of erroneous target predictions. For example, when a target is selected in error, the actual intended target is usually the one nearest the selected target. This information will be lost unless a smart controller makes use of it when correcting erroneous selections.

The 2.2 b/s value calculated previously does not include any additional time that may be needed between movements in order to transition between brain states. In the center-out experiments, we arbitrarily set the intertrial-interval to 500 ms, and included a 200 ms delay between the time the target appeared and the time the cursor was allowed to move. The targets were presented in random order, and this delay ensured the subjects had time to perceive and react to the targets. Including this arbitrary 700-ms delay between selections reduces the maximum corrected information transfer rate down from 2.2 to 1.1 b/s. However, additional studies need to be done to pinpoint the true minimum time needed between movements in order to transition between brain states in the case where the subject knows ahead of time the choice sequence he or she is trying to make.

Less target information was conveyed through the brain-controlled robot than cursor. Although the cursor went exactly where the cortical decoding algorithm dictated, the robot, like virtually all physical systems, had its own dynamics and inherent noise. The robot accelerated more slowly than the cursor resulting in smaller initial movements. Jitter and vibration hindered target prediction most in the beginning of the movements when the trajectories had not yet progressed very far toward the targets. However, once the movement got under way, the information transmission rate of the robot was similar to that of the cursor.

Fig. 3 also demonstrates the effects of the robot's dynamics on the movements. With the brain-controlled cursor, the animal tended to make relatively sharp 180° changes in direction when returning the cursor to the center target. However, when controlling the robot, the animal tended to make wider loops through the targets. The robot's mass and inertial properties may have made it difficult to perform sharp changes in movement direction. However, the animal adjusted to the physical properties of the robot system and was still able to successfully perform the task. This demonstrates that brain-control skills acquired in a computer-based environment can be applied to the control of practical physical devices, although the control strategies may need adjusting, and the quality of the performance may degrade when information is lost with the physical system.

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Multimodal Neuroelectric Interface Development

Leonard J. Trejo, Kevin R. Wheeler, Charles C. Jorgensen, Roman Rosipal, Sam T. Clanton, Bryan Matthews, Andrew D. Hibbs, Robert Matthews, and Michael Krupka

***Abstract*—We are developing electromyographic and electroencephalographic methods, which draw control signals for human-computer interfaces from the human nervous system. We have made progress in four areas: 1) real-time pattern recognition algorithms for decoding sequences of forearm muscle activity associated with control gestures; 2) signal-processing strategies for computer interfaces using electroencephalogram (EEG) signals; 3) a flexible computation framework for neuroelectric interface research; and d) noncontact sensors, which measure electromyogram or EEG signals without resistive contact to the body.**

***Index Terms*—Brain-computer interfaces (BCI), electroencephalogram (EEG), electric field sensors, electromyogram (EMG), neuroelectric interfaces.**

I. Introduction

We define a system that couples the human nervous system electrically to a computer as a neuroelectric interface—a sensing and processing system that can use signals from the brain or from other parts of the nervous system, such as peripheral nerves, to achieve device control. We regard brain-computer interfaces (BCIs) [1] as a subset of neuroelectric interfaces. Our current focus is on using features from electroencephalograms (EEGs) and electromyograms (EMGs) as control signals for various tasks, such as aircraft or vehicle simulations and other graphic displays.

Our long-term goals are to: 1) develop new modes of interaction that cooperate with existing modes such as keyboards or voice; 2) augment human-system interaction in wearable, virtual, and immersive systems by increasing bandwidth and quickening the interface; and 3) enhance situational awareness by providing direct connections between the human nervous system and the systems to be controlled. Our near-term goals include: 1) a signal acquisition and processing system for real-time device control; 2) automatic EMG-based recognition and tracking of human gestures; and c) feasibility testing of EEG-based control methods.

In this paper, we will survey selected results and demonstrations of EMG- and EEG-based neuroelectric interfaces. We will describe an EMG-based flight stick, an EMG-based numeric keypad, an EEG-based interface for smooth, continuous control of motion in a graphic display, and comparison of algorithms for modeling the EEG patterns associated with real and imagined hand motion. Finally, we will discuss recent developments of noncontact electric field sensors for EMG and EEG recording.

Our approach is to describe a body of developmental research, which is still in progress, and to indicate methods that have potential for engineering development. Given the BCI focus of this Special Issue, descriptions of purely EMG-based interfaces will be brief. We will describe the EEG results and the new sensor developments in more detail.

II. EMG Interfaces

A. EMG-Based Flight Stick

In our first demonstration, a computer transformed EMG signals recorded from four bipolar channels placed on the forearm of a subject into control signals for an aircraft simulator. Thus, the processed EMG signals controlled an imaginary flight stick [2]. EMG samples were processed in real time using a flexible signal-processing framework developed in our laboratory. Our feature extraction procedures included routines to filter out redundant and meaningless channels with a mutual information metric [3]. The features were moving averages of the EMG signal from overlapping windows, where the data within a window are nearly stationary.[1] Our model for mapping EMG signal features to gestures uses mixtures of Gaussians within a hidden Markov model context. We tested and validated this system with many trials over a two-year period in three subjects, who flew and landed high-fidelity simulations of a Boeing F-15 Eagle or a Boeing 757-200 freighter aircraft. Control of both aircraft was adequate for normal maneuvers. For the 757, a real-time landing sequence under neuroelectric control was filmed at NASA Ames Research Center (see on-line demos [4] and [5]).

B. EMG-Based Numeric Keypad

We have also found that EMG signals from the arm can distinguish typing of one key from another on a "virtual keyboard." In this demon-

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L. Trejo, K. R. Wheeler, C. C. Jorgensen, R. Rosipal, and B. Matthews are with the NASA Ames Research Center, Moffett Field, CA 94035 USA (e-mail: ltrejo@mail.arc.nasa.gov; kwheeler@mail.arc.nasa.gov; cjorgensen@mail.arc.nasa.gov; rrosipal@mail.arc.nasa.gov; bmatthews@mail.arc.nasa.gov).

S. Clanton is with OEIC, Worthington, OH 43085 USA (e-mail: sclanton@oeic.net).

A. D. Hibbs, R. Matthews, and M. Krupka are with Quantum Applied Science and Research, Inc., San Diego, CA 92121 USA (e-mail: andy@quasarusa.com; robm@quasarusa.com).

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[1]We used overlapping moving averages of the rectified, unfiltered EMG signal, sampled at either 500 (joystick task) or 2000 Hz (typing task). The windows contained 128 points and overlapped preceding windows by 96 points. We tried other types of features such as autoregressive coefficients, wavelets, and short-time Fourier transforms, but the moving averages provided the most robust response for everyday use.