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TOWARD PREDICTING CONTROL OF A BRAIN-COMPUTER INTERFACE

Human-Computer Interaction

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Abstract

Individuals suffering from locked-in syndrome are completely paralyzed and unable to speak but otherwise cognitively intact. Traditional assistive technology is ineffective for this population of users due to the physical nature of input devices. Brain-computer and biometric interfaces offer users with severe motor disabilities a non-muscular input channel for communication and control, but require that users be able to harness their appropriate electrophysiological responses for effective use of the interface. There is currently no formalized process for determining a user's aptitude for control of various biometric interfaces without testing on an actual system. This study presents how basic information captured about users may be used to predict their control of a brain-computer interface that is based on electrical variations in the motor cortex region of the brain. Based on data from 55 able-bodied users, we found that the interaction of age and daily average amount of hand-and-arm movement by individuals correlates to their ability in brain-computer interface control. This research may be expanded into a more robust model linking individual characteristics and control of various biometric interfaces.

Keywords: Brain-computer interface, biometric interface, assistive technology, mu rhythm, control, locked-in syndrome

Introduction

The most severe physical disability, *locked-in syndrome,* is complete paralysis coupled with the inability to speak. Half a million people worldwide are considered locked-in, essentially prisoners in their own bodies (National Organization for Rare Disorders (NORD) 2000). Paralysis and the inability to speak can be caused by a variety of conditions including diseases and injuries such as stroke, Amyotrophic Lateral Sclerosis (ALS), cerebral palsy, Parkinson's disease, and head injury. Even more people have severe motor disabilities that prevent the use of conventional assistive technology (AT) devices to aid communication and environmental control. Augmentative communication and environmental control devices can significantly improve quality of life by facilitating conversations and providing access to television, radio, and comfort controls such as thermostats and light levels in the room. Unfortunately, traditional input devices such as a mouse, keyboard, and switches require small, but consistent, muscle movements.

Developments in biometric interfaces, such as brain-computer interfaces (BCIs) and galvanic skin response (GSR) systems, provide non-muscular input and rekindle hope for restoring communication and environmental control for people with little or no muscle movement but who are otherwise cognitively intact. For example, by using biometric interfaces, people suffering from locked-in syndrome have been able to accomplish tasks ranging from producing reliable yes/no responses (Moore et al. 2004a; Wolpaw et al. 2002) to navigating the Internet (Moore et al. 2004b). The effectiveness of biometric interfaces is, however, limited by the ability of users to provide distinguishable changes in their electrophysiological input in conjunction with the provided control interface. Various factors affect this ability and range from the person's current fatigue level to physiological makeup.

Currently, there is a disparity in goals between researchers and assistive technology practitioners investigating biometric interfaces; researchers focus more on technology characteristics, and practitioners focus more on user characteristics, resulting in available biometric interface technologies often being matched to users through trial-and-error. Unfortunately this approach can waste valuable time and resources, as users sometimes have diminishing abilities or suffer from terminal illnesses. There have been efforts to characterize the degree of controllability of a biometric interface by an individual (Randolph et al. 2005a; Randolph et al. 2005b), but there are no distinct ties between controllability and an individual's characteristics.

The objective of this research is to investigate whether an individual's characteristics may be used to predict a person's ability to control a particular biometric interface. To accomplish this objective, individuals were surveyed for measures of their basic physiological characteristics, such as age and amount of physical activity. These characteristics were then correlated to a measure for strength of control of an electroencephalogram (EEG)-based BCI. The following sections provide further background on BCIs and describe how individual characteristics may be considered for a model to predict control.

Brain-Computer Interfaces

Research in the field of BCIs spans several disciplines including computer science, electrical engineering, cognitive psychology, and neuroscience, all working to discover the most appropriate alternatives for users with severe physical disabilities. There are a number of different types of BCIs available that vary according to the type of electrophysiological signal recorded, method used for recording, and cognitive tasks employed. Most applications target disabled users who are cognitively intact but have such severely limited mobility that system input through physical movement (e.g. using a keyboard, mouse, joystick, switches, or eye-gaze devices) is infeasible. Brain-computer interfaces, therefore, provide non-traditional assistance for controlling computers using neural input. They provide users with capabilities for communication and control of environmental, navigational, and prosthetic devices. As a result, people who might not otherwise have an outlet can interact with their friends and family members and take more proactive roles in their lives. Thus, severely disabled users who are able to effectively utilize BCI technologies experience a significant improvement in their quality of life (Moore 2003). Figure 1 illustrates the continuum of input devices that may be employed when taking the user's physical abilities into consideration.

Figure 1. Modified Continuum of Human Physical Abilities (Moore et al. 2005)
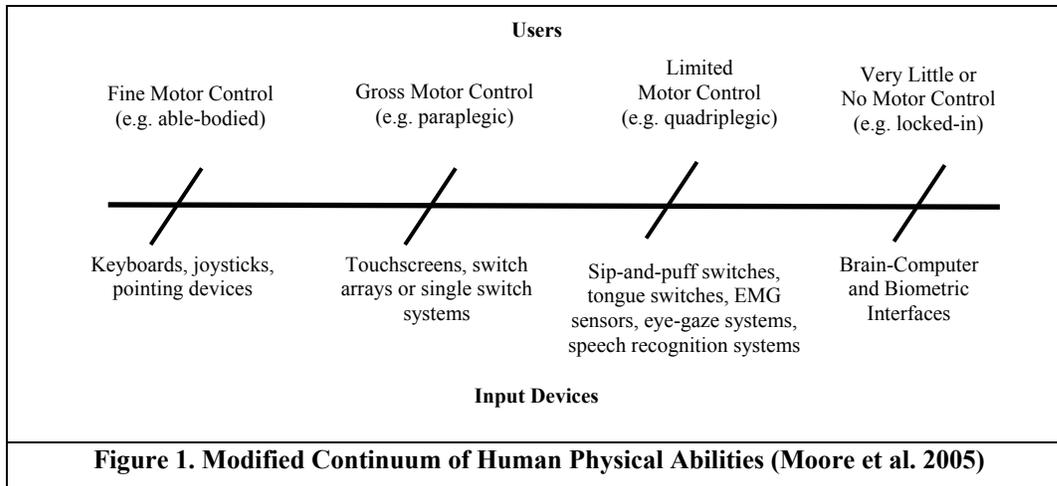
Mu-Based BCIs

In addition to techniques such as magnetoencephalography (MEG), positron emission tomography (PET), and functional magnetic resonance imaging (fMRI), there are various types of electrical brain signals recorded by EEGs that can serve as the input to BCI systems. One such brain signal, the mu rhythm, is based on continuous electrical variations in the motor cortex region of the brain according to real and imagined movement. Other signals include slow cortical potentials, P300 potentials, and beta rhythms. When properly filtered and translated, these signals are output as machine-readable commands to interface with an application or control a device. For example, these signals can be used to move a cursor on the screen and make selections. Mu-based BCIs can take advantage of the difference in signal properties between idle and active imagery within the motor cortex region of the brain to produce a control signal. The proportional difference in signal properties is measured by an R-squared value and indicates the control signal strength or how well the person has control over the particular brain signal (Wolpaw et al. 1994; Wolpaw et al. 1991). The Wadsworth Center in Albany, New York (Wolpaw et al. 2000) has worked extensively with mu rhythms for BCI control, as well as the Georgia State University (GSU) BrainLab (Moore 2003) and the Pfurtscheller team in Graz, Austria (Pfurtscheller et al. 2000).

Since the mu rhythm is associated with movement, we can understand the ties found between the strength of the mu rhythm and a person's physical ability (Tran et al. 2004). However, no one has devised a process to determine users' potential for mu-based BCI control according to their varying levels of physical activity. In this case, we could use the R-squared value as a measure of control by an individual with a mu-based BCI.

Research Method

This exploratory study was conducted post-hoc based on data obtained from screening individuals for training on a mu-based brain-computer interface system. The screening took place in a university lab setting and was conducted by a team of trained researchers.

Subjects

A total of 72 non-trained, able-bodied people underwent screening to begin training on a mu-based BCI system and completed a related initial questionnaire; however, only 55 of these people properly completed the questionnaire for use in analysis. Seventeen of the 72 questionnaires had missing data or contained answer types that were incompatible with the question being asked or difficult to interpret post-hoc. For example, the question may have asked "how much time per day do you spend…" and the subject may have answered "all day" instead of providing a number value. The average age was 23 but ranged from 17 to 52,

and there were 19 males and 36 females involved. Subjects were recruited via word-of-mouth and through university psychology classes. They were compensated with class credit or payment for their time. Able-bodied subjects have been used in similar studies as an indication of ability by individuals with physical disabilities, such as those with locked-in syndrome (Wolpaw et al. 1994).

Experimental Procedure

All subjects began their screening session by answering a paper-based questionnaire, which included demographic information and information related to physical activity. Then, all subjects underwent a procedure to assess which areas of their brains were most active in response to requested imagery and actual movement of hands and feet. Electrical recordings from 64 channels of scalp electrodes were analyzed offline to determine the strength and position of the mu signal measured by an R-squared value and head mapping. These values were then used to calibrate the system to best detect the related mu signal for use in subsequent training with a mu-based BCI.

The screening procedure lasted 35 minutes and consisted of 12, two-minute data runs separated by one-minute breaks. Each run consisted of 15, four-second trials with four-second intertrial intervals. During the trials, a vertical bar was presented on the left or right edge of the screen or a horizontal bar was presented on the top or bottom of the screen and the screen was blank during the intertrial intervals. When a vertical bar was presented, subjects were asked to repeatedly open and close the hand on the same side as the bar or imagine doing so. When a horizontal bar was presented, subjects were asked to repeatedly open and close both of their hands if the bar was on the top of the screen and tap their feet if the bar was on the bottom of the screen or imagine doing so. During the intertrial intervals, subjects were asked to do neither and remain relaxed and at rest.

Subject performance was measured according to the difference between the distribution of mu rhythm amplitudes when the subject was attempting a trial versus when they were at rest. The R-squared value was calculated as the proportion of total variance due to the difference between states. The screening procedures mirrored those used by the Wadsworth Center (McFarland et al. 2000; Wolpaw et al. 1991).

Measures

The researchers administered the questionnaire to subjects at the beginning of the screening session. In our study, we examined four quantitative variables resulting from questions that concerned the subject's age, time spent on typing per day, time spent on activities requiring hand-and-arm movement per day, and time spent on activities requiring most of the body per day for each subject. The difference interpreted between the three degrees of movement (i.e., typing, hand-and-arm, and full-body) is that typing is considered to be fine movement of the fingers, and this is contrasted with playing computer or video games or a musical instrument, which are considered to include larger movements of the hand and arm but still less movement than playing a sport that requires most of the body. Using multiple linear regression, a subject's quantitative answers were then correlated with his or her R-squared value for control signal strength resulting from the subsequent screening process. The R-squared value served as the dependent variable. Subjects with an R-squared value greater than 0.2 were then asked to enroll in training.

Data Analysis

The multiple linear regression technique is widely used for predicting a dependent or response variable based on a number of independent variables or covariates and provides an objective means for assessing this predictive power (Hair et al. 1998). In this study, we apply multiple linear regression to explore the predictive nature of an individual's characteristics on control signal strength. Our proposed regression models take the following general form. If y is the response variable to covariates $x_1, x_2, ..., x_k$, then the multiple linear regression model for y depending on the given k covariates is defined as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k,$$

where any x_i could be represented as $x_i = x_m \times x_n$, constrained to $1 \leq i \leq k$ and $1 \leq m \leq k, \ 1 \leq n \leq k$, and in that case x_i is recognized as the interaction covariate between x_m and x_n.

In the matrix notation above model could be written as, $\boldsymbol{y} = \mathbf{X}\boldsymbol{\beta}$

To check if each regression coefficient has significant impact on the response y or not, we have to first test each coefficient, β_j, where $j=1,2,...,k$, within the model, in order to determine if that individual parameter should be dropped from the model. We do this according to the following tests.

Hypothesis Tests

$H_0 : \beta_j = 0 \rightarrow \beta_j$ can be dropped from the model

$H_a : \beta_j \neq 0 \rightarrow \beta_j$ cannot be dropped from the model with a specific level of significance

Testing Each Coefficient

We have a test statistic as: $\qquad t_{observed} = \dfrac{\hat{\beta}_j}{se(\hat{\beta}_j)}$

where $\hat{\beta}_j$ is the estimated value of the coefficient, β_j, and se ($\hat{\beta}_j$) is the standard error for $\hat{\beta}_j$. Standard error is the estimated standard deviation of the statistic from the sample data. The standard error is calculated as follows,

$$se\,(\hat{\beta}_j) = \sqrt{(MS_{Res} \times C_{jj})}$$

where MS_{Res} = Mean Square Residual = $(\boldsymbol{y'y} - \hat{\beta}\,\boldsymbol{X'y})$ / degrees of freedom

and C_{jj} is the diagonal element of $(\boldsymbol{X'X})^{-1}$ corresponding to $\hat{\beta}_j$.

This test statistic $t_{observed}$ follows a t-distribution with degrees of freedom given by: $df = n\text{-}k\text{-}1$. So, for α level of significance, the p-value for this test is found as:

$$p\text{-value} = 2 \times P(t_{df} \geq t_{observed})$$

The p-value for a test is the probability, computed assuming that the null hypotheses (H_0) is true, that the test statistic would have a value as extreme or more extreme than that actually observed. The smaller the p-value, the stronger the evidence against the null hypotheses provided by the data. If the p-value is so small that it stays outside the limit of the confidence level on the t-distribution curve, then it is considered to be small enough to take the decision. Now, we would reject the null hypothesis, H_0 (i.e., we would drop β_j from the model), if p-value $\leq \alpha$, where α is considered to be the level of statistical significance (i.e., the confidence level is $(1\text{-}\alpha)\%$) (Montgomery et al. 2001).

Results

We used SAS/STAT Software (SAS Institute 2006) to run four different linear regressions using the data from the initial questionnaire. The following describes the four approaches taken and the results of each.

First Approach

We defined our initial regression model containing the covariates only as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4$$

where y = Y_R2 ← R-squared value for control signal strength

x_1 = IQ_AGE ← age

x_2 = IQ_TYP ← typing per day

x_3 = IQ_MOV ← hand-and-arm movement per day

x_4 = IQ_ACT ← full-body activity per day

and β_0 = Intercept

Considering the statistical significance level $\alpha = 0.05$ (i.e., with 95% confidence), we found that only the p-value for β_1, the coefficient for age covariate, was less than 0.05 at a value of 0.0130. Therefore, the coefficient for age was significant at a 5% significance level. Figure 2 illustrates the positive relationship found between age and control signal strength. Figure 2 indicates that while there is no exact linear relationship and the sample data does not have the same number of samples present in the different age groups, an overall pattern of a positive linear band is observable.
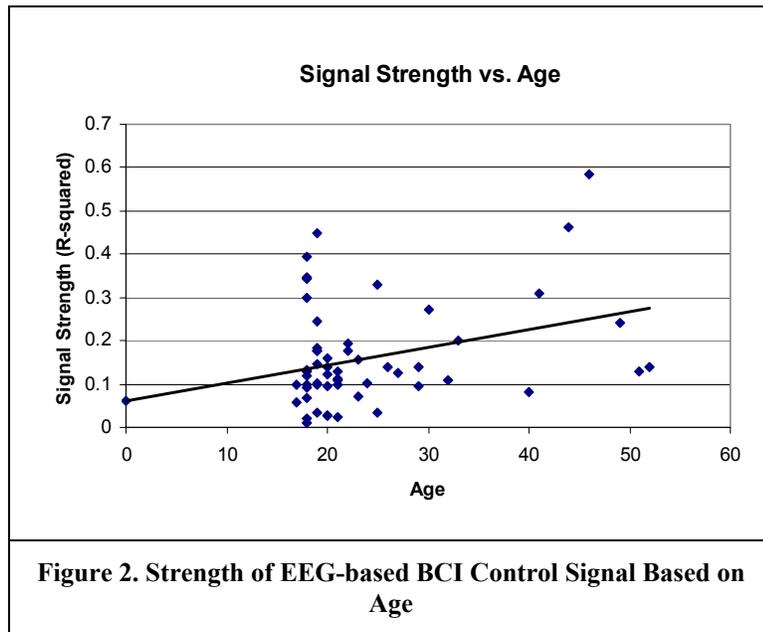

Figure 2. Strength of EEG-based BCI Control Signal Based on Age

Second Approach

We defined our next regression model containing the covariates and the interaction terms of the second degree between them as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_1 x_2 + \beta_6 x_1 x_3 + \beta_7 x_1 x_4 + \beta_8 x_2 x_3 + \beta_9 x_2 x_4 + \beta_{10} x_3 x_4$$

where y, x_1, x_2, x_3, x_4, and β_0 are the same as before and

$x_1x_2 =$ int_AGE_TYP ← the interaction of age and typing

$x_1x_3 =$ int_AGE_MOV ← the interaction of age and hand-and-arm movement

$x_1x_4 =$ int_AGE_ACT ← the interaction of age and full-body activity

$x_2x_3 =$ int_TYP_MOV ← the interaction of typing and hand-and-arm movement

$x_2x_4 =$ int_TYP_ACT ← the interaction of typing and full-body activity

$x_3x_4 =$ int_MOV_ACT ← the interaction of hand-and-arm movement and full-body activity

Here, we found that the p-values less than 0.05 were for β_0 at a value of 0.0355 and for β_6, the coefficient for the interaction between age and hand-and-arm movement per day, at a value of 0.0075. Therefore, the intercept and the coefficient for the interaction between age and hand-and-arm movement per day were significant at a 5% level. Furthermore, the coefficient for interaction between age and hand-and-arm movement per day was less than 0.01 and thus significant at the 1% level, as well.

Third Approach

We defined our next regression model containing the covariates and their second degree and third degree interaction terms as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_1 x_2 + \beta_6 x_1 x_3 + \beta_7 x_1 x_4 + \beta_8 x_2 x_3 + \beta_9 x_2 x_4 + \beta_{10} x_3 x_4$$
$$+ \beta_{11} x_1 x_2 x_3 + \beta_{12} x_1 x_2 x_4 + \beta_{13} x_1 x_3 x_4 + \beta_{14} x_2 x_3 x_4$$

where all variables are the same as before and

$x_1x_2x_3 =$ int_AGE_TYP_MOV ← the interaction of age, typing, and hand-and-arm movement

$x_1x_2x_4 =$ int_AGE_TYP_ACT ← the interaction of age, typing, and full-body activity

$x_1x_3x_4 =$ int_AGE_MOV_ACT ← the interaction of age, hand-and-arm movement, and full-body activity

$x_2x_3x_4 =$ int_TYP_MOV_ACT ← the interaction of typing, hand-and-arm movement, and full-body activity

Considering the statistical significance level $\alpha = 0.1$ (i.e., with 90% confidence), we found that the p-values less than 0.1 are for β_0 at a value of 0.0359 and for β_6, the coefficient for the interaction between age and hand-and-arm movement per day, at a value of 0.0862. Therefore, the intercept and the coefficient for the interaction between age and hand-and-arm movement per day were at a 10% significance level.

Fourth Approach

We defined our final regression model containing the covariates and their second, third, and fourth degree interaction terms as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_1 x_2 + \beta_6 x_1 x_3 + \beta_7 x_1 x_4 + \beta_8 x_2 x_3 + \beta_9 x_2 x_4 + \beta_{10} x_3 x_4$$
$$+ \beta_{11} x_1 x_2 x_3 + \beta_{12} x_1 x_2 x_4 + \beta_{13} x_1 x_3 x_4 + \beta_{14} x_2 x_3 x_4$$
$$+ \beta_{15} x_1 x_2 x_3 x_4$$

where all variables are the same as before and

$x_1x_2x_3x_4$ = int_AGE_TYP_MOV_ACT ← the interaction of age, typing, hand-and-arm movement, and

full-body activity

Considering the statistical significance level $\alpha = 0.06$ (i.e., with 94% confidence), we found that the p-values less than 0.06 were for β_0 at a value of 0.0253 and for β_6, the coefficient for the interaction between age and hand-and-arm movement per day, at a value of 0.0582. Therefore, the intercept and the coefficient for the interaction between age and hand-and-arm movement per day were at a 6% significance level.

Fifth Approach

From the results of the prior approaches, we observed that the interaction term for age and hand-and-arm movement had significant effect throughout the different models. Therefore, we defined a fifth model concerning the response variable, the R-squared value for control signal strength, with only the covariate as the interaction term for age and hand-and-arm movement:

$$y = \beta_0 + \beta_1 x_1 x_3$$

As expected, we found that the p-value for the coefficient concerning the only interaction term in the model was 0.0573, which was at a 6% significance level.

Validation

A stratified random sampling of 35 subjects taken from the original data set was used to validate the correlation between the R-squared strength value and the interaction term for age and hand-and-arm movement using the second and the fifth models presented. To ensure that we had a fair representation of ages in our sampling, we chose each different age as strata, and within each stratum we chose a ceiling of one-half and then randomly selected half the number of available data. We found that the significant effect of the interaction between age and amount of hand-and-arm movement per day and the R-squared value for control signal strength of a mu-based brain signal held with 93% confidence overall for both models.

Summary

Using the multiple linear regression technique, we found that a positive interaction between age and amount of hand-and-arm movement per day had a significant effect (with 94% confidence) on the strength of the EEG-based control signal tested. The second regression approach, which introduced the interaction terms, yielded the best results where the interaction between age and hand-and-arm movement had a significant effect on the control signal strength held with 99% confidence. This was validated using a stratified random sample, which showed the same correlation with 93% confidence.

Discussion and Conclusions

The results of correlating age and varying levels of physical activity with a measure for strength of brain signal control indicate that we can show a significant effect on EEG-based BCI control with high confidence based on a survey of individual characteristics. Interestingly, the resulting positive interaction of age and hand-and-arm movement on control signal strength indicates that as individuals become older and participate in more activities such as playing musical instruments, they may have greater mu-based BCI control. This information may influence rehabilitation procedures for the aging and lead to more efficient screening procedures for helping match locked-in users with appropriate biometric interfaces given their history of activity. This study should help provide a better understanding of individual user characteristics as they relate to biometric interface technologies and move the field a step closer to better design of brain-computer and biometric interface systems.

In the future, researchers should consider the following limitations to this study. First, the characteristics surveyed represent a small subset of individual characteristics; there could be additional characteristics not yet considered that also have significant impact on a wider range of biometric interface control. The characteristics considered here were theoretically tied to the particular type of BCI investigated by being based on levels of physical activity; however, these characteristics may have less of an impact on control when correlated using another type of BCI. Second, the R-squared value used as a measure of strength of brain signal control is just an indication of control of a BCI but may not result in actual control. Systems like the mu-based BCI used in this study still require weeks of training to achieve higher levels of accuracy (Wolpaw et al. 1994; Wolpaw et al. 1991). Additional factors, such as user interface design and motivation, may also have a significant impact on performance. A longitudinal study may be conducted to investigate the effects of initial control strength on long-term BCI control. Finally, repetition of questions and an automated survey would ensure greater consistency of answers from subjects for analysis. Resource constraints discourage observations of the actual activity of numerous subjects, and so we must rely on self-reported data.

Acknowledgements

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