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Adaptive Control and System Identification for Direct Brain Control of Artificial Limbs

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Abstract— **Developing a non-invasive direct brain control of artificial limbs is both challenging and desirable. Such a sensory and control system, if successful, will have profound impact on the disabled. In this paper, we present the design of a control algorithm capable of automatic reconfiguration to account for changing sensor conditions, selection of an appropriate transfer function based on input characteristics, and adaptation to adjust output strength based on the user's activity. This algorithm is designed for use with our developed hybrid non-invasive brain monitoring technique for the purpose of artificial limb control. The development of the algorithm and its initial performance together with our sensory system are presented and discussed.**

I. Introduction

THIS research is focused on the development of a non-invasive sensory system for the purpose of monitoring brain intentions as part of the goal of developing engineering systems to improve the quality of life for the disabled. The sensory system is specifically designed to monitor the motor cortex of the brain to detect control signals for movement of the musculoskeletal system, which can be utilized for actuation of an assistive robotic system or replacement limb to aid individuals with disabilities [1].

In the United States alone, there are an estimated 1.7 million people who have experienced the loss of a limb and many of those lost multiple limbs [2]. An additional 46 million Americans have been diagnosed with arthritis, which is predicted to increase to 67 million by 2030 [3] and 250 thousand individuals have had a spinal cord injury [4]. Assistive devices to overcome chronic disabilities such as these have traditionally been limited due to technology and the complexity of brain, nervous, and motor control. Advancements in this field of research will have a significant impact on millions of people's lives and the demand for these devices continues to grow.

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As medical science has improved, the prevalence of limb loss has increased due to lower fatality rates in accidents and military theaters. Amputation of a soldier's arm or leg can lead to a disability in an otherwise healthy, young individual and is a primary focus of research in this area. While these trends are of major concern, a commercially available system that provides natural mobility has yet to be produced and current research in this field tends to focus on invasive methods of restoring limb functions [5].

Through the combination of electroencephalography (EEG), near-infrared spectroscopy (NIRS), and electromyography (EMG), a non-invasive control system utilizing an adaptive algorithm and feedforward/feedback sensor integration for real-time control of artificial limbs is being developed for monitoring brain activity across the motor cortex (Figure 1).

Through the combination of the temporal response of EEG with the spatial accuracy of NIRS, a non-invasive control system has been developed and further research continues to result in better accuracy using these techniques. Based on the EMG signals from healthy subjects, we are able to adapt the control system to properly correlate EEG and NIRS input patterns to matching muscle activations. NIRS is used as a second feedback loop to continuously adapt the control system and reduce error (Figure 2). This research will hopefully enable people with disabilities to use their brain to directly control artificial limbs and robotic arms to assist them in their daily activities, without going through an invasive surgery. It is without a doubt that many other

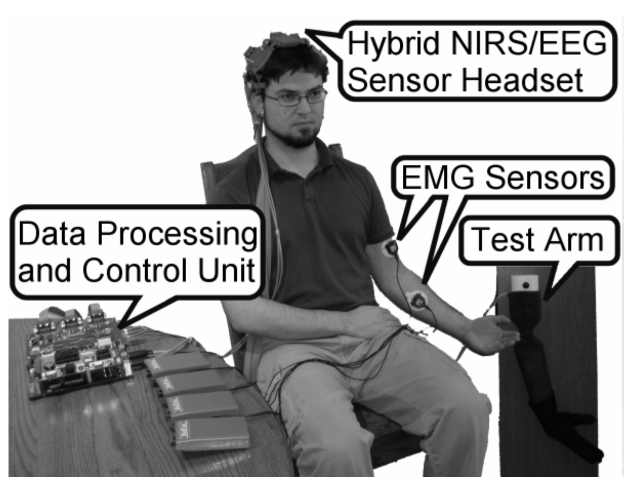

Fig. 1. EEG, NIRS, and EMG Hybrid sensor system for control of an artificial limb.

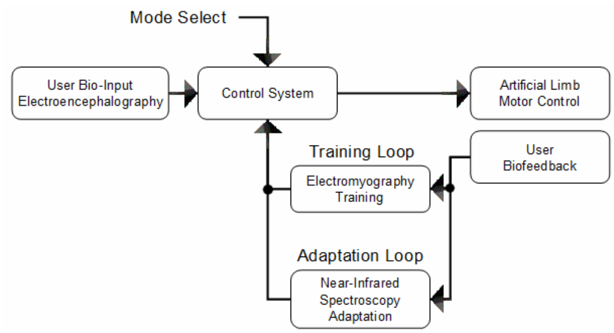

Fig. 2. Control loops for training and adaptation algorithms.

application areas, such as forensics, can benefit from the outcomes of this research [6].

II. TRANSFER FUNCTION CONTROL DESIGN

A. Control System

Prior research by the authors resulted in the design of a control system based on a transfer function design which mapped EEG input signal composition to EMG output strength [7]. This system is designed to mimic the motor control system of the human body, where EEG inputs are transformed into EMG outputs, which in turn are used to drive the motors of the artificial limb. In order to train the system and measure its performance, the calculated EMG outputs are compared to the actual EMG signals measured in healthy individuals. The transfer function is trained by performing a series of generalized arm motions and to achieve accurate control of the artificial limb, the system has to be trained for each new individual and adjusted for each new use in order to obtain similar EEG characteristics. The resulting control system design is described in the following.

The actuators in the test arm are two servo-motors that are position controlled with pulse width modulation. The digital to analog converter that controls this signal works on a scale ranging from 0 to 1023, where 512 is the neutral position for both joints. The output value for each motor is calculated using equation 1. A simple proportional error controller was used for the test arm to limit the rate of actuation. Upon implementing this controller in a system for clinical use, where precision and performance will also be of concern, a more robust controller will be used.

$$P = P + G * (D - P) \tag{1}$$

Where P is the motor position, G is a calculated gain based on the sampling rate, and D is the desired position for each motor. If P is outside of the bounds of the minimum and maximum set for that joint, P is set to the corresponding bound.

The desired position D is set by equation 2 and is the calculated estimate of the EMG values that were used to train the system.

$$D = E_{k1} * E_1 - E_{k2} * E_2 \tag{2}$$

Where E_{k1} and E_{k2} are selected scalar constants based on EMG signal intensity and E_1 and E_2 are the calculated EMG values for opposing sets of muscles corresponding with the selected joint [8]. This functions the same as the human body, where opposing muscle groups produce moments about a joint and the differential of the moments determines the force of the output.

The calculated EMG values are determined by equation 3.

$$E_n = E_t * \frac{\sum_m F_{km} * F_m}{F_t} * \frac{V_k * V}{V_t} * \frac{S_k * S}{S_t} \tag{3}$$

Where F, V, and S represent the FFT, variance, and summation of the EEG input data. The variance is the difference of the maximum and minimum values observed on an input channel during the last 128 samples and the summation is the first index of the FFT for each input channel. E_t, F_t, V_t, and S_t are threshold values for corresponding terms based on maximum values observed during training. F_k, V_k, and S_k are matrices correlating the relationship of each EEG input measure to corresponding EMG output values. The subscript n indicates the EMG channel that the calculation is being performed for and the subscript m indicates the EEG channel. These matrices are normalized prior to use.

B. Training Algorithm

The transfer function is trained by building a correlation between measured inputs and known outputs using the following algorithm. Equations 4-6 are used to train F_k, V_k, and S_k.

$$F_k = F_k + T_k * \frac{E - E_m}{E_t} * \frac{F}{F_t} \tag{4}$$

$$V_k = V_k + T_k * \frac{E - E_m}{E_t} * \frac{V}{V_t} \tag{5}$$

$$S_k = S_k + T_k * \frac{E - E_m}{E_t} * \frac{S}{S_t} \tag{6}$$

Where T_k is a training constant based on the number of data points in the training set, E is the measured EMG, and E_m is a matrix of minimum values observed on each EMG channel.

C. Transfer Function Control System Performance

Tests using a transfer function to calculate desired muscle activity from electroencephalography recordings indicate that this method is suitable for controlling the artificial limb during simple motions. The best results are obtained by training the transfer function using a variety of tasks to create the most diverse mapping of brain activity to muscle activation. The trained constants are then used to calculate motor outputs for the elbow and wrist joints during simple tasks. The system was tested using healthy subject data that had previously been collected. Measured EMG activity during brain monitoring sessions was used to validate the output of the EEG to EMG transfer function.

The motor control based on EEG was very similar to the simulated arm activity generated based on simultaneous recordings with EMG. Motor control in Figure 3 depicts movement of the elbow joint and full range of motion using the transfer function control system during five repetitions of an elbow flexion. Figure 4 indicates that the wrist was flexed as well during bicep curls, as reflected by simultaneous EMG readings indicating the secondary activity took place. In both graphs, the y-axis value represents change from the resting position, with 461 representing full proximal flexion of the elbow, 256 representing full proximal flexion of the wrist, and -256 representing full distal extension of the wrist.

There is a recurring time delay that appears in the correlation between calculated EMG and measured EMG data. This delay is shown in Figure 5, where the delay from peak of measured EMG activation to peak of calculated EMG activation averages 0.57 seconds. This delay is primarily caused by the transfer function utilizing the last one second of data for input parameters. A sufficient amount of indicator data must be present for the net effect of the last one second to correlate to the change in brain activity. This delay is acceptable based on the expectations of the proof of concept but will be addressed once the project has moved into clinical trials.

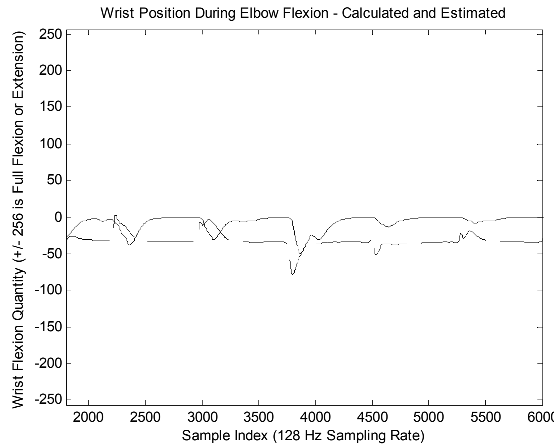

Fig. 4. Measured wrist activity from EMG (Dashed) and calculated values (Solid) during elbow flexion.

III. ADAPTIVE CONTROL DESIGN

To minimize the effect that changes in sensor connection quality have on the transfer function compatibility, the sensor system is recalibrated each time it is used, allowing for the change in signal strength to be the dominating factor and not absolute magnitude. This led to the development of an automated system for establishing system parameters.

A. Automated Transfer Function Selection and Adaptive Adjustment

Two major limitations of the original transfer function training system were the requirement of the system to be trained for each new individual and for values to be selected for the relative effect that each component of the system should affect on the output. The combination of two baseline recordings is used to overcome these limitations. A resting baseline paired with a maximum activation measurement allows for the automated selection of relative weightings as well as the selection of a potential matching trained system selected from a database.

The threshold, minimum, and maximum values that were previously manually set are selected by characterizing the

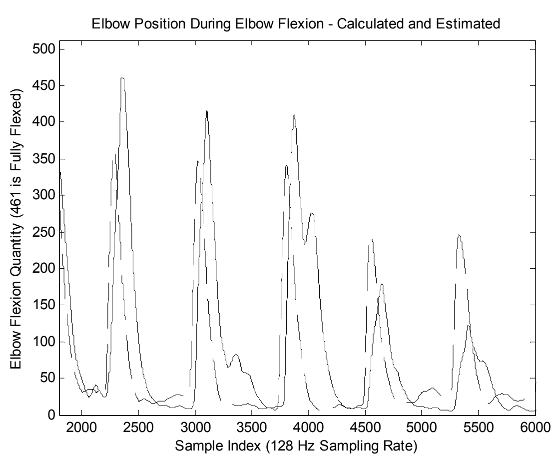

Fig. 3. Measured elbow activity from EMG (Dashed) and calculated values (Solid) during elbow flexion.

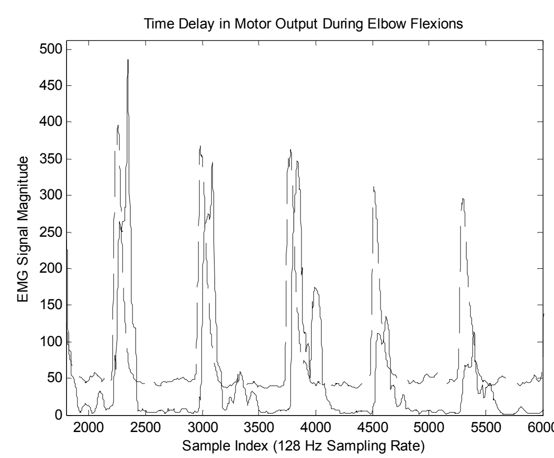

Fig. 5. Measured muscle activity (Dashed) and calculated values (Solid) during elbow flexion.

signal properties automatically. As a result most of the constants that were experimentally determined in the original control system are now automatically calculated at each session based on the baselines, using the components of the data that were originally used to derive those values.

The effect that each calculated EMG value has on the net motor output is also adjusted during the training session. The training activities are assumed to produce maximum flexion of each joint in both directions, therefore the relationship between opposing EMG outputs is modified to achieve a maximum flexion based on the values acquired during the training activity. The value of each EMG channel is recorded at the peak of each activity and stored in the matrix E_t. The values for E_k are then calculated using equations 7-10 to simultaneously solve for the variable sets.

$$E_{k2} = \frac{M_{t1,2} * E_{t1,1} - M_{t1,1} * E_{t2,1}}{E_{t1,2} * E_{t2,1} - E_{t2,2} * E_{t1,1}} \tag{7}$$

$$E_{k1} = \frac{M_{t1,1} + E_{k2} * E_{t1,2}}{E_{t1,1}} \tag{8}$$

$$E_{k4} = \frac{M_{t2,2} * E_{t3,3} - M_{t2,1} * E_{t4,3}}{E_{t3,4} * E_{t4,3} - E_{t4,4} * E_{t3,3}} \tag{9}$$

$$E_{k3} = \frac{M_{t2,1} + E_{k4} * E_{t3,4}}{E_{t3,3}} \tag{10}$$

Where M_t contains the maximum EMG values recorded for each channel.

A second element has also been added to the training algorithms to improve the correlation between input signal strength and net output. Equations 11 and 12 are used to adjust the training matrix values based on the observed error between calculated EMG output and measured EMG for each channel. This adjustment has led to the elimination of using the EEG Summation term in the EMG output calculations since the main purpose of that term was to monitor the relative correlation of the intensity of each input to output.

$$F_{kn} = F_{kn} + T_k * (K_n - E_n) \tag{11}$$

$$V_{kn} = V_{kn} + T_k * (K_n - E_n) \tag{12}$$

Where K_n is the known EMG output and the nth set of elements is modified to better correspond with the nth output.

If the user does not have the ability to attach EMG sensors to a limb, the training exercise is performed with visual stimulus while the user tries to mimic the corresponding output. The artificial limb performs a pre-established set of motions corresponding to the same activities that a healthy subject would have performed during the training session. If the resulting transfer function does not produce desirable results, a pre-trained transfer function may be selected by comparing principle components of the user's baseline data with those in a database of previously trained data and performing a least-squared-error analysis to determine the closest match or an interpolation between two closely matching matrices.

NIRS is used during real-time operation to further adjust the output of the system to better match the activities and desires of the user. The coefficients of the proportional error controller are modified continuously based on the relative brain activity measured through NIRS by making adjustments if there is deviation in relative brain activity compared to motor output. If the NIRS data matches a sustained muscle activity and the recent EEG data isn't producing the same output, the motor transfer function values are adjusted incrementally to adapt the system to better match the desired system output within a bound of values allowing up to two orders of magnitude variation.

B. Adaptive Control Algorithm Performance

Designing the system to calculate all of the required coefficients for training and implementation has resulted in less precise estimation of desired EMG output values (Figure 6), but has produced reasonable motor actuation (Figure 8).

However, further research has lead to the decision to implement a different technique for analyzing the input signals from EEG. Instead of observing each input channel and correlating the characteristics to output data, combining paired sets of sensors into groups and analyzing the difference between channels as well as their average has shown improved results (Figures 7 and 8) [9]. The new control system inputs are obtained with equations 13-16.

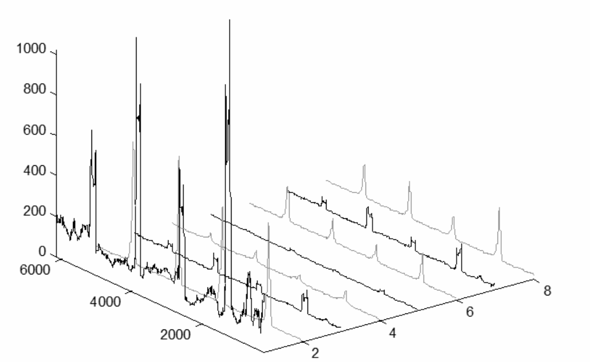

Fig. 6. Calculated EMG values (Black) and Measured EMG Values (Grey) for Each Channel

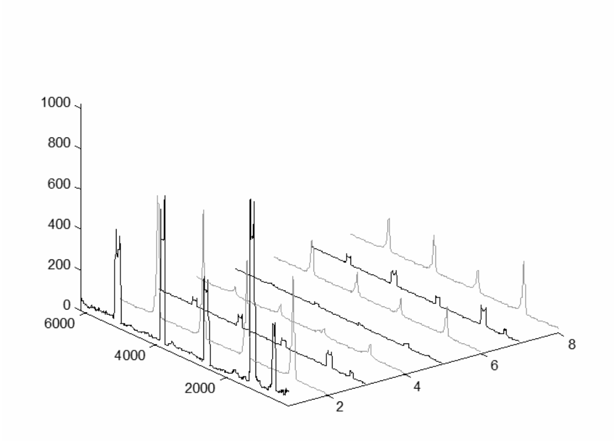

Fig. 7. Calculated EMG values (Black) and measured EMG values (Grey) for each channel

$$F_1' = 512 + \left(F_1 - F_2\right) \quad (13)$$

$$F'_2 = \frac{1}{2}\left(I_1 + I_2\right) \quad (14)$$

$$F_3' = 512 + \left(F_3 - F_4\right) \quad (15)$$

$$F_4' = \frac{1}{2}\left(F_3 + F_4\right) \quad (16)$$

Where F_n' represents the new input used for the control system and F_n represents the original FFT input data from each EEG channel. The values 512 and 1/2 are used to re-center the data on the 0 to 1023 input data range being used.

Figure 8 shows the improvement in activity matching obtained through the difference/average method compared to the original individual channels method. The major activity of the elbow flexion is nearly identical in both cases, but the resting position and sporadic motion in the second method are much improved.

From these results it can be concluded that using the difference and average of corresponding EEG channels is a more effective method for data analysis. While the estimation of EMG activity is similar between methods, the noise cancellation is much improved by this technique.

NIRS is being used in these results to attenuate or amplify the variable gain used for motor control. However, in the limited duration of these results, the cumulative effects of the adaptation algorithm are minor. Extended use should result in a decrease in the actuation speed demonstrated by figure 8.

IV. Conclusion

Based on the results of this study, the combination of EEG and NIRS is sufficient for real-time control of an artificial limb. Training the system through the use of EMG produces the best results, but selection of a previously trained transfer function does produce results sufficient for the current level of system complexity. Additional system customization through the use of baseline reconfiguring and continuous adaptation using NIRS produces sufficient results for typical use.

The next step will be to perform human subject testing with a larger group of healthy volunteers to begin collection of a wide variety of training data as well as make final refinements to the control system design. Additional degrees of freedom may be able to be utilized upon the level of success observed during the healthy subject trials. Once a sufficient amount of data has been collected, the device should be ready for clinical trials as the quality and functionality of the output device are improved.

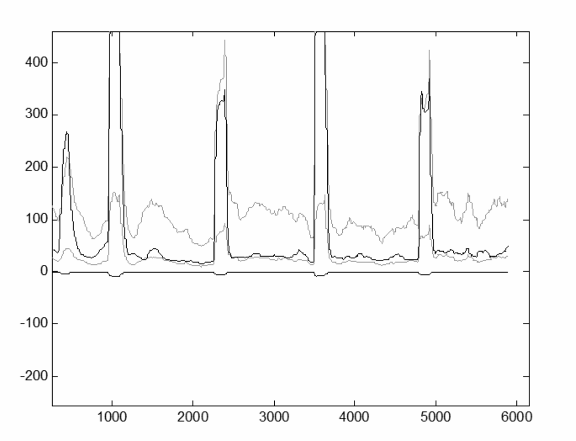

Fig. 8. Motor position for original method (Grey) and difference/average method (Black)

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References

[1] Network. "Assistive Technology Act of 1998." See also URL http://www.section508.gov/docs/AT1998.html June 14, 2010.

[2] Kathryn Ziegler-Graham, PhD, et al. "Estimating the Prevalence of Limb Loss in the United States - 2005 to 2050," Archives of Physical Medicine and Rehabilitation 89 (2008): 422-429.

[3] Center for Disease Control and Prevention. "Arthritis – At A Glance 2009." See also URL http://www.cdc.gov/nccdphp/publications/aag/pdf/arthritis.pdf October 02, 2009.

[4] The National SCI Statistical Center. "Spinal Cord Injury Facts and Figures at a Glance." See also URL https://www.nscisc.uab.edu February 2010.

[5] Defense Sciences Office. "Revolutionizing Prosthetics." See also URL http://www.darpa.mil/dso/thrusts/bio/restbio_tech/revprost/ March 14, 2010.

[6] Puranik, D.A., Joseph, S.K., Daundkar, B.B., Garad, M.V. (2009). "Brain Signature profiling in India. It's status as an aid in investigation and as corroborative evidence – as seen from judgments." Proceedings of XX All India Forensic Science Conference, 815 – 822, November 15 – 17, Jaipur.

[7] Shoureshi, R., Aasted, C., Sarusi, B. "Non-Invasive Hybrid Sensory System for Direct Brain Control of Artificial Limbs." Proceedings of the ASME 2010 Dynamic Systems and Control Conference, 1-8, September 12-15, 2010, Cambridge, Massachusetts.

[8] Winter, David A., Biomechanics and Motor Control of Human Movement, Wiley, 2005, p 87.

[9] Collura, T. F. "Initial Results with 2-channel EEG and Sum/Difference Mode using BrainScape." See also URL http://www.brainmaster.com/tfc/index_files/Publications/2chanbrainscapes.pdf May 16, 2005.