REAL-TIME MYOCONTROL OF A HUMAN-COMPUTER INTERFACE BY PARETIC MUSCLES AFTER STROKE

Seminar Report

Submitted in partial fulfillment of the requirements for the award of degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

of

APJ ABDUL KALAM TECHNOLOGICAL UNIVERSITY

Submitted By

MATHEWS JOSEPH

Department of Computer Science & Engineering
Mar Athanasius College Of Engineering Kothamangalam

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CERTIFICATE

This is to certify that the report entitled **Real-Time Myocontrol of a Human-Computer Interface by Paretic Muscles after Stroke** *submitted by* **Mr. MATHEWS JOSEPH** *, Reg. No.* **MAC15CS036** *towards partial fulfillment of the requirement for the award of Degree of Bachelor of Technology in Computer science and Engineering from APJ Abdul Kalam Technological University for December 2018 is a bonafide record of the seminar carried out by him under our supervision and guidance.*

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ABSTRACT

Stroke, also called a 'brain-attack' shuts down the brain momentarily. As a result, most patients face short-term paralysis. Their rehabilitation is essentially training using simulations and computer games based on the micro electric signals from the muscles. Machine learning can be used to simulate more complex movements than traditional electric signal based methods for faster recovery. The electric signals are acquired from the surface of the skin using electrodes. Instead of using individual muscle signals as in conventional methods, eight muscle signals are fed into the computer as labeled movements. Using principal component analysis and linear discriminant analysis classifiers, these signals are classified into four human hand movement types. Once the model is trained, it is used to simulate a game for the patients in real-time. The biggest advantage of this method is that the patients can now realize complex hand movements. Also using the decoded movements, it is possible to use robotic aids.

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LIST OF ABBREVIATIONS

EMG	Electromyography
HCI	Human-Computer Interface
sEMG	Surface Electromyography
DOF	Degree-of-Freedom
LDA	Linear Discriminant Analysis
PCA	Principal Component Analysis
WE	Wrist Extend
WF	Wrist Flex
FG	Fine Grip
PG	Power Grip

Introduction

Stroke is a neurological syndrome which typically includes motor impairments that compromise independent living. Previous animal and human studies demonstrate that post-stroke recovery relies on the quality, duration, and intensity of motor retraining. Rehabilitative strategies that make use of virtual reality environments provide participants with a motivating and engaging experience while they undergo high-volume, repetitive training of the paretic limb. Some systems use a mouse or joystick to facilitate user interaction with simulated objects, while other computer vision-based approaches track and recognize user movements [1].

Over the past decade, bio signal-based approaches have been developed to control human-machine interfaces [4]. For example, signals from contracting skeletal muscle (ie, surface electromyography, sEMG) [2] have been used in robot-assisted rehabilitation. In these BMIs, single degree-of-freedom (DOF) control strategies maps EMG signals from a single muscle onto mechanical properties of the robot. For example, Song and colleagues used the amplitude of the sEMG signal from the paretic triceps muscle to compute torque ratio during continuous extension of the robotic system. EMG signals can also be used to drive interaction with virtual environments via human-computer interface (HCI) [5]. Myocontrol commands generally depend on decoding tasks of the HCI system. A mode of continuous, multi-command control is conducive to matching the many features of advanced virtual gaming simulations that need to be manipulated.

In the context of motor retraining after stroke, the variety of task-specific behaviors that need to be retrained could be matched to control different aspects of the simulation. However, previous work has only explored the possibility of combining different motions or hand gestures for this purpose in neurologically-intact humans . For example, Dr.Young and colleagues classified simultaneous wrist and hand movements [1]. Using their method, any two DOFs could be classified in combination to activate two commands simultaneously.A potential pitfall of using the EMG signal for continous, multi-command control in stroke motor retraining applications involving HCI is the distorted and highly variable sEMG signals characteristic of paretic muscles. A robust method for myocontrol is needed to facilitate effective, user-friendly interaction with the virtual environment. HCIs that allow multiple DOF control have the potential to provide stroke survivors the opportunity to directly sense and decode their movement while interacting with simulated objects in virtual environments.

The central nervous system is thought to simplify the control of its many degrees of freedom by compartmentalizing them into functional units that are known as ”synergies”. There is evidence that these muscle synergies are selected and activated by descending, cortical control signals onto spinal or brainstem networks. It is therefore possible that synergies may be preserved and operant in paretic muscles of humans with cortical lesions. Accordingly, we hypothesized that muscle activation patterns from the paretic arm would allow real-time myocontrol of a HCI. To test this hypothesis, offline and online experiments were completed. During the offline experiment, sEMG signals were collected while wrist rotations (wrist extend, WE and wrist flex, WF) and handgrips (power grip, PG and fine grip, FG) were performed in isolation or combination. For the online experiment, subjects performed a balloon shooter game, requiring multiple commands that were controlled via wrist rotation and hand grip gestures. Results of these experiments demonstrate that sEMG patterns from paretic muscles allow real-time, continuous multi-command control of a HCI.

Related works

Over the past decade, biosignal-based approaches have been developed to control human-machine interfaces. For example, signals from contracting skeletal muscle (ie, surface electromyography, sEMG) have been used in robot-assisted rehabilitation. In these BMIs, single degree-of-freedom control strategies maps EMG signals from a single muscle onto mechanical properties of the robot. For example, researchers used the amplitude of the sEMG signal from the paretic triceps muscle to compute torque ratio during continuous extension of the robotic system. EMG signals can also be used to drive interaction with virtual environments via human-computer interface. Myocontrol commands generally depend on decoding tasks of the HCI system. A mode of continuous, multi-command control is conducive to matching the many features of advanced virtual gaming simulations that need to be manipulated. In the context of motor retraining after stroke, the variety of task-specific behaviors that need to be retrained could be matched to control different aspects of the simulation. However, previous work has only explored the possibility of combining different motions or hand gestures for this purpose in neurologically-intact humans [6].

2.1 Single degree-of-freedom based training

Three different experiments were conducted. Experiments aimed at exploring the characteristics of EMG signals of stroke patients to better understand the potential of EMG-triggered, robotic therapy (robot assistance off) [3]. Experiments were aimed at testing the EMG game under unassisted and assisted conditions (robot assistance off and on, respectively).

Similar to ongoing robot therapy, subjects were seated in a comfortable chair in front of the InMotion2 robot, restrained by a seat-belt with shoulder straps, and had their elbow supported with a padded wooden support attached to the elbow with Velcro straps. They were asked to move the end-effector of the robot in the horizontal plane to targets shown on a video-screen located in front of them. Targets were presented sequentially in a clockwise direction, starting from target North . The sequence was repeated five times. In the unassisted experiments, if a patient was unable to move back to the central target, the therapist gently guided the patient's arm back to the center position.

In all the experiments, electrodes for EMG recording were placed by an occupational therapist according to established recommendations. Subjects who gave informed consent to participate were tested at Burke Rehabilitation Hospital, White Plains, NY. The experiments and informed consent procedures were approved by the Massachusetts Institute of Technology (MIT) Committee on the Use of Humans as Experimental Subjects and the Institutional Review Board of Burke Rehabilitation Hospital.

2.2 Torque based

EMG signals together with the torque signal and the angle signal were inputted through the data acquisition card into the computer. The software has three functions: 1) it generated a control signal and controlled the motor to provide mechanical help through the card, 2) it provided a task to guide the subject and provided real-time visual feedback to the subject during the task, displaying both the target and the actual elbow joint angle on a computer screen placed in front of the subject, and 3) it stored the EMG, torque and angle signals for further analysis. The mechanical part of a robotic manipulator with 1 DOF[1-5] was designed and fabricated for assisting the movement of elbow flexion and extension. The two layers of aluminum plates were connected by four aluminum pillars. The lower plate was fixed to a table. The direct drive brushless servo motor was fixed to the lower plate. The motor was connected to a torque sensor. The other end of the torque sensor was connected to a manipulandum. An orthosis with a semicircular cross section was attached to the manipulandum. The subject's forearm was placed inside the orthosis and straps were used to secure the forearm in place. The manipulandum had a handle that the subject grasped for the experiment. The position of the handle was adjustable according to the length of the subject's forearm. The upper arm was also fastened by a strap to a support mounted on the upper aluminum plate. The orthosis and manipulandum could guide the forearm to rotate with an axis of rotation in line with the motor and the torque sensor [3]. The torque sensor could measure the interaction torque between the manipulandum and the servo motor. The motor was driven by a servo driver. An optical incremental shaft encoder was attached to the motor shaft for measuring the joint angle. For safety reasons, three steps were taken to protect each subject during the experiment. First, two mechanical stops were used to limit the rotation range of the motor. Second, the software program limited the output torque to a preset range of 5 to 5 Nm, and the operation would be stopped if the motor exceeded this range. Third, an emergency stop could be pressed by the subject to break the power supply to the servo motor if needed.

2.3 Multi degree-of-freedom using linear discriminant analysis classifier

Six non-amputee subjects (three males and three females) and two transhumeral amputees who had undergone TMR surgery (one male and one female) completed the following experiment that had been approved by the Northwestern University Institutional Review Board. For non-amputee subjects, six pairs of electrodes were placed equidistant from each other around the circumference of the upper forearm approximately 2 cm distal to the elbow [6]. A ground electrode was placed on the olecranon, away from the muscles of interest. For amputees, eight pairs of electrodes were placed on the biceps and triceps, over both naturally and reinnervated sites. All data were collected using a Delsys (Boston, MA) Bagnoli-16 Amplifier. Signals were amplified to a convenient value through hardware, digitally sampled at 1000 Hz and high pass filtered at 20 Hz using a 3rd order Butterworth filter to reduce motion artifact, and acquired using a 16-bit data acquisition system using MATLAB (The Mathworks, Natick, MA).

For non-amputee subjects, the motions performed while EMG data were collected were hand open/close, wrist flexion/extension, wrist pronation/supination, no motion and all 2-DOF combined motions using these discrete motions [6]. Because transhumeral patients require elbow movements, the motions performed while EMG data were collected for amputees were elbow flexion/extension and all 2-DOF combined motions using these discrete motions. Combined motions involving greater than 2 DOFs were not trained due to subjects reporting difficulty in visualizing such complex motions during pilot data collection, and the impracticality of collecting training data for every combined motion involving more than 2 DOFs. The data collection sessions were guided using visual prompts from custom designed software.

The subjects were instructed to make medium, constant force contractions to the best of their ability. No feedback was provided to the subjects during the data collection procedure. Non-amputee subjects were seated for the entire data collection session, with their arms resting in a neutral position on an armchair. Amputee subjects were also seated with their residual limb in a comfortable position parallel to their torso. Subjects were unconstrained and could move their arm or residual limb freely during data collection if desired. Ample rest periods were provided during the data collection process to prevent fatigue. Each motion class was collected four times, each consisting of a three second contraction.

EMG data were divided into 250 ms windows with 50 ms frame increment where each 250 ms window was provided to the classifier as a single example for the training procedure. The EMG data were represented using four time domain features which were mean absolute value, zero crossing, number of slope sign changes, and waveform length which have been used extensively as a feature set in previous myoelectric pattern recognition literature. Four-fold cross validation was used to test each classification strategy, in that the windows from three of the four contractions of each motion were provided as training, and the windows of a fourth contraction were withheld for testing. This was done such that each contraction was analyzed as the test contraction one time to obtain an average classification across all four repetitions collected. Additionally, a parallel classification strategy trained with only discrete motions was trained and compared to the parallel classification strategy trained with both discrete and combined movements (as described above).

For each of the three classification strategies (see Background), four different DOF configurations were tested on non-amputee subjects. These four DOF configurations, were chosen based on clinical relevance for transradial amputees. The hand DOF is always included as this is a mandatory function; more discrete and combined wrist movements are included in more complex DOF configurations. The most complex configuration allowed for classification of three DOFs, where any movement from two different DOFs could be activated simultaneously. During the data collection for this study, subjects reported that combined wrist movements

(WF/WE with WP/WS) felt unnatural and were difficult to conceptualize and perform. Thus, a second three DOF configuration was tested in this study in which these four combined wrist motions were excluded.

2.4 The role of muscle synergies in myoelectric control

Muscle synergies are studied extensively in neurophysiology as a potential basis for neural control [2]. Multiple studies support the hypothesis that the human motor system directly initiates movement through flexible combinations of muscle synergies . Other studies interpret these patterns as task and biomechanical constraints rather than direct synergies . There is an ongoing debate between the two theories , and perceived muscle synergies cannot currently be proven or disproven to have a neural origin. Regardless of neurological origin, muscle synergies are influential in myoelectric control schemes due to sEMG inputs directly encoding muscle activation timing, shape and intensity [2]. The imperfect ability to consistently measure muscle activations with sEMG has been well documented . Factors such as muscle depth and thickness, innervation zones, quality of skin contact, skin impedance, timing and intensity of muscle contractions, and cross-talk from nearby muscles all add variability to sEMG recordings . When recording from multiple muscles to extract synergies, many of these complications are magnified. In addition to traditional concerns for robustness due to transient changes in sEMG signals (e.g. electromagnetic interference, skin perspiration, electrode shift and fatigue) , control schemes implementing simultaneous multifunctional control [1] require extra consideration with respect to electrode placement, potential cross-talk, amplitude cancellation , and the number and selection of muscles .

2.4.1 Electrode placement

Electrode placement influences signal-to-noise ratio (SNR) and amplitude due to the spatial variability of muscle activity. When targeting specific muscles,ideal placement is close to the muscle belly away from innervation zones. However, external forces and changing postures shift electrodes relative to underlying muscles during use. Consistent placement between sessions, both absolutely within and relatively between subjects, makes these effects less significant. Large electrodes and/or multiple recording sites per muscle may also reduce the effects and extract robust signals without requiring ideal placement.

2.4.2 Cross-talk

Cross-talk contributes to exaggerated muscle synergies and unnecessary variability when performing tasks. Although the effects can be reduced, identifying cross-talk may add useful information from small or deep muscles that cannot be recorded directly. Independent component analysis and spatio-temporal filters are capable of extracting individual muscle activities from sEMG signals to separate cross-talk as well as any interference from other electrophysiological signals.

2.4.3 Amplitude cancellation

Amplitude cancellation increases at higher activation levels, underestimating the sEMG activity up to 50contraction . Normalizing signals via maximum voluntary contraction (MVC) reduces this effect, but typically causes overestimation at intermediate activations. However, amplitude cancellation has little effect on onset detection, often preserving muscle activation timing and shape of sEMG patterns to cause minimal impact on detected synergies (see section 3.2).

2.5 Muscle selection

Muscle selection also directly impacts control via muscle synergies. Smaller sets of muscles often overestimate explained variance, forming incomplete synergy sets and threatening precision controls. Increasing the number of muscles, selecting dominant muscles from a master set of synergies, or approximating dominant muscles with major muscles can each help maximize precision. Extracting more information through multiple sEMG sites assists with each of the above challenges to effectively characterize natural synergistic muscle behavior. This information can generally be described by linear combinations of muscle synergies which form complex mappings between the synergy and its effect on a limb. Thus, feature extraction from incoming signals is essential to provide descriptive synergistic inputs to a control scheme depicting these mappings.

2.6 Surface electromyography feature extraction

Ideal feature extraction converts a set of incoming sEMG signals into distinguishable and repeatable descriptors, such as synergies, while discarding irrelevant information. The choice of features is often more influential than the choice of control scheme for achieving efficient performance with multifunctional controls. For instance, features capturing low-intensity, low-frequency components of composite sEMG may capture contributions from deep muscles, which offers more functionality (or noise) compared to feature sets removing this information . Moreover, Berniker et al show that linear controllers based on synergy inputs are capable of similar performance to fulldimensional nonlinear controllers. Accordingly, feature evaluation focuses on clustering within and discrimination between tasks. Hudgins et al established the first benchmark for highly discriminant control schemes using a set of features based on simple time domain statistics to distinguish transient patterns in a single sEMG channel. Since then, many extraction techniques have been proposed to separate more complex, multi-channel systems in which Hudgins' features struggled .

2.6.1 Electromyography features

EMG features extract structural characteristics from each channel individually. These features are categorized into their respective domains of time, frequency and time–frequency. Each domain has been extensively described in previous works [2]. They are simply reviewed here in terms of overall influence on simultaneous control schemes.

Time domain

Time domain features are based on signal amplitude, proportional to number and rate of activation of motor units. A few time domain features, such as zero crossings and slope sign changes, give measures closely related to the frequency domain features discussed below. Most others indicate signal energy, activation level, duration of contraction and a relationship to force output. Pattern recognition-based control schemes often employ variations of Hudgins' original set, while motor-learning schemes compute the linear envelope (full wave rectification and low-pass filtering) for each sEMG channel. However, the features are sensitive to amplitude cancellation and noise from the stochastic sEMG signals. Changing contraction levels are managed by either retraining control schemes or recalibrating MVC each session. Noise sensitivity is reduced by computing features over a segmented window of data or after smoothing the signal with a filter. In both cases, the variance is reduced at the expense of increasing bias and delay in the system, altering the synergies detected and used in the control scheme. Smith et al suggest a window length of 150–250ms, and Kamen and Gabriel suggest a low-pass filter retaining 95% of the total power of sEMG as a tradeoff between robust features and minimal delay. Adaptive filters attempt to completely remove delay using varying time constants or Bayesian probabilities at the expense of additional complexity. As an alternative to windowing and filtering, signal whitening and processing multi-channel signals can help reduce the variance of time domain features without increasing the bias. Thus, autoregressive coefficients, and multivariate autoregressive models are often useful additions to time domain feature sets. Due to the non-Gaussian properties commonly associated with sEMG signals, higher order statistics and information theory measures such as entropy have also been proposed. Although good separators for isometric contractions, they are less reliable in dynamic environments and their computational complexity currently restricts any real-time applications.

Frequency domain

Frequency domain features provide information about the rate and shape of MUAPs. Sliding windows incorporate time into the frequency descriptors to describe non-stationary signals, but the commonly used Hamming window destroys energy information at the beginning and end of each segment. The window size also adds a tradeoff between time and frequency resolution in the descriptors. In addition, a comparison between frequency and time domain features by Du et al found that the increased computational costs of spectral features do not significantly increase classifier performance over select time domain features. However, Khushaba et al recently proposed a set of frequency features describing robust power spectrum characteristics which can be efficiently computed in the time domain. This set shows promise for use in future myoelectric control schemes.

Time–frequency domain

Time–frequency features represent transient as well as steady state patterns from dynamic contractions. Multiresolution analysis with wavelets transforms signals to a high-dimensional sparse domain, revealing characteristics that most other extraction techniques miss. Synergistic patterns between sEMG channels are also more likely to be significant than data represented in the above dense domains. Time–frequency features significantly outperform other feature sets when separating data from dynamic movements. However, the high dimensional domain, abstract features and computational complexity may exclude time–frequency features as an option for some applications. Moreover, the choice of wavelet and partitioning has a dramatic effect on the resulting features. Thus, this domain is rarely used in control schemes.

2.6.2 Synergy features

Synergy features extract information from multiple sEMG channels simultaneously to depict time-invariant synergies representing underlying muscle coordination principles while performing various tasks. Different sEMG patterns are then described by different numbers and composition of synergies. By identifying relative activations between synergistic muscles, synergy features are inherently robust to amplitude cancellation and include both biomechanical constraints as well as patterns from different joints in order to reduce control complexity. Thus, linear combinations of synergy features form complex outputs capable of performance similar to nonlinear models. As more channels are used to collect sEMG information, these features help separate robust synergies from variant muscle activity. Methods for extracting synergy features include feature projection and spatial filtering.

Feature projection

Feature projection techniques transform a multi-channel input space into a lowerdimensional subspace reflecting basic coordination principles between channels. These methods portray the linear instantaneous mixtures of sEMG commonly associated with muscle synergies. Tresch et al evaluate different projection techniques in terms of representing robust synergies. Pure synergies are most common, extracted by transforming raw or linear enveloped sEMG channels, but abstract representations have also been formed by projecting other feature sets to lower dimensions, reducing the feature space for more robust inputs to the control scheme. However, the projection loses information, so synergies must be distinguished from irrelevant information

- Non-negative matrix factorization :Non-negative matrix factorization (NMF) is the most common and expressive technique for extracting time-invariant synergies. NMF prescribes a synergy subspace restricting expressible data points to combinations of each non-orthogonal component. It is commonly used as a descriptive measure of specific time-invariant muscle synergies due to relaxed constraints on orthogonality and statistical independence between each component and relative robustness to noisy data. Ajiboye et al show that NMF can also be used as a predictive measure for motions and configurations. Most recently, NMF is used to directly control 2-DOF and 3-DOF simultaneous proportional controls via linear synergy combinations

- Principal component analysis. Principal component analysis (PCA) describes the major orthonormal activation patterns without imposing restrictions within the space defined by these components. With orthogonality constraints between components, PCA describes a synergy space better than specific synergy components, which has shown useful for simultaneous control schemes. Artemiadis et al use PCA to transform seven and nine channels to twodimensional synergy planes for simultaneous control of an anthropomorphic robot arm along a plane and in three dimensions respectively. Muceli et al applied PCA to control a 4-DOF wrist/hand with more comprehensive and lower-dimensional synergy inputs.Yatsenko et al use a variation of PCA to detect orthonormalized principal bases for a set of contractions to provide an orientation for simultaneous control outputs. Hargrove et al extract task-specific synergies with individual PCA from untargeted muscles susceptible to cross-talk, resulting in significantly reduced classification errors. Before synergies were widely recognized in myoelectric control, Englehart et al compared the performance of PCA on different sEMG feature sets (Hudgins' original time domain (HTD), short time Fourier transform, discrete wavelet transform (DWT), and wavelet packet transform (WPT)) to discriminate between 2-DOF in the arm. While PCA and WPT gave the best performance, applying PCA on HTD significantly improved performance over the original HTD set, demonstrating the advantages of transforming single channel feature data into abstract synergy spaces. Nielsen et al perform a similar analysis with simultaneous control, reaching the same beneficial conclusion. Other control schemes create abstract synergies from DWT and spectral features for more robust classifiers.

- Independent component analysis. ICA projects statistically independent muscle synergies from multiple sEMG channels. It is particularly useful to identify subject-independent synergies dominated by a single muscle to eliminate cross-talk and interference from other electrophysiological signals. Naik et al use ICA to identify static synergies associated with six hand gestures.

- Linear discriminant analysis. Linear discriminant analysis (LDA) projects data into task-specific synergies which maximize between-task variance, whereas unsupervised projections may merge tasks utilizing similar synergies. This effect is seen in when comparing supervised and unsupervised PCA [7]. Chen et al project five distinct sEMG feature sets to an abstract task-specific synergy domain separating nine wrist motions. Although this space can be used directly for simultaneous control inputs, LDA is typically used in its classifier form to predict outputs in a control scheme.

2.6.3 Spatial filtering

Spatial filtering is often used to decorrelate channels, similar to ICA. Though not typically used to extract synergy information, two recent studies have incorporated this concept into robust features encapsulating synergies. Huang et al use spatio–spectral filtering to extract common spatio–spectral pattern features. The method generates artificial channels with delayed signals and simultaneously filters in both the spatial and spectral domain to produce spectral features representing muscle synergies at particular spatial locations. The features outperformed HTD, spectral, and spatial analysis methods in offline analysis. Ison and Artemiadis use spatio–temporal filtering to extract multiresolution muscle synergy features. Each individual feature provides information at a particular temporal and spatial resolution, representing a specific muscle synergy at a given resolution. These synergies, along with the resulting feature space, are sparse, which allows a control scheme to detect meaningful synergy patterns, which were shown to be robust across subjets in a user-independent realtime control scheme. However, the method incurs the same concerns that often prevent time-frequency domain features from being implemented in control schemes.

The proposed method

Biosignals from skeletal muscle have been used to control human-machine interface. Signals from paretic muscles of humans with stroke are distorted and highly variable. Here, we examine the stability of surface EMG (sEMG) features from paretic hand muscles to enable continuous, real-time multi-command control of a human-computer interface (HCI) [5]. Subjects with long standing cortical strokes (¿6 months, n=12) and neurologically-intact controls (n=12) performed two wrist rotations (wrist extend and wrist flex) and two grips (power grip and fine grip) with the non-dominant (controls) or paretic (stroke patients) hand [1]. Data reduction analyses revealed a distinct pattern of coactivation across muscles for each gesture. These synergies were similar for control and stroke groups and stable across sessions. Results of offline experiments involving wrist rotation and hand grips confirmed that gestures performed in isolation or combination were recognized at greater than chance level in both groups. In online experiments, HCI control was evaluated with a balloon shooter game. Users in both groups were able to control the direction and speed of a simulated bullet to a balloon target with greater than chance-level accuracy [5]. Taken together, these results demonstrate that sEMG synergy features from paretic hand muscles can be used to drive continuous, real-time multi-command control of a HCI.

3.1 Method

The proposed method filters and samples the sEMG signals acquired through surface electrodes,and the usinf Principal Component Analysis(PCA) [7],reduces the dimensionality.Then a Linear Discriminant Analysis(LDA) mdoel is trained, Which will be used to predict the subject's intented motion.

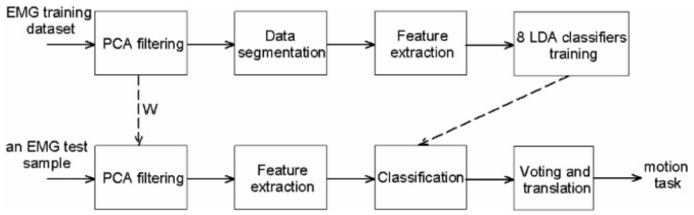

Figure 3.1: Method algorithm

3.1.1 Subject selection

Twelve right-handed, neurologically-intact adults (7 female) and twelve chronic stroke survivors (5 female) with varying degrees of motor impairment participated in this study. Manual muscle testing, a method for evaluating force-generating capacity of a muscle group crossing a particular joint, was used to quantify motor impairment. A 5-point scale was used for scoring, with more severe impairment reflected by a lower score. All subjects gave informed consent to experimental procedures, which were approved by the local ethics committee at the Jinan University and the First People's Hospital of Foshan. The following inclusion criteria were used for patient recruitment:

1) Diagnosis of a single cortical stroke verified by brain imaging.

2) Sufficient cognitive and language abilities to understand and follow instructions

3) Ability to perform the movement tasks with the paretic hand(manual muscle testing score 2).

3.1.2 Surface electromyography data acquisition

sEMG data were recorded from 8 hand and forearm muscles in the left, non-dominant arm of controls and from the paretic arm of individuals with stroke through bipolar disposable Ag-AgCl electrodes secured to the skin over the belly of each muscle(fig 3.2 sEMG electrodes).The skin was cleansed with alcohol before placing electrodes on each muscle. Signals were amplified, filtered (20-2000 Hz), and sampled (1000Hz) using a 16-bit acquisition system (NI USB9002) with MATLAB. The eight hand and forearm muscles included: abductor pollicis brevis (APB), first dorsal interosseus (FDI), abductor digiti minimi (ADM), extensor digitorum (ED),extensor carpi ulnaris (ECU), pronator teres (PT), extensor carpi radialis

(ECR), and flexor carpi ulnaris (FCU). APB, FDI, and ADM contribute to grip. PT and FCU contribute to wrist flexion with ulnar deviation. ECU and ED contribute to extension of four fingers and aid in extension of the wrist. ECR contributes to extension and radial abduction of the wrist.

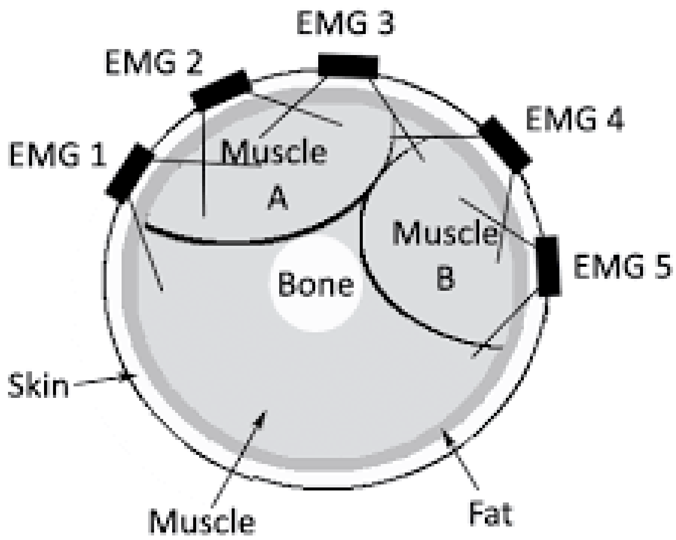

Figure 3.2: sEMG electrodes

3.1.3 Motion tasks and gesture-based control mechanism

The user is instructed to perform wrist rotations (wrist extend, WE and wrist flex, WF) and hand grips (power grip, PG and fine grip, FG) separately or in combination for the sEMG-based HCI system. These gestures are mapped to control commands of a simulated bullet for a balloon shooter game [5]. The graphical user interface (GUI) for the balloon shooter game is shown in Fig 3.3. There is one bullet and six balloons (blue circles) [5]. The following four control commands are used to control bullet trajectory: left turn, right turn, deceleration/shot and acceleration. If WE or WF is detected, then the simulated bullet will turn left or right, respectively. Note that the simulated bullet does not stop during turning. In addition, if PG or FG is detected, then the simulated bullet moves with high speed or low speed, respectively. Note that when the bullet approaches the target balloon, PG is required to command a shot.

3.2 Gesture-based control algorithm

In this subsection, we propose and describe a decision method using synergy features [8] from sEMG to control the simulated bullet through the gesture-based control strategy described above. In this experiment (fig 3.1), subjects performed the abovementioned wrist rotation and hand grips separately or in combination with moderate, isometric contractions to the best of their ability. Before the experiment, subjects completed a pre-training familiarization protocol lasting 5-30 minutes. During the experiment, users were seated with the elbow able to move freely. Before online testing, an offline dataset was collected for classification model training, in which the subject randomly performed ten, three-second contractions of each wrist rotation and hand grip gesture in isolation and in combination (i.e., WF+PG, WF+FG, WE+PG and WE+FG).

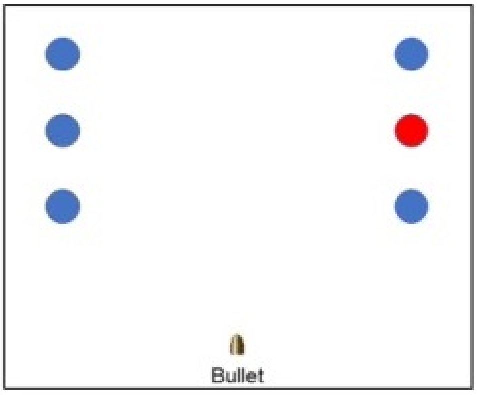

Figure 3.3: Bullet simulator game

Five seconds of rest were given between every two contractions. No feedback was provided during the data collection procedure.Prior to signal processing, we applied motion task-specific decorrelation filters based on principal component analysis (PCA) to find patterns of covariation across the eight muscles and identify muscle synergies. The PCA algorithm projects the original data onto a new coordinate system of lower dimensions such that the first coordinate describes the greatest variance in the data while the last coordinate explains the least variance. In this experiment, analysis of sEMG data demonstrated that the first two principal components accounted for almost 90 percent of the total variance. Consistent with Artemiadis and Kyriakopoulos [4], we used these first two principal components to transform activations of the eight muscles during gestures into the 2-dimensional representation, which is defined as:

$$S = W^T Y \qquad ...(Equ: 3.1)$$

where Wis a 8 x 2 matrix with its columns of the first two eigenvectors resulting from the PCA method and Y is the 8 × n matrix, which is obtained from the matrix of sEMG measurements after subtracting the mean value of each muscle across the n measurements. Thus, the muscle pattern for each hand gesture can be thought of as the weighted combination of eight muscle synergies. After dimension reduction/muscle synergy extraction, data were divided into small segments of 250 ms with 50 ms of overlap, where each segment was used as a single sample for the model training procedure. The acquired samples were converted into four time-domain features including mean absolute value, zero crossing, number of slope sign changes, and waveform length, which have been used as a feature set in previous sEMG pattern recognition literature. These four features of a single sample were concatenated to construct its corresponding feature vector. Using feature vectors, we applied a linear discriminant analysis (LDA) approach to perform classifier training and generalization testing. For the classifier training, feature vectors of the training samples were used to train eight LDA classifiers based on the one-versus-rest method. The purpose of this procedure was to deal with the multi-class classification problem. Specifically, LDA classifiers were trained using the training samples and 8 corresponding scores can be obtained for a sample. For the offline generalization testing, these eight LDA classifiers were applied to the feature vectors extracted from test samples. Hence, eight LDA output scores were obtained. Using a previously described loss-based decoding method, we assigned the test sample a class label of motion task (i.e., WF, WE, PG, FG, WF+PG, WF+FG, WE+PG and WE+FG) corresponding to the maximal score. In addition, for real-time, gesture-based control, a threshold was calculated for the motion task recognition to make the path of bullet more stable and smooth. Using the LDA scores in the training data set, the threshold for the ith motion task can be calculated as in Equ:3.2,

$$Di = mean(s_{i,j}, j \in Ni) \qquad ...(Equ: 3.2)$$

where Ni denote the sample set of the ith motion task in N. During real-time control, eight LDA scores were obtained for a test sample and its class label of motion task was assigned to that corresponding to the maximal score if the maximal score is larger than its corresponding threshold. If not, the class label was assigned to 0 which corresponded to the rest condition. The offline generalization testing classification accuracy, defined as the percent of correct classifications, was used to evaluate classifier performance. The real-time operation phase was commenced after the model was trained. Raw EMG signals are collected and motion-task-specific decorrelation filter is applied, followed by data windowing and feature extraction. Then, motion task was outputted through classification, resulting in the ability to command the bullet for real-time control of a balloon shooter game with the gestures

3.2.1 Principal component analysis

It is an unsupervised dimensionality reduction [7], it is also named the discrete Karhunen Loève transform , and Hotelling transform singular value decomposition and empirical orthogonal function . PCA seeks to reduce the dimension of the data by finding a few orthogonal linear combinations (the principal components PCs) of the original variables with the largest variance. As per the number of the original variables there are as many PCs. The first several PCs explain most of the variance, so that disregarded the rest can be with minimal loss of information, for many datasets. To reduce the dimensionality of the huge data along with retaining as much information as possible in the original dataset, PCA is used. To perform PCA, find the eigenvalues and eigenvectors of the sample covariance matrix. Rearranging the eigenvectors in descending order according to the corresponding eigenvalues, a linear transformation matrix T is formed which generates new vectors from $\tilde{x}$ given by Equ:3.4 as:

$$\tilde{x} = T(x - \mu) \qquad \text{... (Equ:3.3)}$$

The eigenvectors of C are the principal components. In the projected space, the new vectors $\tilde{x}$ are minimally correlated. In order to exploit the dimensionality reduction of PCA, would simply choose the top k(k¡m) eigenvectors of C to form T. This is the common way of choosing the eigenvectors to include in the transformation matrix. An assumption that is made in PCA dimensionality reduction is that most of the information contained in the observation vectors can be adequately represented in the subspace spanned by the first k principal components.

3.2.2 Linear discriminant analysis

Linear Discriminant Analysis (LDA) is supervised dimensionality reduction technique based on a linear projection from the high dimensional space to a low dimensional space by maximizing the between class scatter and minimizing the within-class scatter. LDA is also known as Fisher's linear discriminant. It is mainly used as a feature extraction step before classification and provides dimensionality reduction of feature vectors without loss of information. In LDA for all the samples of all classes, define two measures within-class scatter matrix.

The goal of feature extraction is to reduce the number of features of patterns and retain as much as possible of their discriminatory information. After dimensionality reduction, the classification task, assign feature vector to a predefined class, based on their nature. Feature extraction and dimension reduction can be combined in one step using principal component analysis (PCA), linear discriminant analysis (LDA) techniques, next apply the classifier on feature vectors in reduced-dimension space and perform classification.

Conclusion

Stroke is a major cause of paralysis and cannot be predicted in advance. In most cases it is possible to recover from the state of paralysis. However this depends on the quality and type of training done to the muscles. By using machine learning and combining the muscle synergies, The movement the subject wishes, can be predicted correctly. This realization of accomplishment pushes the recovery period, hence a faster rehabilitation. In addition to the rehabilitation and recovery aid, It is possible to develop robotic aids to the subjects who require it, giving them a possibility of independence.The proposed method can accelerate the recovery and also reduce other complexities including pain and uneasiness associated with the other rehabilitation methods.

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