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General Perspectives on Electromyography Signal Features and Classifiers Used for Control of Human Arm Prosthetics

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INTRODUCTION

Physically handicapped people encounter various kinds of obstacles and difficulties in their daily lives due to the restricted ability of motion. Assistive technologies represent a crucial challenge of scientific studies to overcome such an issue of reducing quality of live. Assistive devices such as wheelchairs, orthoses and prostheses are designed and built to contribute rehabilitation progress and to regain lost functions, as well. Although human body parts have intricate forms and functions, artificial devices and components integrating to the body are anticipated to compensate the fundamental functions related to user's demands. Upper or lower arm amputations also result in severe cosmetic matters. However, what is more important and obtrusive is the loss of primary functions including manipulating and grasping the objects besides the locomotor tasks which are performed by human body during daily activity.

BACKGROUND

Development of human arm prosthetics, which are improved to regain lost functions of amputated limbs, encounters critical and challenging problems to carry out various dexterous tasks. To date, many of revolutionizing design of human arm prosthetics including Boston Arm (Mann & Reimers, 1970), Deka Arm (Resnik, 2010), Otto Bock trans carpal hand (Otto Bock Health Care, Minneapolis, MN), and Shanghai Kesheng Hands (Shanghai Kesheng Prosthese Corporation Ltd.) have been developed. Intuitive and precise control of such prostheses is still one of the main interests of scientific studies. The main deduction from researches could be stated as control of the prosthetics is a particular concern of understanding the nature of the electrical activations of muscles. Imitation of the fundamental patterns of human arm motion depends highly upon the transformation of the neuromuscular activities of residual limbs to a specific control signal for controlling the artificial arm. In this respect, myoelectric signals provide a base of intuitive control, unlike the conventional or direct control. The dexterous control of such myoelectric-based prostheses requires a clear extraction of features from recorded surface electromyography (SEMG) signals and pattern recognition to discriminate the motion and force intentions of the prosthetics users. The progress of feature extraction from SEMG signals has an extensive coverage of myoelectric controlled prostheses studies due to the features in both time and frequency domains have the great potential on representing clear and meaningful information

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of EMG signals. Additionally, the feature classifiers have been given a special scientific interest by researchers. Selection and developing of the case-specific classifiers, which are desired to have the optimal performance to specify motion classes, still continue to be the main goal of current studies. Although, various types of classifiers such as linear discriminant analysis (LDA), support vector machine (SVM), artificial neural networks (ANN) and fuzzy logic (FL) techniques have been utilized to classify human arm motion patterns, merits, shortcomings and pitfalls of the classifiers are still required to be discussed extensively.

FUNDAMENTAL ASPECTS OF EMG

EMG is the electrical activity of skeletal muscles (Basmajian & Deluca, 1985). It represents the summation of the muscle action potentials which cause the contraction of muscle fibers. Recorded EMG data by means of electrodes are amplified and filtered to eliminate the motion artifacts, as well as the environment and device related noises. Rejection of ambient influences on natural muscle activation improves the accuracy and usability of EMG signals. One of the most widely usage of EMG signals is to control the myoelectric-based prosthetics which are used by amputated people. Control scheme for EMG-driven human arm prosthetics includes a sequential series of signal processing (Figure 1).

A condensed and clear control signal is needed to control the EMG-based prosthetics. In order to reduce calculation and to provide stability of signal, EMG data are scanned by sliding segmented windows (Figure 2). Because the raw (amplified+ pre-processed) EMG signal contains a huge burden of data, this signal is needed to be represented in a concise, but accurate ways. Widely used time domain features extracted from signals includes mean absolute value (MAV), root mean square (RMS), Willison amplitude (WAMP), waveform length (WL), variance of EMG (VAR), simple square integral (SSI), zero crossing (ZC) and integrated EMG (IEMG) (Phinyomark et al., 2013). In frequency domain, mean frequency, median frequency, peak frequency, mean power, total power, and spectral power features are commonly preferred (Phinyomark et al., 2013).

EMG SIGNAL FEATURES

Obtained EMG signals during contraction of a muscle or muscle groups are needed to be quantified in order to relate these signals with some certain sets of movement types (Zecca, Micera, Carrozza, & Dario, 2002). Mathematical expression of EMG signals could be defined using feature extraction approach. An EMG signal could be expressed in two domains including time and frequency domains.

Figure 1. Control scheme of multifunctional human arm prosthetics

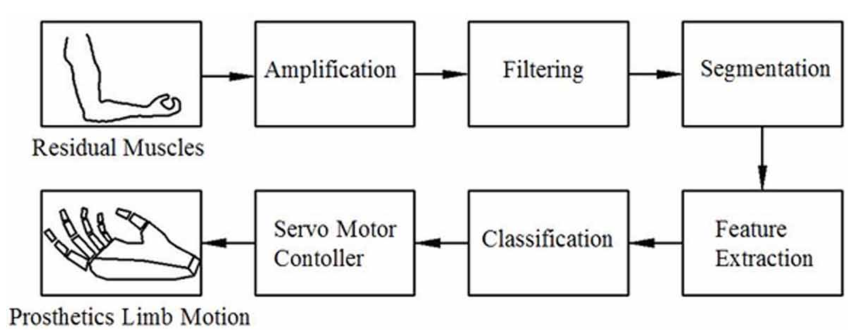
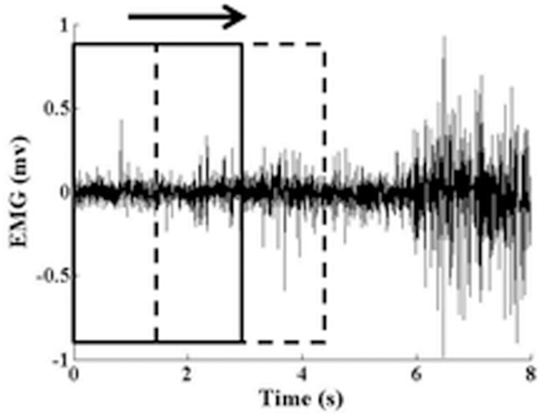


Figure 2. The basic representation of sliding windows



Time Domain Features

Features expressed in time domain are useful for pattern recognition process due to no transformation process is required. Easy and fast calculation of features provides to reduce delay which is a critical concern in control of human arm prosthetics. A wide range of time domain features have been proposed by researchers for the purpose of movement or force classification process (Phinyomark, Phukpattaranont, & Limsakul, 2012). While x_k is the *k*th EMG sample and *N* is the number of samples in each segment, the most widely used time domain features are given as follows.

Mean Absolute Value

Mean absolute value (MAV) of an EMG signal is the average of absolute value of sequential signal amplitudes. MAV is one of the mostly used features and defined as,

$$MAV = \frac{1}{N}\sum_{k=1}^{N}\left|x_k\right| \tag{1.1}$$

Root Mean Square

Root mean square (RMS) feature represents a calculation of amplitude modulated Gaussian random process relating to constant force and non-fatiguing contraction. The mathematical expression of the RMS is given as,

$$RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N}x_k^2} \tag{1.2}$$

Willison Amplitude

Willison amplitude (WAMP) feature is the number of times the EMG signal amplitude exceeds a predefined threshold. WAMP is an indicator of motor unit action potentials (MUAP) and contraction force in muscles and can be expressed mathematically as,

$$WAMP = \sum_{k=1}^{N}\left[f\left(\left|x_k - x_{k+1}\right|\right)\right] \tag{1.3}$$

$$f(x) = \begin{cases} 1, & if\ x \geq threshold \\ 0, & otherwise \end{cases}$$

Waveform Length (WL)

Waveform length (WL) of EMG signal is the cumulative length of the waveform over the time segment. WL feature can be calculated as,

$$WL = \sum_{k=1}^{N-1}\left|x_{k+1} - x_k\right| \tag{1.4}$$

Variance of EMG (VAR)

Variance of EMG (VAR) implies the second-order moment of EMG signal and is a measure of power. VAR feature can be defined as follows,

$$VAR = \frac{1}{N-1}\sum_{k=1}^{N}x_k^2 \tag{1.5}$$

B

Simple Square Integral (SSI)

Simple square integral (SSI) of an EMG signal represents the summation of square values of EMG signal amplitude over time segment. SSI can be expressed as,

$$SSI = \sum_{k=1}^{N} x_k^2 \tag{1.6}$$

Zero Crossing (ZC)

Zero crossing (ZC) feature measures how many times the amplitude of EMG signal crosses zero level. Threshold value is assigned to prevent voltage fluctuations or noises effects. ZC feature calculation could be defined as,

$$ZC = \sum_{k=1}^{N-1}\left[\operatorname{sgn}(x_k \times x_{k+1}) \cap \left|x_k - x_{k+1}\right| \geq threshold\right] \tag{1.7}$$

$$\operatorname{sgn}(x) = \begin{cases} 1, & if \;\; x \geq threshold \\ 0, & otherwise \end{cases}$$

Integrated EMG (IEMG)

Integrated EMG refers to the summation of absolute values of EMG amplitude for each time segment. IEMG feature is also used for clinical applications and could be expressed as,

$$IEMG = \sum_{k=1}^{N} \left|x_k\right| \tag{1.8}$$

Frequency Domain Features

Investigation of EMG signal characteristics in frequency (or spectral) domain is mainly carried out to analyze both the fatigue phenomenon in muscles and the motor unit recruitment (Kallenberg, Schulte, Disselhorst-Klug, & Hermensa, 2007). Various types of features have been proposed to handle EMG signal behavior in the frequency domain. While f_j, P_j and, M represent a frequency value at a frequency bin *j,* the EMG power spectrum at a frequency bin *j* and the length of frequency bin, respectively, some of frequency domain features are given as follows.

Mean Frequency (MNF)

Mean frequency (MNF) is basically the calculation of average frequency dividing the sum of product of EMG power spectrum and frequency by total sum of the spectrum intensity. The mathematical expression is given as,

$$MNF = \frac{\sum_{j=1}^{M} f_j P_j}{\sum_{j=1}^{M} P_j} \tag{1.9}$$

Median Frequency (MDF)

Median frequency (MDF) of an EMG signal is the frequency at which the spectrum is partitioned into two equal amplitude. The MDF feature can be calculated as,

$$\sum_{j=1}^{MDF} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j \tag{1.10}$$

Peak Frequency (PKF)

The frequency containing the maximum power is called peak frequency (PKF). The PKF can be calculated as follows,

$$PKF = \max(P_j) \tag{1.11}$$

Mean Power (MNP)

Average of power spectrum of EMG signals is used to determine the characteristics of signal. The feature could be expressed mathematically as,

$$MNP = \frac{1}{M}\sum_{j=1}^{M} P_j \tag{1.12}$$

Total Power (TTP)

The sum of the power spectrum of EMG signal reveals another feature, namely, the total power (TTP) and it is obtained as,

$$TTP = \sum_{j=1}^{M} P_j \tag{1.13}$$

Spectral Moments (SM)

Spectral moments (SM) is another important approach for feature extraction. Although higher order spectral moment could be calculated, the mathematical expressions of the first (SM_1) and the second (SM_2) order moments are given as follows, respectively.

$$SM_1 = \sum_{j=1}^{M} P_j f_j \tag{1.14}$$

$$SM_2 = \sum_{k=1}^{M} P_j f_j^2 \tag{1.15}$$

EMG signals can also be characterized in joint time-frequency domain (von Tscharner, 2000). In order to observe more accurate description of the signal in physical manner, EMG signals could be transformed to the area at which both frequency and time domain features exist. However, this transformation requires heavy computational costs and likely causes delay in controlling assistive devices. Main features of time-frequency domain are Wavelet Transform (WT), Wavelet Packet Transform (WPT) and Short-time Fourier Transform (STFT).

The above mentioned signal features are needed to be classified to specify the intended motion and force production. To achieve this task, various types of classifiers such as artificial neural networks (ANN) (Arslan, Adli, Akan & Baslo, 2010), fuzzy logic (FL) (Chan, Yang, Lam, Zhang, & Parker, 2000), support vector machines (SVM) (Oskoei & Hu, 2008) and linear discriminant analysis (LDA) (Lorrain, Jiang, & Farina, 2011) are widely employed in literature.

FEATURE CLASSIFICATION AND PATTERN RECOGNITION

Extracted time or frequency domain features are required to be classified to determine the motion or applied force patterns (Oskoei & Hu, 2007). Characterization capability of prosthetic hands is firmly related to the classification performance of the selected classifier due to the classification accuracy reflects the fundamental neuromuscular activity of human muscles. The main consideration of pattern recognition progress of myoelectric signal is that each force or motion class is described by the corresponding muscle activation which is represented by a set of extracted features (Farina et al., 2014). The chosen classifier discriminates separate tasks using trial and test approaches, so that a relation between muscle activation, features and real-world tasks could be built. Thus, selection of appropriate classifier for pattern recognition process is a key issue which is expected to identify accurate patterns and to perform fast sufficiently. A great amount of literature exists to propose an optimal performance of classifiers and thereby selecting the most suitable one (Lorrain et al., 2011). The next section involves fundamental structures and applications of the widely used classifiers including ANN, FL, SVM and LD for the purpose of using in control of myoelectric based prosthetics.

B

Artificial Neural Networks (ANN)

ANN is an artificial intelligence method inspired by the biological structure of human brain and generally referred to as "neural networks" (Haykin, 1999). In human brain, the neural networks is the central of the decision making process. The receptors receive stimuli from the external environment and convert to electrical impulses in order to transmit them to neural nets. Then, neural nets perceive the information and make decision. Finally, the decision is transmitted the effectors to convert the impulses to response as outputs. Setting a linear or nonlinear relation between inputs and outputs, biological and artificial neural networks makes a specific decision.

Surface EMG feature classification using ANN is a popular subject among scientific studies related to control of human arm prosthetics. The basic structure of ANN which is used in pattern recognition process of EMG signals is shown in Figure 3.

The structure, namely the multilayer perceptron (MLP), which consists of a set of one input layer, one output layer, and a number of hidden layers is one of the most simple and commonly used type of ANN. Typical structure of an ANN, which is used for classification of EMG signal features, includes input, hidden, and output layers, so that the features could be related to different force or position classes. Extracted EMG features are fed to ANN as a set of inputs and classified into different force or motion classes as the set of outputs. Each connection between neurons in neighboring layers such as input/hidden layers and hidden/output layers has a weighting factor (w). Moreover, hidden and output layer neurons implement a transfer function to make a mathematical relation between inputs and outputs. The transfer function $f(x)$ of input arrays x, which sets a relation between input and output data arrays, could be selected according to characteristics of the problem. For instance, a logistic sigmoid transfer function is given as,

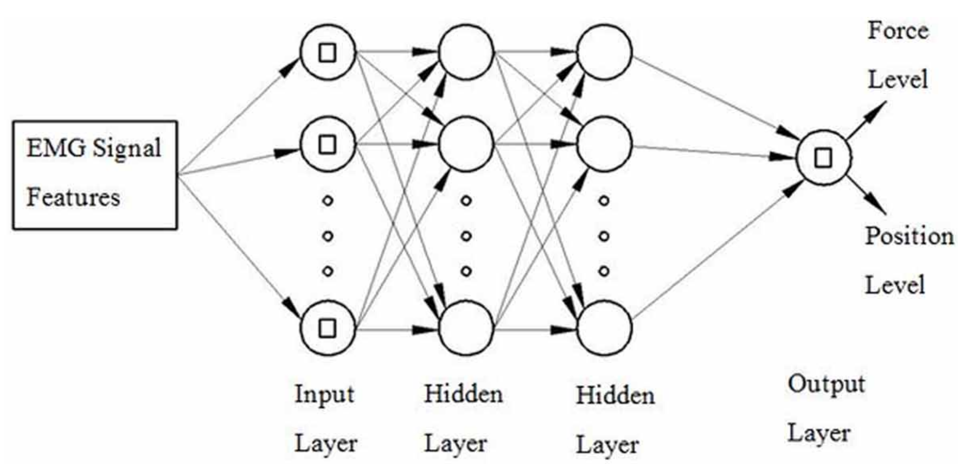
$$f(x) = \frac{1}{1+e^{-\beta x}} \tag{2.1}$$

where

$$x = \sum_{n=1}^{k} w_n a_n \tag{2.2}$$

means the total input of neuron, where w_n, β and a_n are the weight, coefficient and input of ith element, respectively. Although many transfer functions are available, the most widely used transfer functions in pattern recognition of EMG

Figure 3. Schematic representation of an artificial neural network



signals are logistic sigmoid and hyperbolic tangent sigmoid transfer functions. The number of layers and neurons are adjustable based on obtained results. Using huge numbers of training data and neurons could lead to overfitting and make a complex networks structure which has to carry out more tasks and likely produces delays. To overcome such issue, some dropout techniques could be operated and train-test proportion of data is proposed to be adjusted.

Neural networks have been utilized to obtain the closest values of output for targeting the real world results by changing the weights (training stage). Adaptation of weights is implemented according to the desired results which is called supervised learning. In the cases of supervised learning of EMG signals, desired results can be position, hand/muscle force, joint torque or motion trajectory. ANN have been operated as a classifier to predict arm and joint trajectories (Cheron, Draye & Bourgeios, 1996), to estimate hand and wrist motion trajectories in the control of a virtual hand (Sebelius et al., 2005), to classify types of limbs motion (Hudgins et al., 1993), to recognize motion patterns based on signal time scale features (Zhao et al., 2006) and to predict the kinematics of shoulder and elbow (Luh, Chang, Cheng, Lai, & Kuo, 1999).

Fuzzy Logic (FL) System

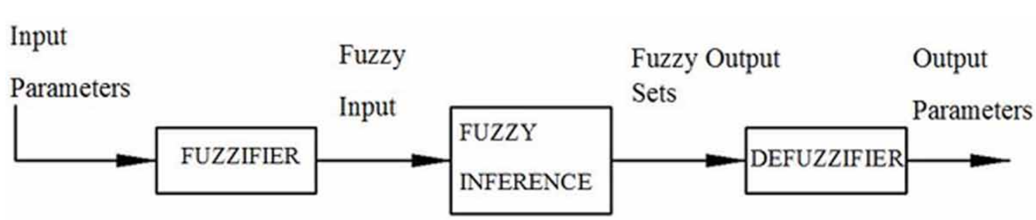
FL systems are beneficial in signal processing and classification, especially for biomedical signals which are not always repeatable, and may even be conflicting (Zadeh, 1973). One of the most useful properties of fuzzy logic systems is that discrepancies in the data can be tolerated. Moreover, it is possible to detect the patterns in data which are not easily identified by other methods using trainable fuzzy systems. Thus, the experience of medical experts or clinicians could be integrated and benefitted. It is possible to incorporate this incomplete but precious knowledge into the fuzzy logic system, due to the system's reasoning style, which is similar to that of a human being. This is a substantial advantage over the artificial neural network (ANN). Fuzzy logic systems better reflect the human decision-making ability than the ANN (Chan et al., 2000). The fundamental of a fuzzy system is the fuzzy inferring engine. Fuzzy production rules are identified according to the available knowledge or well-classified examples (Wang, 1994).

In the fuzzy method, none of operations are random. Information involving a certain amount of suspense is expressed as reliable as possible, without the deformation of forcing it into a "crisp" mold, and it is then handled in a suitable manner. Figure 4 shows the schematic representation of a fuzzy logic system with a fuzzifier and a defuzzifier phases. Fuzzy Logic Systems architecture has three main (Figure 4). These are

1. Fuzzification Module (transforms the system inputs into fuzzy sets),
2. Fuzzy Inference Engine (simulates the human decision making process by making fuzzy inference on the inputs),
3. Defuzzification Module (transforms the fuzzy sets into output parameters).

The inference engine maps each rule's fuzzy input sets into each rule's fuzzy output set. Rules have a critical influence on the performance of a

Figure 4. Schematic representation of a fuzzy logic system



FL system. The rules operate only when the inputs are applied to them.

In order to predict the rules for a fuzzy logic system, dataset is trained. To begin, a certain number of input-output training pairs are selected. The next step is to convert the training dataset into a set of fuzzy rules (IF-THEN, IF-THEN-ELSE, etc.).

The fuzzy rules are mapping from the inputs to the outputs and this mapping can be denoted quantitatively. This kind of FL system is very common and widely used in many engineering applications, such as in fuzzy logic controllers and signal processors. It is also known as fuzzy system, fuzzy controller, fuzzy model or fuzzy expert system.

In recent years, FL systems have been used for decision making process in biomechanical science (Reaz, Hussain, & Mohd-Yasin, 2006). FLS system has been performed to control the elbow and shoulder joint angles of the exoskeletons to design a controller of multifunction prosthetics (Kiguchi, Tanaka, Watanabe, & Fukuda, 2003).

Support Vector Machines

Support vector machines (SVM) is a modern and sophisticated machine learning method (Cortes & Vapnik, 1995). Since EMG-based classification process for prosthetic control problems requires high accuracy and short duration of time to obtain outputs, SVM has become a prevalent and widely used classifier (Lorrain et al., 2011). Although the main notion of the classification progress is to assign the inputs to predefined groups or categories, SVM basically separates the classes operating an optimal hyperplane. In order to discriminate the data among a vast number of classes, a combination of multiple SVM is used. SVM classification process, briefly, is described as follows (Leon, Gutierrez, Leija & Munoz, 2011),

Let x_i and y_i are inputs and outputs, respectively, for $x_i \in R^i$ and $y_i \in \left\{-1,1\right\}^l$. The hyperplane, which divides them into two previously determined groups, is defined as,

$$w^T \phi(x) + b = 0 \tag{2.3}$$

where *w* and *b* are weight and bias parameters of hyperplane. Additionally, ϕ is a mapping function which transforms x_i vector into higher dimensional space.

For a classification case, a various number of hyperplane could separate data into two classes. However, there must be only hyperplane, which satisfies maximum margin between the classes, is defined as,

$$\min[\frac{1}{2}\left\|w\right\|^2 + C\sum_{i=1}^{m}\xi_i] \tag{2.4}$$

subject to $y_i(w\phi(x_i)+b) \geq 1-\xi_i$ and $\xi_i \geq 0$ where ξ_i is the slack variables that related to error between training data. In order to obtain optimal hyperplane with limited error equation, equation (2.4) is solved, While α_i and $k(x_i, x_j)$ are Lagrange multipliers and Kernel function, respectively, the equation is reduced as follows,

$$\max[\sum_{i=1}^{\infty}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{m}\alpha_i\alpha_j y_i y_j k(x_i, x_j)] \tag{2.5}$$

The equation of optimal hyperplane is expressed as,

$$w = \sum_{i=1}^{m} y_i \alpha_i \phi(x_i, x_j)$$

which satisfies

$$\sum_{i=1}^{m}\alpha_i y_i = 0 \text{ and } 0 \leq \alpha_i \leq C \tag{2.6}$$

The inputs x_i which satisfy $\alpha_i \neq 0$ are called support vectors. The maximization process to build decision function of the classifier is related to choose suitable kernel function which is generally selected based on inputs type and structure.

The most common used kernel functions are linear, polynomial, sigmoid and radial basis functions. The major components of SVM is shown in Figure 5.

Lucas et al. (2008) implemented the SVM method as a supervised classification of multi-channel surface electromyographic signals with the aim of controlling myoelectric prostheses. They concluded that the SVM classification rule can be effectively implemented with fast algorithms (after training) for real-time applications.

Linear Discriminant Analysis (LDA)

Linear discriminant analysis (LDA) has become a prominent classifier with the intent of grouping very complex EMG data arrays. This section summarizes, briefly, that how LDA method works. The method is based on deriving the combination of parameters that optimally discriminates the priori defined groups (Cao & Sanders, 1996). It is assumed that the vector of features is given as $X = [x_1, x_1, ..., x_m]$. The mean values of X for the ith class are expressed as $\mu_i = [\mu_{i1}, \mu_{i2}, ..., \mu_{im}]$. The main procedure of LDA method is to maximize the following function which is known as linear discrimination or gate function (Kim, Choi, Moon, & Mun, 2011),

$$f_i(x) = x^T S^{-1} \mu_i - \frac{1}{2} \mu_i^T S^{-1} \mu_i + \log(\pi_i) \quad (2.7)$$

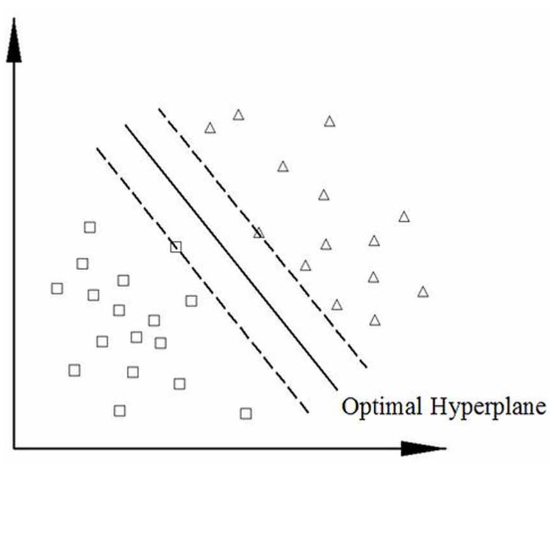
where S is the pooled covariance matrix of input data and π_i is a prior probability of inputs coming from class i. Using the combinations of the equation, misclassification could be minimized by obtaining higher likelihood index for each defined class.

LDA method has been applied to identify EMG signals to discriminate the patterns of EMG linear envelope of healthy subjects and patients with anterior cruciate ligament injury (Alkan & Gunay, 2012) and to classify the features to enhance the controllability of a powered prosthetics (Hargrove, Scheme, Englehart, & Hudgins, 2010).

It is necessary to make an extensive evaluation of the performance of these listed classifiers in pattern recognition process besides shortcomings and merits of them. Arslan et al. (2010) employed ANN to predict externally applied forces to human hands using EMG signal features. The study, which was aimed to estimate the forces accurately, showed that the classifier predicted the targeted force values in a range of 0.34 and 0.05, and of 0.24 and 0.09 root mean square difference (RMSD) for isometric and anisometric contraction experiments, respectively. In this study it was clearly stated that ANN method could built a successful non-linear relation between force and EMG signal features. However, the authors highlighted that it is not possible to propose a standard ANN design for training the EMG signal efficiently. Even tough ANN is a powerful classifier, the absence of a conceptualized and standardized training method represents an important disadvantage.

Chan et al. (2000) performed a fuzzy logic based classification procedure to control prosthetics. They also provided a comparison between ANN and fuzzy systems in pattern recognition process. In the study, it was shown that 8% and

Figure 5. The basic representation of support vector machine. Optimal hyperplane is represented with solid line which divides optimal margin between two classes. Square and triangle on dashed lines are support vectors.



11.3% of error rates were obtained by Fuzzy and ANN classifiers in pattern recognition, respectively. Some advantages of fuzzy systems were listed as *i)* slightly higher recognition rate than obtained by ANN, *ii)* insensitivity to overtraining, and *iii)* consistent outputs demonstrating higher reliability. The main drawback of the method was noted that requiring more human intervention at initialization stage in order to get the minimum inter-class cross-over. Hence it was stated that the procedure is not automatic to the same extent as ANN.

LDA is becoming a prominent tool for pattern recognition in EMG studies. Chu et al. (2007) conducted a study which includes an EMG feature discrimination process. After a real-time pattern-recognition progress, it was shown that the proposed method achieves the recognition accuracy rate of 97.4%. Phinyomark et al. (2013) also reported that LDA shows a better performance in the classification of fluctuating EMG signals compared to several classifiers such as quadratic discriminant analysis (QDA), random forests (RFs) and k-nearest neighbor (KNN).

The performance of SVM as a machine learning method is needed to be assessed. Subasi (2012) compared the performance of a group of classifiers and reported that classical SVM method provided 96.75% accuracy, while the kNN and the radial basis function (RBF) classifiers achieved the process with 95.17% and 94.08% accuracy, respectively. In the study, it was also noted that SVM performance could be enhanced with some modifications.

FUTURE RESEARCH DIRECTIONS

Though rapid improvements of assistive technologies and specifically artificial human hand prosthetics have been observed, challenging problems are still remaining to be solved in terms of EMG signal pre-and post-processing operations with the intention of providing dexterous control of prosthetics.

Feature Selection

Features extracted from EMG signals for both in time and frequency domains are used at present. However, new features may be proposed for better representation of EMG signals. Furthermore, effect of sliding windows for calculation of features should be investigated in detail. Used features presently are calculated by means of differentiation or summation of neighboring EMG signal amplitudes. New approaches such as measuring energy consumption for each EMG signal maybe employed for time domain in future studies, as well.

Classification Methods

The classifier performance is investigated by researchers extensively. Selection of training and test data for discrimination process has a great influence on classification accuracy and operation duration. Selection of the optimum cross-validated EMG signal arrays should be a purpose of next studies. Additionally, using the combinations of time and frequency domain features for training and test may provide higher accuracy of classification. Furthermore, semi-supervised learning, which is one of the fundamental aspects of classification methodology for cases that it is hard to obtain sufficient training data, should be studied in more detail.

CONCLUSION

The chapter provides a general overview on the EMG signal features and their classification methodologies which are critical issues for controlling of human arm prosthetics. EMG-driven human arm prosthetics are highly sensitive to the scientific and technological advances. Through the last decades, many of EMG signal features calculation and discrimination methods have been proposed and applied to prostheses. Precise and intuitive control of prosthetics depends mainly upon the type of extracted feature and classification techniques. Making a significant difference or advancing the dexterity in the control of prosthetic devices depend on achieving the optimum signal feature and classifier architecture. Needless to say that in addition to the control structure, mechanical structure of the prosthetics also plays a major role in the completion of complex motor tasks which deserves to be extensively dealt with in a separate report.

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KEY TERMS AND DEFINITIONS

Assistive Technology: A branch of technology is used to regain the lost functions of human body parts.

Feature Classification: A pattern recognition technique that is used to categorize a huge number of data into different classes.

Feature Extraction: A method to obtain meaningful and clear data of a signal.

Human Arm Prostheses: Assistive devices which enable to perform lost functions of human arm due to upper or lower arm amputations.

Pattern Recognition: A machine learning process which identifies the pattern of physical systems using data belong to investigated systems.

Rehabilitation: A series of therapy to make injured or amputated people regained lost skills or functions.

Surface Electromyography: A type of electromyography signal recording method carrying out by means of adhering electrodes to skin surface.