A NEW REAL-TIME FUZZY INFERENCE SYSTEM FOR EMG PATTERN RECOGNITION SUITABLE FOR HAND PROSTHESIS CONTROL

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Electromyography (EMG) is the study of muscle function through the inquiry of the electrical signals that the muscles emanate. EMG signal collected form surface of the skin can be used in different applications such as recognizing patterns of hand prosthesis movements. We used intelligent approach based on artificial neural network (ANN) and Fuzzy inference system (FIS) with a real-time learning method to identify motion commands. For this purpose and to consider the effect of user evaluation on recognizing hand movements, vision feedback has been applied to increase the capability of this system. The myoelectric signals considered to classify were six movements of the hand. Features chosen for EMG signal were in time-frequency domain. These features were local maxima and zero crossing of the wavelet transform (WT) coefficients. In this work we evaluated the capability of an EMG pattern recognition system using ANN and FIS as classifier with a real-time learning method. Our results demonstrated that the utilized real-time FIS approach with a 95% average accuracy was superior to the previously introduced ANN real-time scheme [4].

Introduction

The myoelectric signal, recorded at the skin surface (SEMG), has been used for many diverse applications. The EMG signal gives us information about the neuromuscular activity from which it originates, and this has been fundamental to its use in clinical diagnosis, and as a source for control of assistive devices. It has been proposed that the EMG signals from upper limb musculature can be used to identify motion commands for the control of an externally powered prosthesis hand. EMG is a complicated signal influenced by various factors such as physiological and anatomical properties, characteristics of instrumentation and differs from one person to another. In earlier studies, the system learned the characteristics of EMG signal in an offline manner which could not adjust its inner states correspond to operator's variation in real-time [1]-[3]. To decrease these effects on EMG pattern recognition system and eliminating dependence on individual subject, real-time methods to train this system were introduced [4].

Accurate feature extraction from EMG signals is the main kernel of classification systems in both real-time and offline systems and is essential to the motion command identification. Previous works have shown that time-frequency features present better results in EMG pattern recognition application [3]. This is due to the effect of combining time domain and frequency analyses which yields a potentially more revealing picture of the temporal localization of a signal‘s spectral characteristics.

In this study, we propose a new real-time method suitable for hand prosthesis control. In this non-invasive system, two channel surface mounted electrodes are utilized. We use time-frequency representation (TFR) specifically local extrema and zero crossing of the wavelet transform (WT). After extracting the suitable features of signal, we employ a classifier to identify each movement with a high degree of correctness. In this work we use two intelligent schemes, namely ANN and FIS as classifier to compare the ability of our proposed approach to the previously introduced real-time learning method [4].

1. Real-time scheme of EMG pattern recognition system

The real-time scheme of EMG pattern recognition system used in this work is shown in Figure 1. The five major components are, EMG preprocessing and conditioning, feature extraction, Dimensionality–reduction, classifier (pattern recognizer) and trainer units.

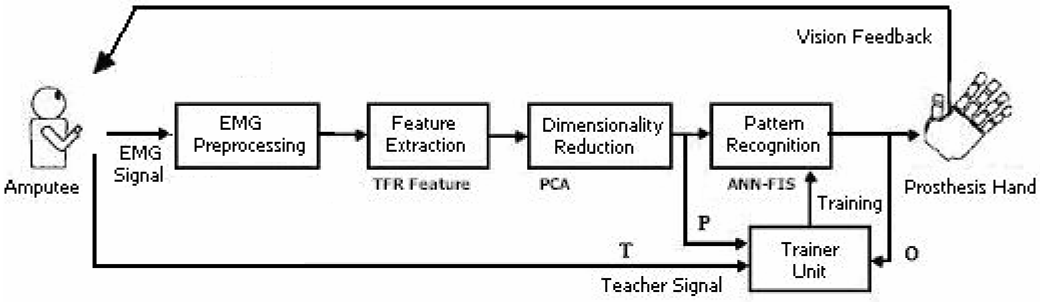

Figure 1 - Conventional Scheme for hand prosthesis control

The goal of preprocessing step is to prepare and amplify the signal for the subsequent steps and to reduce noise artifacts. Six movements of hands have been considered and EMG signal for each movement has been extracted, namely hand opening and closing, pinch, thumb flexion and wrist radial flexion and extension. These movements are shown in Figure 2.

During the feature extraction step, EMG signal is processed in order to emphasis relevant structure. In this phase we use time-frequency features. These features are local extrema and zero crossing of wavelet transform coefficients. For discrete wavelet transform (DWT) defined by,

$$DWT_x(j,n) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-n.2^j}{2^j}\right)dt \qquad (1)$$

Where $\psi(t)$, is the mother wavelet. The analysis determines the correlation of the signal with shifted (by $n.2^j$) and scaled (by 2^j) versions of the mother wavelet, where $n, j \in \mathbb{Z}$. Therefore, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet and the wavelet coefficients may constitute an effective feature set. However there is a fundamental drawback for the DWT which is lack of shift invariance. If the signal to be analyzed is shifted, the coefficients of wavelet transform vary in a complicated manner. This matter may present a significant problem in the pattern recognition system. To overcome this problem, we utilized shift invariant features of DWT, namely local extrema and zero crossing (ZC) [3].

Next, we used dimensionality reduction to simplify the task of classifier. For this part of the system, principle component analysis (PCA) was introduced. The role of dimensionality reduction is to retain information that is important for class discrimination and discard irrelevant information.

In the next step, we determined the type of motion commands suitable to control prosthesis hand by utilizing two different real-time intelligent classifier approaches, namely ANN and FIS.

Finally, in the last section of this system called trainer unit, system learned the relation between actual EMG patterns and generated control commands and furthermore adapted to the operator's characteristics (This part does not exist in off-line learning method).

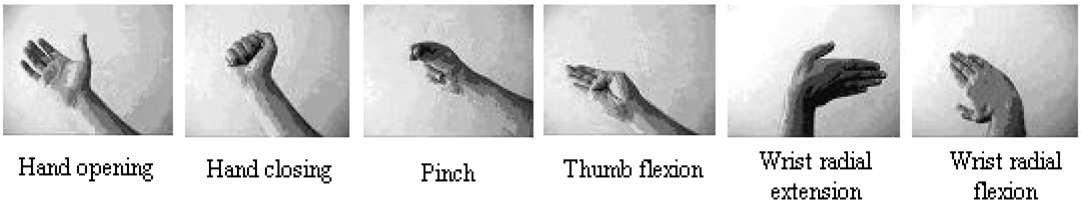

Figure 2 - Representation of six distinct hand movements

2. EMG pattern classification using intelligent classifiers

There are several techniques for classifier but in this work we focused on two intelligent techniques that have generalization property, namely ANN and FIS [5,6, and 7]. One of the simplest and widely used ANN for EMG pattern classification is multilayer perceptron (MLP). This network consists of a set of inputs, number of hidden layer and an output layer. Each input connected through a set of weights to hidden layer. Also each neuron in hidden layer connected to output layer. Hidden and output neurons have a transfer function. In this network hardlimitter, logistic sigmoid and hyperbolic tangent sigmoid are used as a transfer function. The connection weights between and neuron threshold are varied by back propagation (BP) algorithm. Let a training example denoted by $\left[x(n), d(n)\right]$, with the input vector $x(n)$ and the desired response vector $d(n)$. With the use of logistic for the sigmoid non-linearity, the output of neuron j in the layer l is given by,

$$y_j^{(l)}(n) = \frac{1}{1 + \exp(-\sum_{i=0}^{p} w_{ji}^{(l-1)}(n) y_i^{(l-2)}(n))} \qquad (2)$$

where $w_{ji}^{(l)}(n)$ is the weight of neuron j in layer l that is connected to to neuron i in layer $(l-1)$. For neuron j in the first and last layer (i.e. input layer $l = 1$ and output layer, $l = L$) We have: $y_j^{(1)}(n) = x_j(n)$, $y_j^{(L)}(n) = o_j(n)$. Where $x_j(n)$ and $o_j(n)$ are the jth elements of input vector and output layer respectively.

FIS is another classifier that we consider in this study. FIS can emulate human decision making by using fuzzy rules in the form of IF-THEN [5]. The fuzzy systems at first fuzzify inputs into membership degrees of fuzzy sets then infer by fuzzy logic through rules which usually come from experience. The output of FIS system defined by,

$$y = \sum_{i=1}^{L} \left\{ \frac{\left(\prod_{j=1}^{n} MF_j^i(x_j) \right) . \left(y^i \right)}{\sum_{i=1}^{L} \left(\prod_{j=1}^{n} MF_j^i(x_j) \right)} \right\} \qquad (3)$$

Where MF_j^i is the jth membership function in ith rule also x_j and y^i are jth input and the output of ith rule. The fuzzy system used in the present study is Sugeno type. This system with weight average defuziffier, product inference rule, non-singleton and Gaussian membership function can be described by equation 3.

3. Role of trainer unit in real-time pattern recognition

In real-time learning method for the application of pattern recognition there is a mechanism for evaluating the system's performance by the operator. In the case of offline methods previously mentioned, there is no need for considering the time as a cost function.

The real-time method must be able to evaluate the accuracy of system in recognizing hand movement that performed by operator. The trainer unit makes training data which contains a teacher signal from the operator and reduced features from dimensionality reduction unit. Next, this training data is fed to the pattern recognition unit. When the trainer unit receives the teacher signal ($\{T = 1, 2, ..., n\}$ where n is the number of movement or EMG signal) from operator, it creates the teaching vector as,

$$t = (t_1, t_2, ..., t_n) \quad , \quad t_i = \begin{cases} 1, & if \quad i = T \\ 0, & otherwise \end{cases} \tag{4}$$

The trainer unit creates the reduced feature set (p) with teaching data (t) in the form of $\Gamma(p, t)$ and sends this teaching vector to pattern recognition unit. The trainer unit updates the state of pattern recognition unit in the interval that control command from EMG signal is generated. This process is continued until the control command (o) of output in compare with (t) is not correct or RMS value that defined by formula (5) exceeds a constant value 0.1:

$$RMS = \frac{1}{n}\sum_{i=1}^{n}(o - d)^2 \tag{5}$$

4. Experimental results:

To implement the real-time EMG recognition system, we used a PC with Pentium4 processor. The proposed controller was implemented by MATLAB software. A key on the keyboard was pressed as an interface to send the teacher signal to the trainer unit. A computer graphic simulated the working of a prosthesis hand. The operator watched the monitor and sent the motion command by pressing the corresponding keys. He sent new motion command when he judged that the controller has learned the previous command motion completely.

Therefore the subject watched the monitor and also re-sent a teacher signal for the past motion if it was not performed correctly. Figure 3 shows the scheme of this process.

Constructing of the feature set by DWT, called for the verification of the parameters which affected it. For this reason, the candidate parameters were considered and the accuracy of the EMG pattern recognition system based on these parameters was calculated. As a result best representative parameters were selected. Specifically, to acquire these results we considered amplitude of DWT as a feature and compared the results by implementing ANN and FIS schemes. Finally to choose most suitable DWT, a collection of mother wavelets were compared and an appropriate depth of decomposition was chosen. The selection of the candidate mother wavelet for EMG pattern recognition was determined empirically where the DWT decomposition was terminated prior to a full decomposition when necessary.

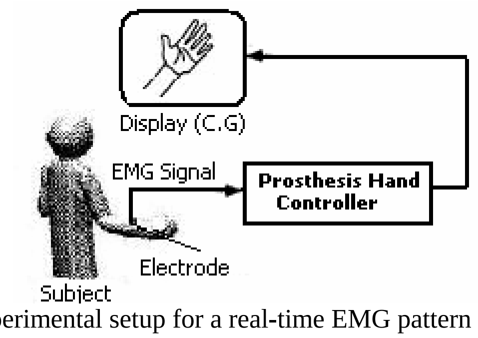

Figure 3 - An experimental setup for a real-time EMG pattern recognition system

For a signal with length of N samples, the maximum depth of decomposition is $J = \log_2^N$. The EMG signal in this work has 500 samples, thus the maximum depth of decomposition will be 9. Figure 4 shows the effect of mother wavelet and depth of decomposition on EMG pattern recognition system. To obtain these results, we used different types of mother wavelet such as haar, daubechies, symlet, coiflet and biorthogonal. The results indicated that Haar was the most suitable mother wavelet with 9 level of decomposition providing the best performance to recognize EMG patterns.

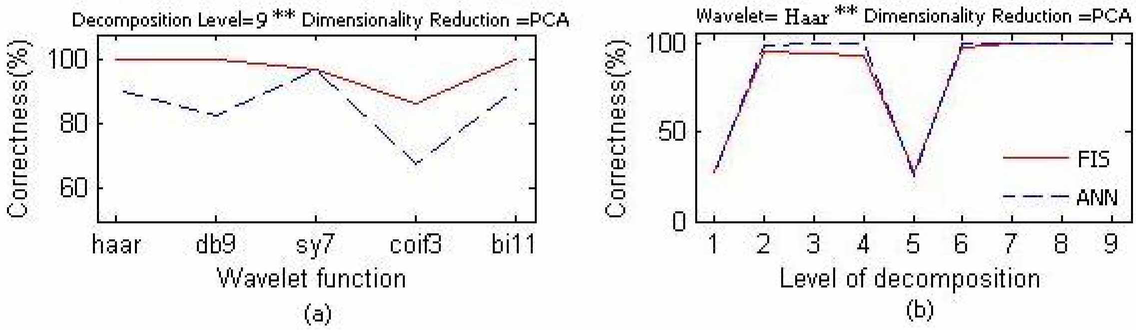

Figure 4 - Selection of best WT and performance

After extracting the features, the accuracy of ANN and FIS based systems were evaluated and compared. Also the effectiveness of the real-time method was compared to the offline approach. Table-1 depicts the results of implemented EMG pattern recognition system using six hand movements previously noted.

The results indicated FIS superior performance as compared to ANN. Also the real-time method for learning EMG pattern recognition system (because of considering the user evaluation) was shown to produce better results. Hence by using FIS real-time learning method, we were able to successfully discriminate among six descriptive and distinct hand movements with an average accuracy of 95%.

Table 1 - Comparing acquired results by ANN and FIS
Using real-time and offline learning method (%)

Classifiers		Hand open	Hand close	Pinch	Thu-flex	Wr-exten	Wr-flex	Average
Off line Learning	ANN	86	90	84	76	88	88	85.3
	FIS	94	98	90	82	94	92	91.67
Real-time Learning	ANN	90	96	84	84	88	86	88
	FIS	98	100	94	90	94	96	95.3

Conclusion

In this work we designed an EMG pattern recognition system to discriminate among six movements of hand. For designing this system we used two time features of WT, namely local extrema and zero crossing. To create the feature set we considered the best parameters of WT, for which Haar was chosen as the best mother wavelet and nine level of decomposition were exerted for best performance. Also in order to consider the effect of real-time learning on recognizing six distinct hand movements, operator vision feedback was utilized. This study showed that FIS real-time learning method can provide acceptable results for a surface EMG pattern recognition system suitable for hand prosthesis control.

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