ELECTROMYOGRAPHY BASED FINGER MOVEMENT IDENTIFICATION FOR HUMAN COMPUTER INTERFACE

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Abstract: This paper reports experiments conducted to classify single channel Surface Electromyogram recorded from the forearm with the flexion and extension of the different fingers. Controlled experiments were conducted where single channel SEMF was recorded from the flexor digitorum superficialis muscle for various finger positions from the volunteers. A modified wavelet network called Thresholding Wavelet Networks that has been developed by the authors (D Kumar, 2003) has been applied for this classification. The purpose of this research was towards developing a reliable man machine interface that could have applications for rehabilitation, robotics and industry. The network is promising with accuracy better than *85%*.

1 INTRODUCTION

With greatly improved computational power, and use of computers having exploded into every walk of life, there is a greater need for flexible, natural and reliable human computer interface. Hand movement gestures play a very important role in the interactions between people. But most of the interaction with computers is based static events such as a key press, and the information contained in the dynamic gesture is lost, greatly reducing the scope of machine interaction. There is thus need for simple and reliable methods for human hand action identification by machines. This paper reports a new technique for automatic recognition of human hand movements.

Skeletal movement is caused by or prevented by muscle contraction. Muscle contraction is a result of electrical stimulation received from the nerves to individual muscle fibres. The resultant electrical activity can be recorded by electrodes kept in the close proximity of the muscles. Surface electromyography (SEMG) (J Cram, 1998) is the recording of the electrical activity of skeletal muscle from the skin surface. It is a result of the superposition of a large number of transients (muscle action potentials) that have temporal and spatial separation that is semi-random.

SEMG signal is the electrical recording from the surface and represents the summation of the electrical activity from all the muscle fibres and thus the summation of all Motor Unit Action Potentials (MUAP) in the region of the electrodes. The origin of each of the MUAP is inherently random, non-stationary, and the electrical characteristics of the surrounding tissues are non-linear. Distribution of the magnitude of SEMG can be approximated by a Gausian function (J Cram, 1998).

SEMG is used for a number of applications including control of Human Computer Interface (HCI), prosthesis control (Hudgins, 1993, D Graupe, 1975,F Chan, 2000), muscle diagnostic and biofeedback. Amplitude and spectral information of EMG have also been exploited to estimate muscle fatigue and force of muscle contraction and torque (K Englehart, 1999). These applications require automated analysis and classification of SEMG. The complexity of the signal makes this a challenging task. The authors have reported using combination of three channels SEMG from the forearm to identify the hand action. The difficulty of using multiple channels is the need for precise positioning of the electrodes by an expert.

For automated classification of SEMG related to movement, it is essential to develop the system that can extract appropriate features of SEMG with respect to the movement and have a mechanism for relating these features to the movement generating the signal without the need for multiple channels. The earlier SEMG classification techniques were based on the statistical analysis of the signal properties (Hudgins, 1993). Auto Regressive (AR)

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model (Graupe, 1975), of the SEMG signals representing limb positions and were able to classify a single channel recording with *85%* success rate. The techniques relied on the fixed thresholding levels determined by manual inspection of the tendency of the signal's parameters. But this system was highly dependent on the subject and recording and required high degree of manual intervention.

Hudgins et al (Hudgins, 1993) reported the first major work of SEMG classification using Artificial Neural Networks (ANN). The ANN was used to introduce the flexibility and self-learning ability to the classification technique. The accuracy of the classification technique was ranging from *80%* to *90%*. However, the technique was only applied to the initial stage of the contraction. The technique is sensitive to the window size and the appropriate selection of the signal's features (F Chan, 2000).

Englehart (K Englehart, 1999,K Englehart, 2001), the authors (D Kumar, 2003) and others have reported the results of classification of SEMG against resultant movement and muscle status using various signal features. Some of the features reported include time domain features, Short Time Fourier transform (STFT), Wavelet Transform (WT) and Wavelet Packet Transform (WPT). It has been reported that WT and WPT were superior in the classification SEMG against muscle status during steady-state contraction. It has also been reported that the technique was sensitive to the appropriate selection of signal features to be included in the classification and that the technique could be improved by including the adaptive feature selection process.

The Thresholding Wavelet Network (TWN) has been developed by the authors (D Kumar, 2003) and has been applied in this paper for SEMG classification. This combines the WT, ANN and wavelet thresholding. The combination enables the network to extract time-scale features from the signal and adaptively select the appropriate features for the classification task. This paper reports the architecture of the network and the network's performance in the classification of SEMG recorded for various finger movements.

This paper is organised into six sections. Section 2 reviews the basic concept of WT and wavelet networks while Section 3 details the architecture and learning process of the TWN. Section 4 presents the experimental method and results while Section 5 discusses the results. Section 6 concludes the paper.

2 THEORETICAL BACKGROUND

A. Wavelet Networks

Wavelet network (S Mallat, 1999) is a class of ANN (D Kumar, 2003, M Hagan, 1996) that includes WT in its algorithm. The combination provides a tool that can calculate wavelet coefficient in parallel mode and adaptively select the proper wavelet coefficients for the approximation or classification task. The wavelet networks are grouped in two different categories:

Approximation Wavelet Networks (AWN): Wavelet networks are designed for the purpose of function approximation or representation and iteratively generate the wavelet coefficients as well the inverse wavelet transforms to approximate the signal.

Classification Wavelet Networks (CWN): Wavelet networks that are designed for the purpose of function classification. These are based on computing and determining the wavelet coefficients to classify the signal.

AWN optimises its parameters based on a cost function that is sensitive to energy content. The approximation is only useful in a classification task if the distinguishing factors are immersed in the high-energy region of the signal. But the features that discriminate a class of SEMG signals from the other classes are not necessarily immersed in the high-energy region of the signal.

The basic principle of CWN is to iteratively locate wavelet coefficients (scale and translation)

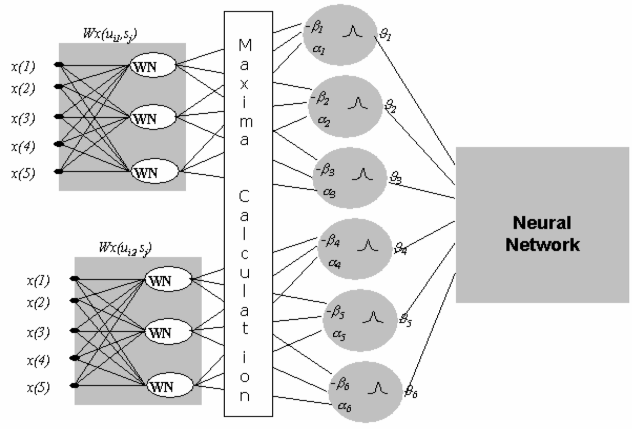


Figure 1: A Thresholding Wavelet Network constructed by six thresholding nodes (three for each scale).

that contrast the difference between signals of different classes, while enhancing the commonality between signals of the same class. But these networks are temporal dependent and sensitive to the time location of significant events in the input signal such as the singularity points. This limits its application in SEMG signals where the action potentials are semi-randomly located (J Cram, 1998).

3 THRESHOLDING WAVELET NETWORKS

The authors have introduced a new type of wavelet network, the thresholding wavelet network (TWN) (D Kumar, 2003). This is suitable for classifying signals such as SEMG. The wavelet coefficients are thresholded with an upper and lower bound. TWN selects wavelet coefficients that identify a signal based on magnitude for the relevant scales making it is less sensitive to the time location of the coefficients while more sensitive to signal features (instantaneous frequency and singularity) represented by the magnitude of wavelet coefficients. An example of the network is shown in Figure 1.

The TWN consist of four blocks of network layer: a wavelet layer, maxima layer, thresholding layer and neural networks layers (figure 1).

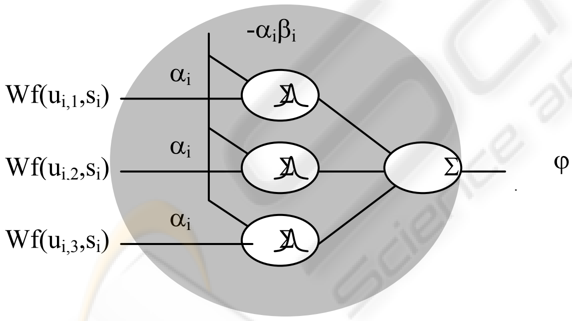


Figure 2: The Wavelet thresholding node.

The input signal x(n) is applied to the wavelet layer, the output is the magnitude of wavelet coefficients $|Wf(s,\sigma)|$. The wavelet maxima layer selects wavelet coefficients that are locally maxima.

The input to the thresholding layer is the wavelet maxima at each scale of interest. The thresholding levels (θ_l,θ_h) for one scale are the same. The scale-dependent thresholding levels allow the network to apply different thresholding levels to different scales. The output of wavelet thresholding node φ is the number of wavelet maxima with magnitude between θ_l and θ_h.

The bias β determines the centre of g(x) while α determines the width of the function. The combination of α and β determines the upper and lower thresholds. Figure 2 illustrates the thresholding wavelet node.

The network is a supervised learning algorithm based system. The parameters of this network (α, β and neural network weights and biases) are initialised with random values. During the iterative learning process, the values of these parameters are changed to reduce the classification error using input and target output examples. The cost function used is the sum-squared error (*SSE)*, the difference between target output φ_T and the actual output φ.

$$E = \tfrac{1}{2}(\varphi_T - \varphi)^2 \qquad (1)$$

In each thresholding node, the learning is the process to locate the lower and upper threshold levels (θ_l and θ_h) of each node. Determining the optimum value of the threshold parameters ensures number of wavelet coefficients with magnitude $\theta_l \leq |Wf(s,\sigma)| \leq \theta_h$ can best categorise the class of input signals.

The change of the parameters for each iteration is determined using the gradient descent algorithm (equations 9 and 10), and the learning rate coefficient ρ.

$$\alpha_{new} = \alpha_{old} - \rho \frac{\partial SSE}{\partial \alpha_{old}} \qquad (2)$$

$$\beta_{new} = \beta_{old} - \rho \frac{\partial SSE}{\partial \beta_{old}} \qquad (3)$$

The learning process is repeated until the sum-squared-error *SSE* falls below a predefined maximum error E_T. At this stage the network is considered as able to classify the training pattern with an error less than E_T.

4 EXPERIMENTS

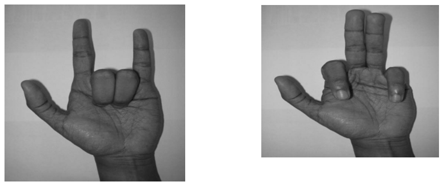
The aim of this study was to determine the possible use of single channel SEMG from the forearm to identify the various movements of the fingers. Towards this aim, the TWN has been employed to identify the hand gestures by classifying the SEMG signal based on the difference in shape and amplification of action potentials due to the proximity of muscle fibers to the surface electrodes. This problem has three levels of complexity; (i) where all the fingers move together, (ii) where two fingers move together and (iii) where each of the finger are independent. As the first level of complexity may be considered as trivial, two sets of controlled experiments were conducted.

Single channel SEMG was recorded from the flexor digitorum superficialis muscle using BIOPAC System EMG100C at *2000 Hz* sampling rate. The SEMG recording system had HPF at *10 Hz*, LPF at *1000 Hz* and a notch filter at *50 Hz* to eliminate power-line interference and with gain of *2000*. Three male volunteers were tested on three separate occasions.

The experiments were repeated and the network was trained with *10* signals from each class. The length of each signal for training purposes was *500* samples. TWN used had *500* nodes at its wavelet layer, *498* nodes at maxima layer, *8* nodes at its thresholding layer and *100* nodes at its hidden layer. The TWN used *Db2* wavelet at scale *1*. The experimental results are shown in Table 1.

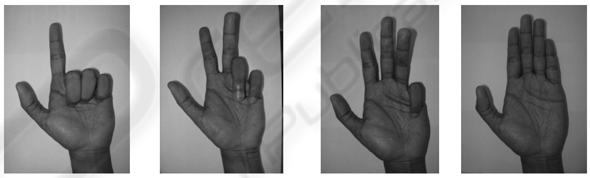
The first experiment had two finger positions classes. Class A signals were recorded when the middle and ring fingers were flexed, while class B signals were recorded when the index and little fingers were flexed (Figure 3). These were selected because the tendons of middle and ring fingers are superficial compare to the tendons of index and little fingers (J Cram, 1998, N Palastanga, 1994). The muscle fibers of middle and ring fingers are more superficial then the fibers of distal tendons. Thus the shape and magnitude of recorded action potentials when flexing the middle and ring fingers are different to the action potentials when flexing the index and little fingers. The results are presented in Table 1.

The second set of experiments involved the classification of SEMG signals for four different fingers (flexion and extension). The finger positions for the experiments are shown in Figure 4, 5 and 6, while the experimental results are shown in Table 2, 3 and 4.



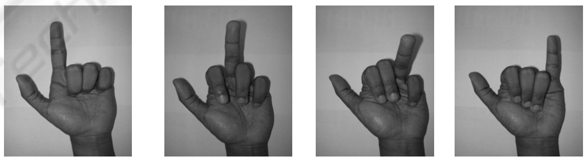
(a) (b)

Figure 3: The finger positions for experiment 2. a) The finger position when class A signals were being recorded. b) The finger position when class B signals were being recorded.



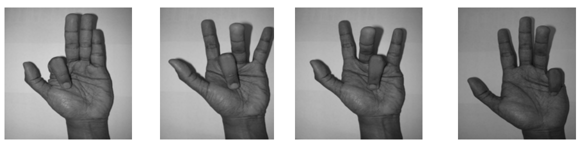
(a) (b) (c) (d)

Figure 4: Finger positions for experiment 3.



(a) (b) (c) (d)

Figure 5: The finger positions for experiment 4.



(a) (b) (c) (d)

Figure 6: The finger positions for experiment 5.

Table 1:

	Class A	Class B	Average
Subject 1	16.67%	0%	8.33%
Subject 2	0%	10.0%	5.0%
Subject 3	16.67%	3.33%	10.0%
Average	11.11%	4.44%	7.78%

Table 2: The Classification Error of Experiment 3

	Class A	Class B	Class C	Class D	Average
Subject 1	10.0%	6.67%	20.0%	6.67%	10.83%
Subject 2	13.33%	30.0%	13.33%	0%	14.16%
Subject 3	16.67%	26.67%	33.33%	0%	19.16%
Average	13.33%	21.11%	22.22%	2.22%	14.72%

Table 3: The Classification Error of Experiment 4

	Class A	Class B	Class C	Class D	Average
Subject 1	0%	6.67%	6.67%	46.67%	15.0%
Subject 2	0%	6.67%	40.0%	6.67%	13.33%
Subject 3	40.0%	13.33%	0%	0%	13.33%
Average	13.33%	8.89%	15.56%	17.78%	13.89%

Table 4: The Classification Error of Experiment 5

	Class A	Class B	Class C	Class D	Average
Subject 1	0%	13.33%	0%	0%	3.33%
Subject 2	33.33%	6.67%	20.0%	13.33%	18.33%
Subject 3	0%	20.0%	33.33%	13.33%	16.67%
Average	11.11%	13.33%	17.78%	8.89%	12.78%

5 RESULTS AND DISCUSSION

The results of the experiments are tabulated in tables 1 to table 4. From these tables it is observed that single channel SEMG when classified using the magnitude of the wavelet coefficients gives high level of accuracy, ranging from *93%* to *85%*.

From the results it is also observed that the classification performance using the TWN decreases as the complexity increases (number of classes increases). The error for the classification of two classes of signal was *7 %*, while the error for the classification of four classes ranged between *12%* and *14%*.

The experiments confirmed the effectiveness of using wavelet transform in feature extraction stage of the classification process. The TWN could extract wavelet's time-scale features of input signal and adaptively select the proper features necessary for the classification through wavelet thresholding mechanism. The thresholding mechanism eliminates the need for manual feature selection process. The network initialisation did not require the priori knowledge of the signal to be considered.

The experiments also demonstrated the efficacy of TWN to classify SEMG signals recorded during low-level, steady state contractions. All the SEMG signals used in the experiments were recorded when the fingers were bended with a minimal needed contraction. This advantage enables the TWN to be applied in SEMG classification of natural finger movement where the contraction level is minimal. Also this classification technique can be applied in the system that responds to steady state contraction rather than the transient of contraction as in Hudgins network (Hudgins, 1993).

6 CONCLUSION

This paper presents a new technique where single channel SEMG from the flexor digitorum superficialis muscle is used to accurately determine the movement (flexion and extension) of the individual fingers. The authors have used a wavelet network that has been developed by them (D Kumar, 2003). The network classifies SEMG signals by extracting time-scale features with wavelet transform, and adaptively adjusts its thresholding level during its learning process to select wavelet maxima with certain magnitude that characterised the input signals.

The experimental results of the SEMG classification using TWN are extremely promising. From the results, it is observed that:

a) This technique provides high accuracy of classification, accuracy ranging from *93%* to *85%*.
b) The accuracy of increases as the number of signal class decreases.
c) The TWN can be applied to classify low contraction level SEMG signals. This advantage allows the network to be applied in SEMG-based finger posture classifier and may find applications for other tonic muscle contractions such as muscles of the back.
d) The TWN is less sensitive to the window size.

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