Muscle Fiber Conduction Velocity Determination Using Neural Networks

H. Sajedi, M.B Menhaj
Amir-Kabir University of Technology
Department of Electrical Engineering, Tehran, Iran
Phone: 009821-6466009, Fax: 009821-6406469
Menhaj@cic.aku.ac.ir

ABSTRACT: Knowing that average conduction velocity measurement of action potential along muscle fibers has an important application into muscle fatigue study and ergonomics, this paper presents a neural network based approach for canceling the adjacent muscle EMG signal interference for accurate calculation of muscle fibers' conduction velocity. After testing our method on artificial generated multi-channel surface EMG, we applied the proposed method to Flexor Carpi Radialis linear array multi-electrode surface EMG. The simulation results highlight the merit of our neuro-based approach.

KEYWORDS: Muscle Fibers, Conduction Velocity, Electromyography, Neural Network

INTRODUCTION

It is very important for muscle fatigue study and ergonomics to be able to measure the average conduction velocity of action potential along muscle fiber. This velocity for an entire muscle's fibers helps to observe the neuromuscular disorders diagnosis. With array type of surface electrode one can measure the surface ElectroMyoGram (EMG) [Yamada (1991)]. As observed in Fig.1, the EMG is propagated from the motor end-plate (innervation zone) in both directions along the muscle fibers. Proper detection of the propagation delay makes the muscle fiber's conduction velocity measurement possible. It is worth noting that interference (or distortion) of the other muscle fibers action potential near the main muscle deteriorates the conduction velocity measurement, Harba (1987).

Buchthal was the first one in the 1950's found a way for innervation zone determination. and conduction velocity calculation as well [Davis (1987)]. Barker *et al.* in 1980's have developed a technique for estimation of the distribution of conduction velocities in human nerve trunks [Davis (1987)]. Masuda (1985) studied the innervation zone and its distribution in biceps Brachii by 1×13 linear array electrode surface and modified his technique using a 30×24 matrix array surface electrode [Masuda (1988)]. Graham in 1984 used the polarity cross correlation for conduction velocity estimation in biceps brachii. Broman (1985) measured conduction velocity in isometric contraction using cross correlation method. The effects of conduction velocity variations in different levels of muscle contraction have been studied in [Sadoyama (1987)]. Yamada *et al*. have also calculated the muscle fibers' conduction velocity in biceps Brachii in normal and patient people [Sadoyama (1987)] and studied the relationship between neuromuscular disorders and muscle force using a 6×10 matrix array surface electrode in [Yamada (1991].

As indicated above, the measurement of the average conduction velocity of action potential along muscle fiber plays a crucial role in muscle fatigue study and ergonomics, in this paper we present a neural network based method for canceling the neighboring muscle EMG signal interference; this makes the accurate muscle fibers'conduction velocity calculation possible. To show how the proposed method works, we first tested our method on artificially generated multi-channel surface EMG, we then applied that on Flexor Carpi Radialis linear array multi-electrode surface EMG. The simulation results are promising and highlight the merit of our neuro-based approach.

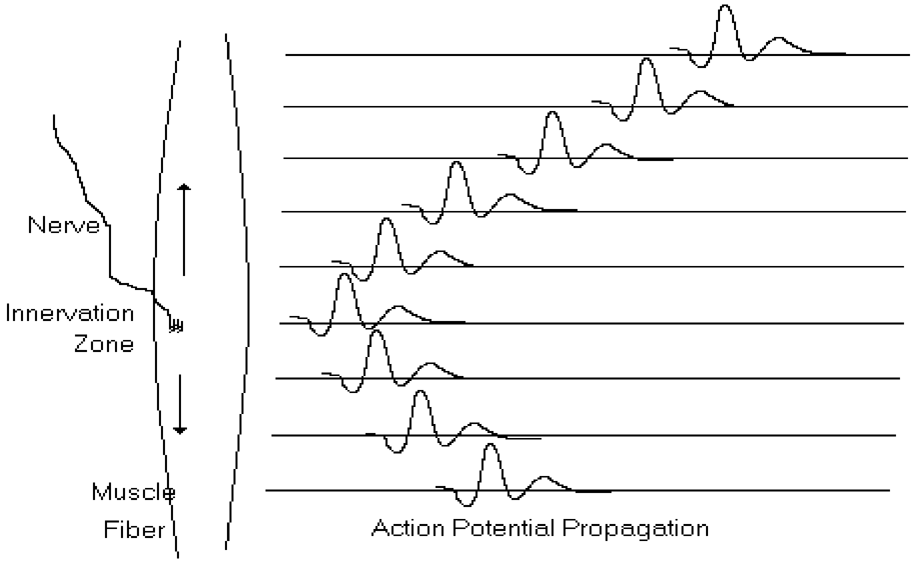

Fig. 1. Action Potential Propagation along the muscle fiber

PROBLEM STATEMENT

This section aims to present the neuro-based approach for canceling the neighboring muscle EMG signal interference. Figure 2 represents a block diagram illustration of the proposed method which is explained below.

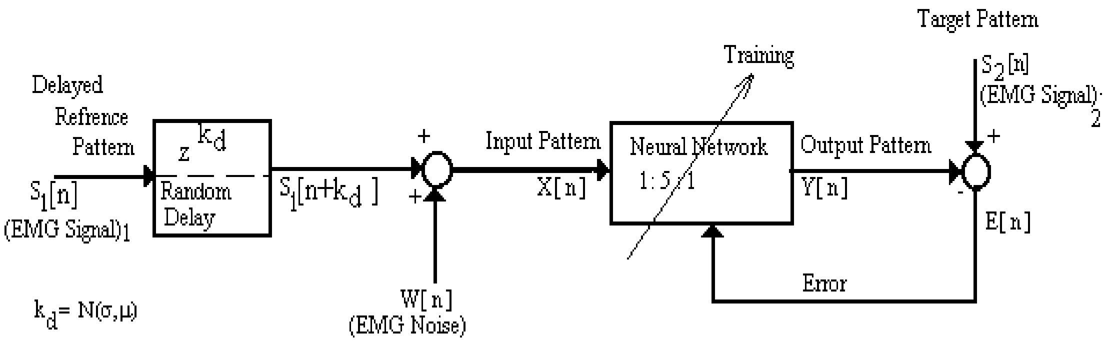

Fig 2. Block Diagram of the proposed method

Assume that there is a relation between the EMG signals of two neighboring pairs of electrodes as follows:

$$S_2(n) = S_1(n + n_d) + W(n) \tag{1}$$

where $S_1(n)$ and $S_2(n)$ are the EMG signals of two neighboring pair-electrodes, n_d is the propagation delay of action potential in muscle fiber and W(n) represents the neighboring muscle EMG signal interference. The goal is to estimate muscle fiber conduction velocity by the distance between the electrodes and the calculated propagation delay of action potentials along the muscle fiber as:

$$V = \frac{\Delta l}{n_d . T_s} \tag{2}$$

V: Muscle fiber conduction velocity

Δl : Distance between the electrodes
T_s : Sampling time in data acquisition
$n_d . T_s$: Propagation delay of action potential

To do so, we are required to have n_d in advance. This can be done by the structure shown in figure 2. The objective of neural network is to make the output of neural network approximate $S_1(n+n_d)$ by filtering the signal interference W(n). The network used in this paper as shown in figure 2 is a multi layer perceptron with a topology of (1-5-1) ; i.e. one input , one hidden layer with 5 neurons and one output. Each hidden neuron has the bipolar sigmoidal (tangent hyperbolic) type of activation function; i.e. $f(x) = \frac{1-e^{-x}}{1+e^{-x}}$. The input patterns of the net, X(n), are generated by the following equation:

$$X(n) = S_1(n + K_d(n)) + K_w W'(n) \tag{3}$$

In the above ,
$K_d(n)$ is a random variable and is generated by the following formula (see figure 3):

$$K_d(n) = g(\ N(\mu_d, \sigma_d)\ ) \tag{4}$$

where,
N (.,.) : Gaussian distribution ,
μ_d : Pre-specified value for time-delay between signals,
σ_d : Standard deviation gaussian distribution variance of $K_d(n)$,
g(x) is defined as:

$$g(x) = \begin{cases} \mu_d - B_d & x \le \mu_d - B_d \\ x & \mu_d - B_d < x < \mu_d + B_d \\ \mu_d + B_d & \mu_d + B_d \le x \end{cases} \tag{5}$$

B_d : Maximum deviation of $K_d(n)$ around μ_d ,

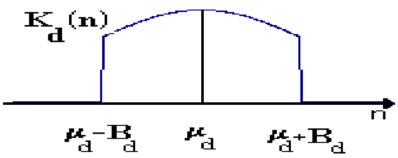

Figure 3. $K_d(n)$ generation

$W'(n)$: an EMG signal, which is uncorrelated with both $S_1(n)$ and $S_2(n)$, models interference for network input patterns ,
and,
K_W : it is a gain which is used for selection of the desired SNR.
The desired output of the network is provided by the following equation:

$$Y_d(n) = S_2(n) \tag{6}$$

For the purpose of noise filtering in specified interval time with length of N_W during which muscle fiber conduction velocity is estimated, the network is trained with the input patterns of $X(n)$ obtained by equation 3. which are normalized in the range of [-1,1] and the output of the network are the target patterns $Y_d(n)$ for n = 1,2,…, N_W .

After training, will have $Y(n) \cong S_1(n + n_d)$ and the time delay n_d between $S_1(n)$ and $Y(n)$ can be estimated by cross correlation method. To see how this method works, next section presents the simulation results.

Finally, we estimate time delay between by cross correlation method. The simulation results of proposed method for is presented in next section.
Our neural network based method cancel the neighboring muscle EMG signal interference and extract the common time-delayed pattern of EMG signal of two channels. After training and pattern matching and noise canceling, the common time-delayed pattern of input and target pattern is presented in output of neural network, and then we calculate

the average time delay between input pattern and the extracted output pattern of neural network by cross correlation method.

SIMULATION RESULTS

This section presents the simulation results of the proposed method for artificially generated multi-channel EMG and actual multi-channel EMG of Flexor Carpi Radialis muscle. Figure 4-a shows the EMG patterns which are artificially generated for neural networks training purpose. Figure 4-b and figure 4-c respectively show the conduction velocity estimation error before and after training. As one may easily observe from figure 4-a the output signal keeps the general transient shape of the reference signal which was the main concern of the paper.

We tested method on artificially generated multi-channel surface EMG and evaluated the efficiency of our method. Surface EMG of Triceps muscle that sampled by A/D at a rate of 10000 Hz has been used as the main signal and the channel signals are time-delayed versions of the main signal. For the purpose of simulation the actual signal, $S_2(n)$ is generated artificially by adding up different EMG signal to the second channel signal. The amplitude of this interference signal is tuned by the desired signal to noise ratio (SNR) of artificially generated multi-channel surface EMG. A method is said to be efficient if it could estimate perfectly the time-delays for low SNR. The measure for perfect estimation can be taken as the mean square errors between estimated and actual time-delays in different SNRs

The mean square error (MSE) of time-delay estimation by neuro-based method and that of the classic method for different SNRs are depicted in figure 5. As one can easily observe, the neuro-based (proposed) method estimate the time-delays more accurately for lower SNRs; consequently we use this method for measurement of muscle fiber action potential conduction velocity in clinical experiments. This is given below.

The proposed method is tested on actual multi-channel surface EMG signals which have been obtained experimentally in the lab. Figure 6 shows the EMG signals and the results. The subject was a normal volunteer man (aged 30 years). The Flexor Carpi Radialis (one of the arm muscles) was examined. The linear array multi-electrode used in this study was composed of 12 Ag electrodes (1×12) which were arranged on a flexible gum board with 5mm distance between two neighboing electrodes. These electrodes were fixed in place by bandages in parallel with longitudinal axis of the muscle fibers. After cleaning the skin and using jell, bipolar EMG was recorded.

Acquisition and analysis of EMG signals were performed by a microcomputer system. The EMG signals were amplified through a bandwidth of 20-1000 Hz and sampled by an A/D converter at a rate of 10000 Hz for 3 secs. Length of window during which muscle fiber conduction velocity is estimated, was 50 msecs and the window was shifted by 5 msec steps to cover all of the signals. Average conduction velocity measured in each window undergoes the variation of muscle fiber conduction velocity along the time. Variations of average action potential conduction velocity as a function of time are shown in figure 6-b.

Since, the actual muscle fiber conduction velocity cannot be measured by noninvasive methods, thus the comparison of our method with the others gives no useful information.

The proposed neuro-based method is a powerful tool for cancellation of uncorrelated interference in multi-channel surface EMG signals. This tool is very useful for study of muscle fiber conduction velocity and innervation zone in arm muscles surrounded by many neighboring muscles. With this method and construction of experimental setup in lab, we can study the variations of action potential conduction velocity along the muscle fiber in normal person and patients with myopathy and neuropathy and then present a clinical feature for neuronascular disorders.

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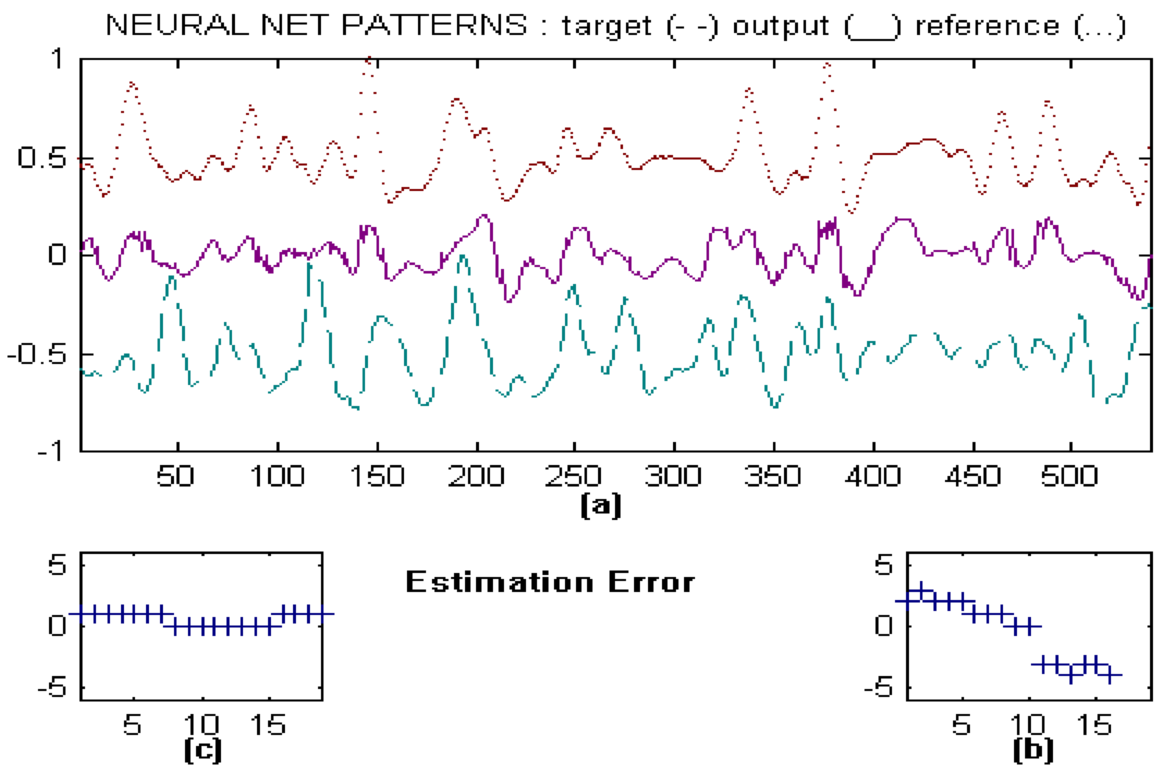


Figure 4. Simulation results for artificially generated two channel EMG

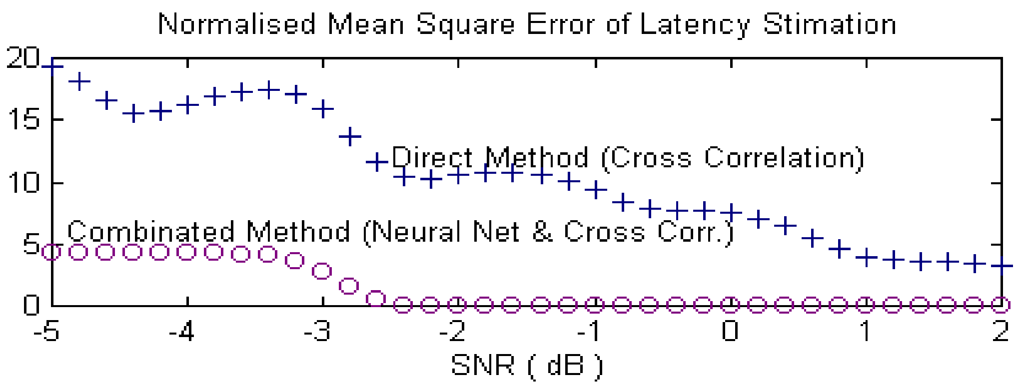
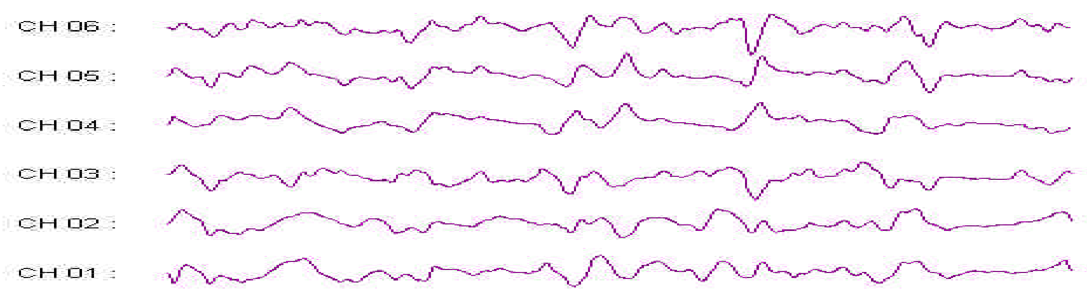
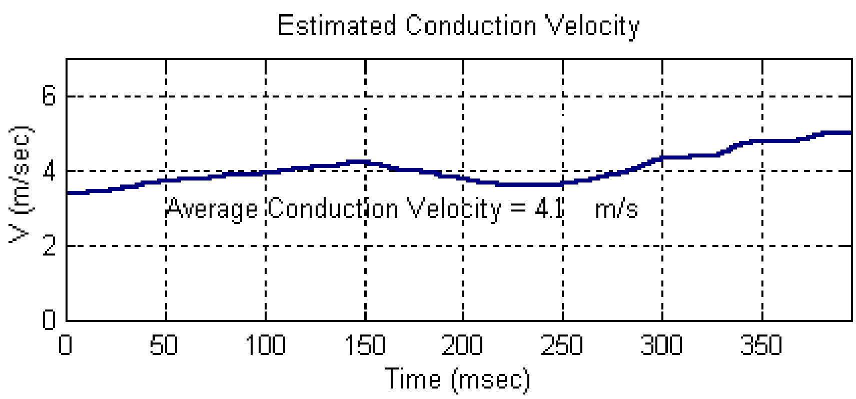


Figure 5. Comparison the neuro-based method and cross-correlation method



(a)- Flexor Carpi Radialis linear array multi-electrode surface EMG



(b)- Conduction velocity which is estimated by the proposed method

Figure 6. Simulation results for actual EMG