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Interference cancellation in EMG signal Using ANFIS

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Abstract- **In this paper, Adaptive Neuro Fuzzy Inference System (ANFIS) is proposed to cancel the electrocardiogram (ECG) interference in electromyogram (EMG) signal. Conventional filtering techniques are not suitable due to an overlap in spectral content of the desired signal (EMG) and the interference. Comparison of results is made between the proposed technique and the other artificial intelligence techniques like Back Propagation Network (BPN), and Cascade Correlation Network (CCN). The performance evaluation of the proposed technique is done in terms of signal to noise ratio, mean square error, and convergence time. It shows that ANFIS successfully cancel the interference in EMG signal.**

Index Terms- **Interference cancellation, EMG signal, BPN, CCN, ANFIS.**

I. INTRODUCTION

Electromyogram is the electrical activity of the activated motor units in muscle. It is a very powerful diagnostic modality for evaluating the peripheral nervous system and it provides valuable information that is not obtainable with any other diagnostic test. The EMG signal is mainly applicable to the study of skeletal muscle which is attached to the bone. Its contraction is responsible for supporting and moving the skeleton. The clinical applications of the EMG include neuromuscular diseases, low back pain assessment, kinesiology and disorders of motor control. Surface Electromyogram (SEMG) recordings provide information about many fibers in superficial muscles and have amplitudes ranges from 0 to 10 mV with most of the power lying between 10 Hz and 400 Hz. The EMG signal depends on the anatomical and physiological properties of muscles. It acquires noise while traveling through different tissues. Moreover, the EMG detector which is placed on the surface of the skin, collects signals from different motor units at a time and the interaction of these signals generates artifacts or interferences. The different artifacts that occur in EMG signal are noise due to electrode, ambient noise, motion artifact and biological artifacts. The most common of these is the ECG, which is frequently present when the EMG is recorded from electrode sites on the trunk and neck.

The weighted low-pass differential filter for the analysis of EMG signals is proposed in [1]. An adaptive filtering algorithm specifically developed for the rejection of the ECG corrupting SEMG is proposed in [2]. A comparison of wavelet and classical digital filtering procedures for denoising of SEMG signals is made in [3]. The main advantages of wavelet technique are that no artificial information is introduced into the filtered signal and that the signal components may be independently thresholded in order to generate the filtered signal. This allows for some flexibility that may be required in different applications. The main drawback of this method is that a mother wavelet has to be defined apriori and this choice may influence the final results. A method based on the combined use of wavelet transform and ICA is presented in [4]. In this preliminary study, an user interface is needed to identify the artifact. An event-synchronous interference canceller for cancellation of ECG interference in EMGdi signals is addressed in [5]. Elimination of ECG artifacts from the myoelectric prosthesis control signals, taken from the reinnervated pectoralis muscles of a patient with bilateral amputations at shoulder disarticulation level is investigated in [6]. A denoising method using ICA and a HPF to effectively suppress the interference of ECG in SEMG recorded from trunk muscles is discussed in [7]. The instantaneous frequency estimation method which provides the frequency components of the ECG signal as well as their time of occurrence is used in [8]. The removal of ECG artifacts in real time for myoelectric prosthesis control, a clinical application that demands speed and efficiency is investigated in [9]. Each method has its own advantages and disadvantages. This paper explains the efficiency of ANFIS to cancel the ECG interference in EMG signal.

II.METHODS AND MATERIALS

A.Concept of Adaptive Interference Cancellation (AIC)
Fig.1 shows the schematic diagram of the AIC [10].

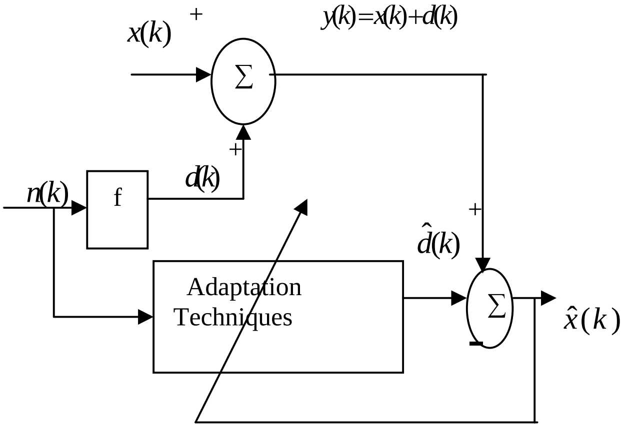

Figure 1. Schematic diagram of AIC

In Fig.1, $x(k)$ represents the required signal which is to be extracted. The noise signal $n(k)$ goes through an unknown nonlinear passage dynamics (f) and generates a distorted and delayed version of $n(k)$ i.e. the interference signal $d(k)$, which is then added to $x(k)$ and forms the measurable signal $y(k)$. The aim is to retrieve $x(k)$ from $y(k)$. In symbols, the measured signal (composite singal) is expressed as

$$y(k) = x(k) + d(k) = x(k) + f(n(k), n(k-1), n(k-2), \ldots .. \quad (1)$$

The function $f(.)$ represents the human body that the noise signal $n(k)$ goes through. If $f(.)$ is known exactly, it would be easy to recover $x(k)$ by subtracting $d(k)$ from $y(k)$ directly. However, $f(.)$ is usually unknown in advance and could be time varying due to changes in the environment. Moreover, the spectrum of $d(k)$ may overlap with that of $x(k)$ substantially, invalidating the use of common frequency domain filtering techniques. A clean version of the measurable noise signal $n(k)$ that is independent of the required signal is needed to estimate the immeasurable interference signal $d(k)$. However, $d(k)$ cannot be accessed directly because it is an additive component of the overall measurable signal $y(k)$. The proposed adaptation techniques based on AI are used to estimate the unknown interference $d(k)$ in $y(k)$. Let the output of adaptation algorithm be denoted by $\hat{d}(k)$. When $\hat{d}(k)$ and $d(k)$ are close to each other, these two get cancelled and the estimated output signal $\hat{x}(k)$ is very close to the required signal. The learning rule tries to minimize the error, i.e. $[e(k)]^2$

$$[e(k)]^2 = [y(k) - \hat{d}(k)]^2$$

$$= [x(k) + d(k) - \hat{d}(k)]^2 \quad (2)$$

$$= [x(k) + d(k) - \hat{f}(n(k), n(k-1), n(k-2), \ldots)]^2$$

Expanding equation (2),

$$[e(k)]^2 = [x(k)]^2 + [d(k) - \hat{d}(k)]^2 + 2x(k)\, d(k) - 2\, x(k)\, \hat{d}(k) \quad (3)$$

Taking expectations on both sides and assuming that $x(k)$ is not correlated with $d(k)$ yields

$$E[e^2] = E[x^2] + E[(d - \hat{d})^2] - 2E[x\hat{d}] \quad (4)$$

If $x(k)$ is a random signal with zero mean, then $E[x] = 0$ and

$$E[e^2] = E[x^2] + E[(d - \hat{d})^2] \quad (5)$$

It may be noted that $E[x^2]$ is not affected when the adaptation mechanism is adjusted to minimize $E[e^2]$. Therefore training the system to minimize total error $E[e^2]$ is equivalent to minimizing $E[(d - \hat{d})^2]$, such that function f can be as close as possible to the passage dynamics $f(.)$ in a least squares sense. The adaptation techniques used in this paper are BPN, CCN and ANFIS.

B. Back Propagation Network

BPN is a feed forward, multilayer network that uses the supervised mode of learning. It makes use of gradient descent algorithm to minimize the nonlinear and non-stationary interferences. The BPN architecture consists of input layer, hidden layer, and output layer [11].The number of inputs, hidden layers, neurons in each layer and outputs vary depending on the application. Though BPN gives better performance, it also has many limitations like a very long training process with problems such as local minima and network paralysis. Another neural network called CCN is used in this paper to overcome these limitations. It further reduces the Mean Square value of the required signal and the convergence time and also increases the SNR.

C. Cascade Correlation Network (CCN)

Cascade correlation is an architecture which uses supervised learning algorithm for artificial neural networks [12]. Instead of just adjusting the weights in a network of fixed topology, CCN begins with a minimal network, then automatically trains and adds new hidden units one by one, thus creating a multilayer structure. Once a new hidden unit is added to the network, its input side weights are frozen.CCN offers the advantages like no need to guess the size, depth, and connectivity pattern of the network in advance, CCN learns fast thereby it is suitable for large training sets, the weights of only one layer in the network are trained at any given time, it retains the structures it has built even if the training set changes, CCN is less likely to get trapped in local minima than BPN.

D. Adaptive Neuro Fuzzy Inference System (ANFIS)

Neural network recognizes patterns and adapt them to cope with changing environments. But it takes longer time to train the network and produce the desired output. In a conventional FIS, the number of rules is determined by an expert who is familiar with the target system to be modeled. In cases where no experts are available, the number of membership functions (MFs) assigned to each input variable is chosen empirically. For data sets with more inputs, conventional FIS is not very effective. Hence, their applicability suffers from several weaknesses of the individual models. Therefore, combination of neural network with fuzzy system is proposed, where both models complement each other. The general architecture of ANFIS [13] is shown in Fig. 2.

Let X and Y are two sets in which x and y are any two input variables. The architecture has two inputs x and y and one output *z*, where z is a function of 'f'. Assume that the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type.

Rule1:If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$

Rule2:If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$.

Fig. 2 (a) illustrates the reasoning mechanism for Sugeno model [13]. The corresponding equivalent ANFIS architecture is shown in Fig. (b) where nodes of the same layer have similar functions.

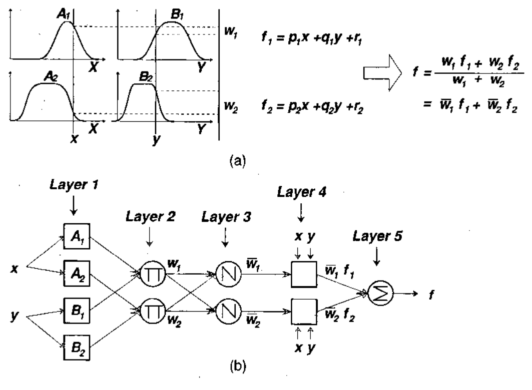

Figure 2. ANFIS architecture (a) A two input first order Sugeno fuzzy model with two rules (b) Equivalent ANFIS architecture

A membership function is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The commonly used MFs are triangular, trapezoidal, gaussian, generalized bell type (gbell) etc. Piecewise linear MF like trapezoidal or triangular are preferred, because of their simplicity and efficiency with respect to computability. But in some applications, the modeling requires continuously differentiable curves and smooth transitions, which the trapezoids do not have. Since gbell has the advantage of smoothness and concise notation, it is used for tuning the FIS parameters in nonlinear applications.

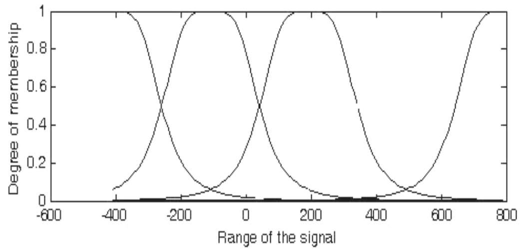

Figure 3. Bell shape membership function

ANFIS uses a hybrid learning algorithm which combines least squares and back propagation gradient descent methods to identify the MF parameters of the Sugeno type FIS. In the forward pass of the hybrid learning algorithm, the node outputs go forward until layer 4 and least squares estimator method is used to identify the consequent parameters. In the backward pass, the error signals propagate backward and the premise parameters are updated by gradient descent. In this work, ANFIS is used to identify an unknown nonlinear passage dynamics that transforms a noise source into an interference component. Once the ANFIS yields an estimate of the interference it is subtracted from the measured signal to retrieve the required signal.

A biokit equipment consists of data acquisition unit, amplifiers and software which can run on windows environment is used in this paper to acquire the EMG signal. This EMG signal is recorded from the forearm position. It acts as the measured (target) signal and is shown in Fig.4. The EMG signal which is shown in Fig. 4 is contaminated mainly by ECG signal. Hence, it is necessary to cancel the ECG artifact. The ECG signal used for AIC is recorded using electrodes placed on the fingers and is shown in Fig. 5. The frequencies of EMG signal are higher (up to 3 KHz) when compared to the ECG signal (1 Hz -100 Hz). The HPF can be used to filter out the ECG component. However, it may remove a portion of the required EMG signal also. Hence, AIC is required to cancel the ECG interference in the EMG signal. In this work, 3 AI techniques namely BPN, CCN, and ANFIS are employed to cancel the ECG interference in the EMG signal.

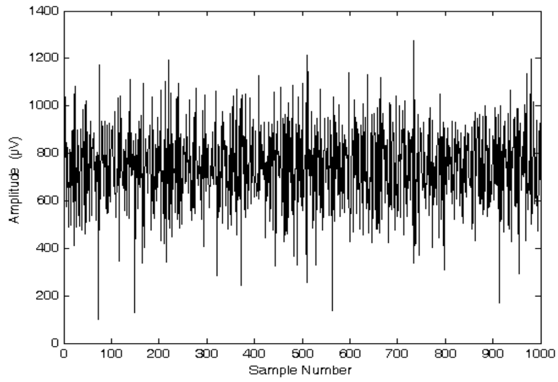

Figure 4. EMG signal recorded from the forearm position

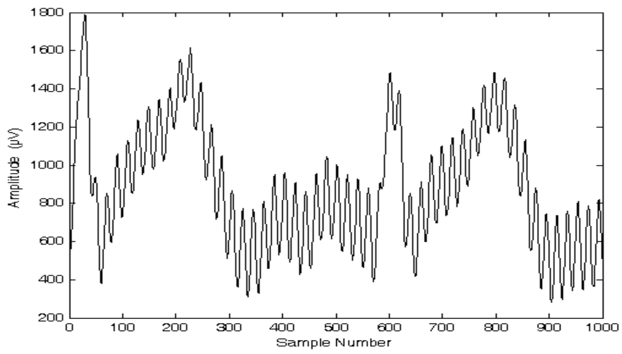

Figure 5. ECG signal

III. RESULTS AND DISCUSSION

The parameters used for training BPN to cancel the ECG interference are epochs =30, goal = 0.65, momentum =0.9, show = 5, time = infinity and learning rate = 0.5. The BPN architecture has two neurons in the input layer, 35 neurons in the only hidden layer and one neuron in the output layer. The known ECG signal and the delayed ECG signal are given as two inputs. The measured EMG signal is the target in the training process. The training stops as soon as the performance goal (mean square value of the estimated EMG) reaches a minimum or the maximum number of epochs is reached. The result of AIC using BPN is shown in Fig.6.

The ECG signal recorded using appropriate electrodes is shown in Fig. 6 (b). The estimated ECG interference in EMG using BPN is shown in Fig. 6(c). The estimated EMG signal using AIC is shown in Fig. 6(d).It is passed through a Butterworth filter of order =2 and normalized frequency = 0.7 to get the noise. Since BPN gives a rough estimation of the interference, the amount of noise in Fig. 6(e) is high.

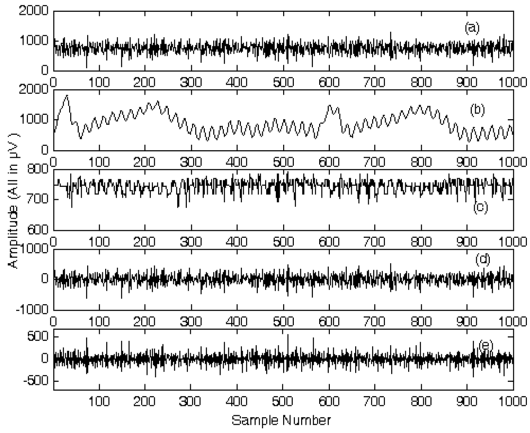

Figure 6. Results of AIC in EMG using BPN (a) Contaminated EMG (b) Reference ECG (c) Estimated ECG interference in EMG (d) Estimated EMG (e) Noise after AIC

The parameter values used for training CCN are same as that used for training BPN. The CCN architecture has two input nodes and one output node. It is assumed that 35 hidden nodes (arranged into 3 sets with each set containing 10, 10 and 15 nodes) are available for selection. The covariance for all the three sets is calculated. Then, the set which has the highest covariance is selected and the other two sets are rejected. The results of AIC using CCN are shown in Fig.7. It is noted from Fig. 7 (e) that the noise generated using CCN is slightly less than that with BPN.

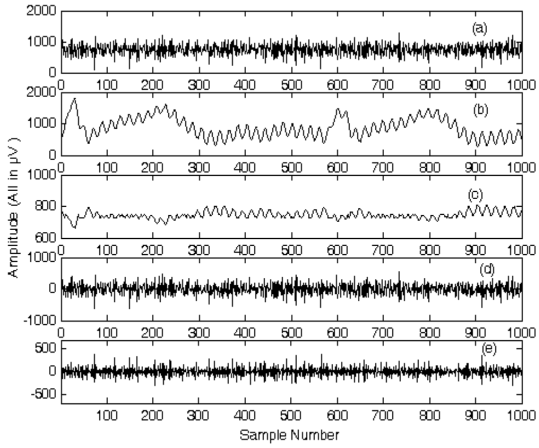

Figure 7. Results of AIC in EMG using CCN (a) Contaminated EMG (b) Reference ECG (c) Estimated ECG in EMG (d) Estimated EMG (e) Noise after AIC

The parameters used for ANFIS training are: Number of nodes = 35, number of linear parameters = 27, number of nonlinear parameters = 18, number of training data pairs = 1000 and number of fuzzy rules = 9. The results of AIC using ANFIS are shown in Fig. 8. It is observed from Fig. 8(e) that the magnitude of the noise is very much reduced.

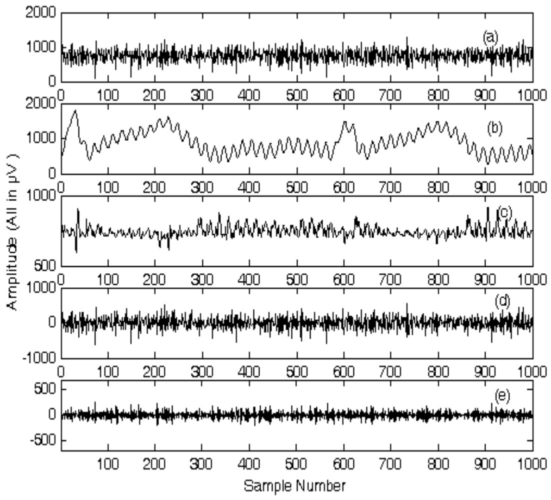

Figure 8. Results of AIC in EMG using ANFIS (a) Contaminated EMG (b) Reference ECG(c) Estimated ECG in EMG (d) Estimated EMG (e) Noise after AIC

It is observed from Fig. 8 (e) that the noise after AIC in EMG signal is very less. Quantitative analysis of the different AI techniques used for ECG interference cancellation in EMG signal is given Table 1. It shows that the Mean Square value of the estimated EMG signal and convergence time is less when ANFIS technique is used. Also SNR is maximum for the same technique.

TABLE 1.
QUANTITATIVE ANALYSIS

Sl. N o.	**Technique**	**MSE**	**SNR (dB)**	**Convergen ce time(s)**
1	BPN	2.7950 e004	6.0052	6.1560
2	CCN	2.7646 e004	10.7861	4.0940
3	ANFIS	2.6664 e004	16.1870	3.0 450

IV. CONCLUSION

The EMG signal is contaminated by various noises such as electrode noise, power line interference, EEG and ECG. Conventional methods are used to remove the non-physiological noises. Since some of the characteristics of EMG signal are similar to ECG signal, it is necessary to use AIC. Three AI techniques are employed to cancel the ECG interference in EMG signal. Quantitative analysis reveals that ANFIS outperforms the other techniques. The results obtained indicate that ANFIS is a useful AI technique to cancel the nonlinear interferences from the EMG.

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