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An approach of adaptive filtering ECG Noise Reduction using neural network classifiers and fuzzy multi-criteria assessment

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Abstract: Electrocardiogram (ECG) signal processing has been the subject of intense research in the past years, due to its strategic place in the detection of several cardiac pathologies. However, ECG signal is frequently corrupted with different types of noises such as 60Hz power line interference*, *baseline drift, electrode movement and motion artifact, etc. This paper presents a new ECG denoising approach based on noise reduction algorithms in complex wavelet transform (CWT) domains and artificial neural network (ANN) and method of integrating classifiers using fuzzy multi-criteria decision is used. In this way, the exchange between the criteria is permitted. The mechanisms of decision-making, is the best of the possible options, as selected option, have the highest degree of satisfaction of the criteria.Isproposed for ECG noise reduction based on excellent localization features: in complex wavelet transform and the adaptive learning ability of neural network.The accuracy of the developed CWT based approach is tested on real ECG data from the MIT-BIH database and compared with one of the previously suggested CWT -based methods. Both quantitative and qualitative results of the work are presented.

Keywords: **complex wavelet transform, Artificial Neural Network, Support vector machine**, **Noise Reduction, ECG.**

I. INTRODUCTION

The electrocardiogram (ECG), the recording of the cardiacactivity, plays a key role when it comes to clinical, and particularly cardiac, diagnosis. However, under practicalcircumstances, the recorded ECG may lead to an inaccurateanalysis due to the noise corrupting the original signal.Several sources of noise may corrupt the signal. [1]

Moreover, several electrical and mechanical noise components are also added to the signal, making it difficult to extract key features. In general, measured ECG signal data contains white noise, muscle artifact noise, baseline noise, electrode moving artifact noise, and 60Hz power line noise [2].

Interference cancellation in bio-signals can be implemented using non-adaptive and adaptive methods. Non–adaptive techniques such as fixed filters [3], averaging techniques, morphological filtering [4] Empirical mode decomposition [5], Wavelet analysis [6] and Independent Component Analysis [7] are based on prior knowledge of the signal and the noise characteristics and have been widely used for interference cancellation in ECG.
Different techniques have previously been proposed on the removal of the interferences in the ECG signals. Some of them consisted of a median filter for impulsive noise reduction and a linear filter for white noise reduction. For example, an FIR median hybrid filter which was a cascade of linear phase FIR filters and a median filter was proposed in [8]. The Method in [9] presented an IIR median hybrid filter [10]. For baseline removal, the technique of baseline estimation using cubic spline in [11] is proposed. The threshold is claimed asymptotically optimal in minimax sense but it would over-smooth signals in practice. Since Donoho's pioneer work, a numerous threshold-based denoising schemes have been proposed [12-14]

As a Karhunen–Loève like expansion, wavelet transform (WT) [15] can decorrelate random processes into nearly independent coefficients [16], which can then be more effectively modeled statistically.WT has been successfully applied to coding and denoising. The proposed method presented in this paper does not involve such hybrid combination. Rather, the complex wavelet technique is used as a feature extraction, aiding the neural network and multi-criteria decision in capturing useful information on the dynamic of complex time series. However, for the sake of completeness, a complex Wavelet Neural Network is also introduced. The

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remainder of this paper is to this, in the second section, we introduce the method of feature extraction, and the third section, we will discuss the classifier, and the fourth part of the proposed method, which involves classifiers are combined using fuzzy multi-criteria decision-making, is introduced, and the fifth section, we provide the results and findings, and section VI, we express our conclusions.

II. PROPOSED METHOD

Figure (1) displayed following block diagram of the proposed method.

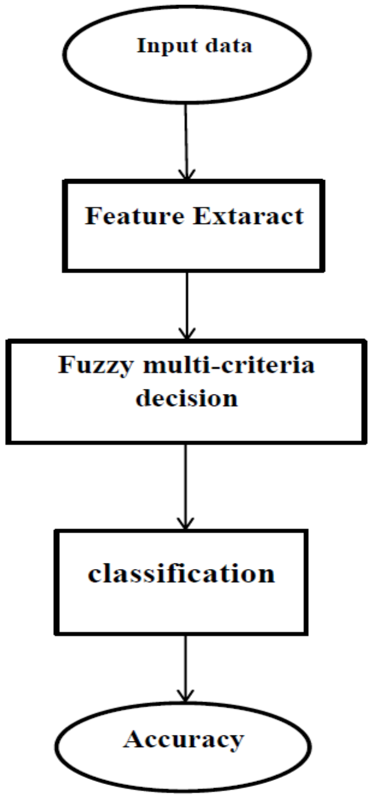

Fig.1. Block diagram of the proposed method

A. Complex wavelet transform features

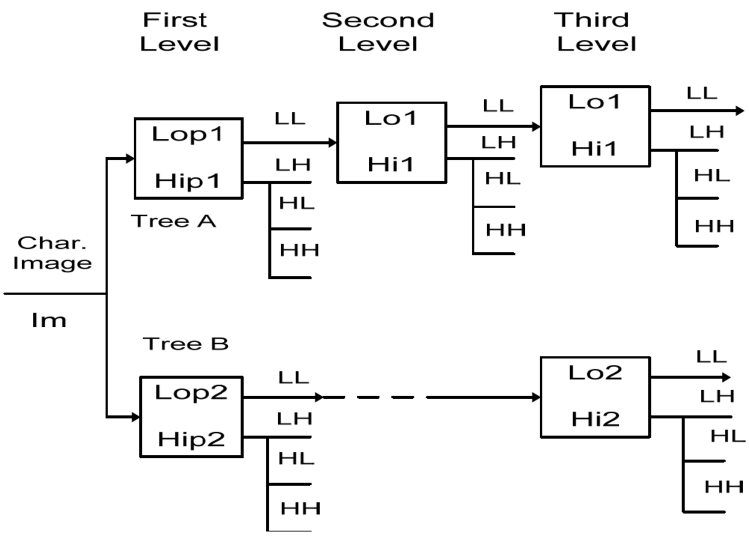

Fig. 2. Schematic complex wavelet transform algorithm [17]

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In complex wavelet transform (CWT) feature extracting method, in addition to the fact that transform features are maintained, we also exploit the lack of sensitivity to small displacements in image. In this method, first, low-pass and high-pass filters are applied to the image, then each image is divided into four sub bands. This procedure consists of three stages. Wavelet factors used in this method are extracted from level-3 LL sub band which finally will produce the ultimate feature vector [17]. Figure (2) demonstrates a schematic algorithm of complex wavelet transform.

B. Fuzzy multi-criteria decision

Algorithms Boosting [18], are the most popular methods for classification assemblies. They develop, D classification assembly, adding a classification, at the same time. Classification, the integrated assembly, in step k, the ECG signal has been sampled, Z training samples. Distribution model starts from the beginning, and will lead to the increase of the data difficult. Thus, distribution, updates, at each step.

1. Merge classifiers using fuzzy multi-criteria decision

The mechanisms of decision-making, is the best of the possible options, as selected option, have the highest degree of satisfaction of the criteria. Here, the problem of multi-criteria decision is reviewed. Multi-criteria decision-making is one of the areas that are growing rapidly [19]. In this paper, we have described a method for fuzzy decision problems. In this way, the exchange between the criteria is permitted, and this means that the weakness of the criteria, be compensated by establishing other criteria. This model is called as a compensatory model. In this model, it may not meet all the criteria, if the rest of the criteria, have been able to compensate for it. Decision problems, often expressed by the following matrix:

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} c_1 & c_2 & \cdots & c_n \end{array} \\ \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \end{array}$$

Where, Ai is decision criteria cj. Options, and the way that we present here is based on the analysis of the relationships between the criteria. There are three types of relationships between criteria: relationship conflict, relationship compatibility, and independent. The definition of these criteria is presented in the next section.

2. Multiple decision making, based on analyzing the relationship between measures

In this way, the preferred option is done in four steps: calculation of the degree of conflict and harmony, for both criteria, the criteria are divided into two classes, by applying the algorithm to calculate the fulfillment of the criteria for each class, for each option, and create a regular list of options. In this section, first, we offer a definition of conflict 1 and 2 comply, and then using these definitions, calculations are necessary, and the proposed algorithm, the classification criteria, and then criteria defined, sorting options, according to this division. Suppose there are two criteria, and A, is the set of all possible options. Two options, the relationship conflict, defined in this way.

$$\mathrm{CF} = \left\{ \left(a_i, a_j\right) | \mu_c(a_i) - \mu_c\left(a_j\right) \times \left(\mu_{c'}(a_i) - \mu_{c'}\left(a_j\right)\right) < 0 \right\} \quad (1)$$

$$\mathrm{CP} = \left\{ \left(a_i, a_j\right) | \mu_c(a_i) - \mu_c\left(a_j\right) \times \left(\mu_{c'}(a_i) - \mu_{c'}\left(a_j\right)\right) > 0 \right\} \quad (2)$$

$$\mathrm{IR} = \left\{ \left(a_i, a_j\right) | \mu_c(a_i) - \mu_c\left(a_j\right) \times \left(\mu_{c'}(a_i) - \mu_{c'}\left(a_j\right)\right) = 0 \right\} \quad (3)$$

Set of pairwise combinations of options is shown with Ap:

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$$A_p = \{(a_i, a_j) \mid \forall a_i, a_j \in A, i \neq j\} \quad (4)$$

Ap, is defined with respect to both criteria, and the relations (5-8) are established according to two criteria relevant.

$$A_p = IR \cup CP \cup CF \quad (5)$$

$$IR \cap CP \cap CF = \emptyset \quad (6)$$

$$cf(c,c') = \frac{\sum_{a_i,a_j \in CF}(|\mu_c(a_i) - \mu_c(a_j)| + |\mu_{c'}(a_i) - \mu_{c'}(a_j)|)}{\sum_{a_i,a_j \in Ap}(|\mu_c(a_p) - \mu_c(a_p)| + |\mu_{c'}(a_p) - \mu_{c'}(a_p)|)} \quad (7)$$

$$cp(c,c') = \frac{\sum_{a_i,a_j \in CP}(|\mu_c(a_i) - \mu_c(a_j)| + |\mu_{c'}(a_i) - \mu_{c'}(a_j)|)}{\sum_{a_i,a_j \in Ap}(|\mu_c(a_q) - \mu_c(a_q)| + |\mu_{c'}(a_q) - \mu_{c'}(a_q)|)} \quad (8)$$

Relations between criteria for optimal fussy decision making, is most important, because it can reflect interactions between criteria, and it shows the user preferences, to a standard. The importance of the relationship between standards and criteria are important in decision making problems.

III. CLASSIFICATION

The local linear model for WNN (LLWNN) was proposed by [14] in which the connection weights between hidden layer units and output units are replaced by a local linear model. By doing so, this particular network will gain advantage over the traditional design in high dimensional as well as more complex problems. In traditional designs of ANN and WNN alike, the complexity of the network increases as the dimensions of the input increases. Because a network with higher hidden units provides larger capacity necessary to handle large input dimensions, higher dimensional problems usually translate to an increase in the number of the hidden units.In this paper, the LLWNN classification is used.

IV. RESULTS

The effectiveness of the proposed method is demonstrated in this section. First, the network is trained to remove one type of noise at a time. By doing so, one can examine the results closely to the reaction of the individual noise whether or not the network performance meets the acceptable margin. Next, the simulation will combine all the noises as it would in a real ECG diagnosis situation and have the network train to remove those noises. To further test the effectiveness, the network is trained with different patients' ECG as well. The test also measures the performance and consistency of how well the network is able to learn by repeatedly training it with the same training data set and also testing it with the same testing data set. The only different is the initialization of the parameters. Finally, the experiment runs several comparisons with alternative selections of network models and shows the actual improvement of the proposed method over traditional method.

A. Removal of single noise

These two are also easy to remove despite the non-stationary characteristic of baseline drift. Both baseline and Gaussian noise are located at the very low-end and wide-band frequency spectrum, respectively. The upper-end of Gaussian white noise frequencies were already removed through the threshold process of CWT. The output of 64 coefficients from CWT to a neural network contains a scaling coefficient which represents the lowest end of a spectrum of 1.4 Hz and lower. This coefficient contains both noise as well as an ECG signal. Due to maximum level restriction of DWT, this scalar cannot be split any further. Thus, a neural network performed most of the filtering to remove baseline noise**.**(figure(3-4))

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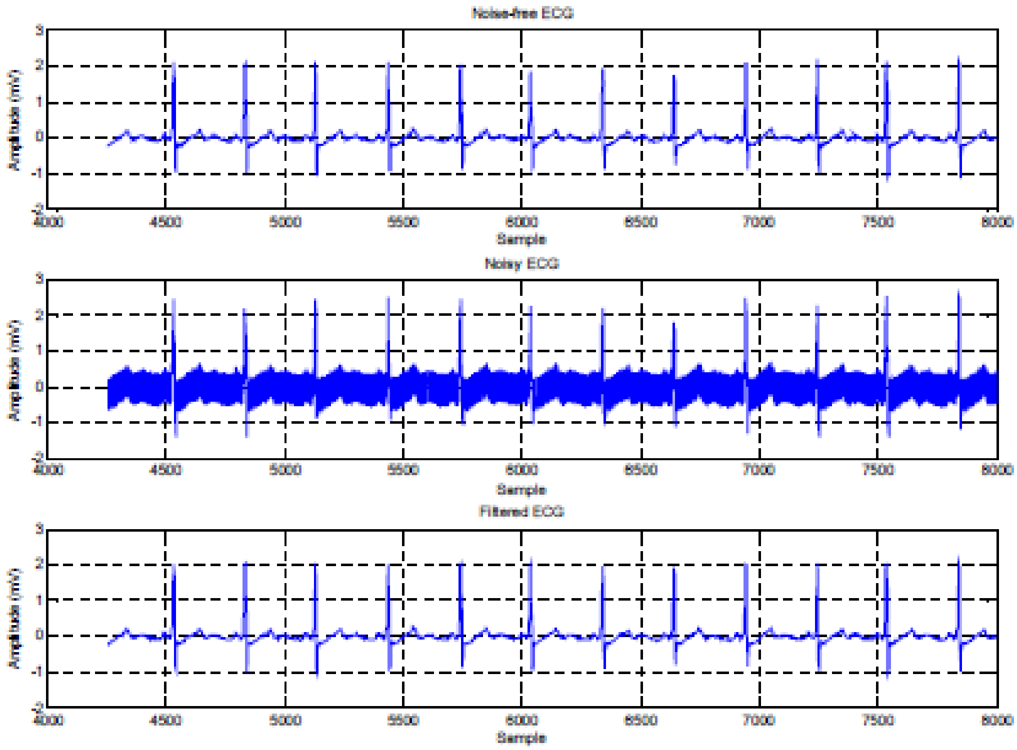

Fig.3. 60 Hz power-line removal

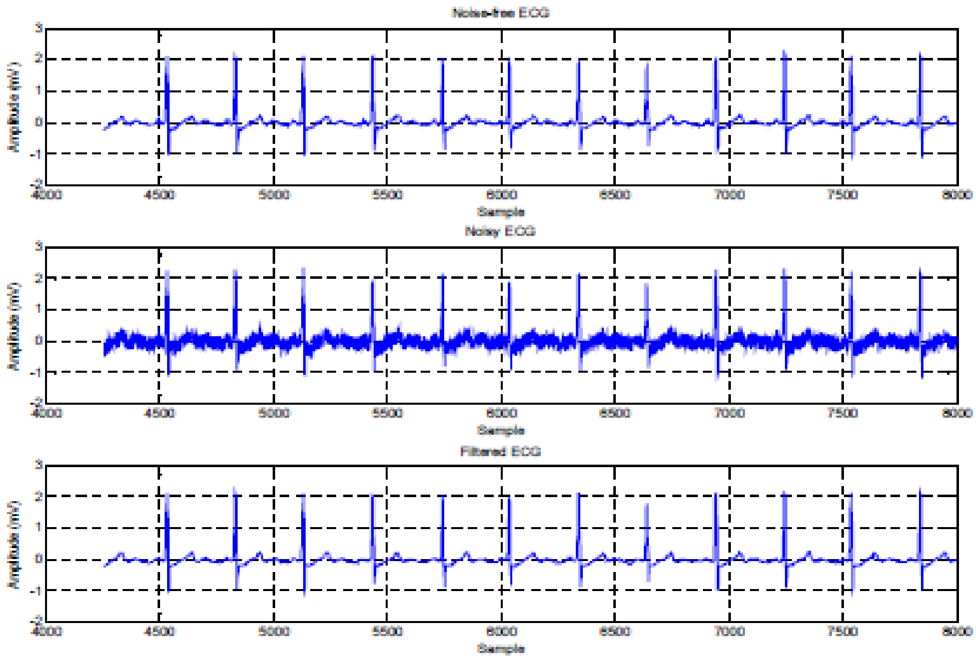

Fig .4. Gaussian white noise removal

Clearly, SNR improvement of the alternative method is no where match the proposed method. This is mainly because of CWT and its frequency decomposing ability. The keyinfluence of the neural network to learn does not always depend solely on the size of itsstructure. The pre-process step of transforming the signal into categories of frequencies band such as decomposition can also improve the learning performance of the network

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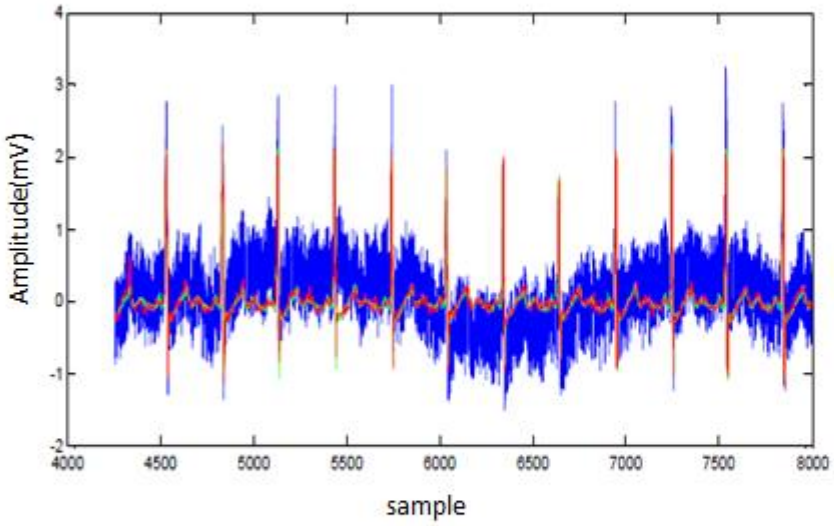
as well. In other words, the learning efficiency of neural network improves if its inputs are more organized. This will allow the neural network to determine the relationship between input and output easier. The sample of graphical comparison results are shownin figure (5) where the blue represents noisy signal, green is noise-free, and red is the filtered signal.



Fig, 5. Result for proposed method

V. CONCLUSION

The method of complex wavelet decomposition and neural network classifiers and fuzzy multi-criteria decision presented in this paper has demonstrated its noise reduction capability of highly non-linear and nonstationarysignals through an application of electrocardiogram (ECG). In the specificmodels given, the delayed values of relevant signals in the system are used as inputs to complex wavelet decomposition. Its outputs are, then, filtered through the process of coefficient thresholding which removes the majority of coefficients that are not relevant to thesignal of interest. Next, these remaining coefficients are used as inputs to a multilayerneural networks. Methods for the adjustment of parameters in generalized neuralnetworksclassifiers and fuzzy multi-criteria decision are treated, and the concept of back propagation was introduced in paper to generate partial derivatives of a performance index with respect to adjustable parameters. Once trained, the neural network can recognize the wavelet decomposed coefficients of a particularpatient and can reconstruct the signal with most of the noises removed. With sufficienttraining, the network may be applied to process the ECG signals in real-time.

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