Feature Extraction and Classification for ECG signals Processing based on Stationary Multiwavelet Transform and Artificial Neural Network

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Abstract

This paper proposes an algorithm that uses mix of Stationary Multiwavelet Transform and Artificial Neural Network (ANN) algorithm for classification of Electrocardiograph (ECG) signals. The MIT-BIH arrhythmia database is used to measure the performance of the suggested method and compare the results with conventional techniques. The Stationary Multiwavelet Transform (SMWT) and the Minimum Average Maximum strategy (MAM) is suggested to calculate the useful features of the signal before utilizing ANN algorithm for classification. Since SMWT is a translation invariant, therefore, it enhances the classification performance and reduces mean square error (MSE). Repeated Row Processing exists in this scheme to make it more suitable for feature extraction compared with Stationary Wavelet Transform (SWT), Multiwavelet Transform (MWT) and Principle Component Analysis (PCA). SMWT and MAM reduce dimensional space and decrease the complexity of classification circuit. ECG signal is classified using ANN. Finally, the results of the proposed method are realistic compared with SWT-ANN, MWT-ANN, and PCA-ANN. The obtained results emphasize the excellence of the presented algorithm than the traditional techniques. The SMWT-ANN achieves classification accuracy of 100% and mean square error of $1.4 * 10^{-3}$.

Keywords: ECG signals, Stationary Wavelet Transform, Stationary Multiwavelet Transform Neural Networks.

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1. Introduction

An Electrocardiogram or ECG is an important physiological signal used in the investigation of heart disease [1]. It helps in distinguishing the unbalance in the function of the heart and evaluating its performance. It offers important information that is given by ECG signal about the work of the heart and blood vessels that are helpful for saving the life of the human. A fundamental waveform of ECG of one cardiac cycle is shown in Figure 1. The waveform ECG is formed from P, Q, R, S and T elements [2] .

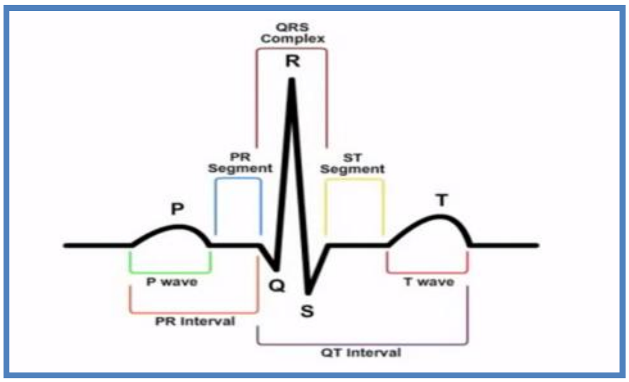


Figure 1: Components of a typical ECG signal

Multiwavelets are a new addition to the body of wavelet theory. The multiwavelet uses more than one scaling function and wavelet function. Several properties such as perfect reconstruction (orthogonality), good performance on the boundaries (symmetry), and high order of approximation (vanishing moments) can be provided by multiwavelet, so scalar ones could not perform [1].

The Stationary Wavelet Transform (SWT) (it is also called undecimated wavelet transform) depends on the concept of no decimation to make the wavelet decomposition time invariant [2]. It could restrain the fake fluctuation which occurs in the switching of the signal [3].
Neural Network consists of the processing elements or neurons operating in parallel. It was designed to simulate the processing methods found in the brain [4]. Neural Network classifier was designed to identify classes of ECG signals in the MIT/BIH.

2. Related Work

In [5] Extern learning Machine (ELM) is used to analysis and classify the ECG signals and it is compared with Support Vector Machine (SVM), the k-nearest neighbor algorithm (kNN) and the radial basis neural network (RBF). In [6] Discrete Wavelet Transform is used for processing ECG and the Multi-Layer Perceptron (MLP) neural network performs the classification task. The acquired outcomes demonstrate that the characterization precision of this calculation is 96.5% utilizing 10 files inclusive ordinary and two arrhythmias. In [7] genetic with support vector machine (GENETIC-SVM) is given to classify four types of arrhythmia. A genetic algorithm is used to enhance the generalization efficiency of the SVM classifier.

3. Stationary wavelet Transform (SWT)

The Discrete Wavelet Transform (DWT) has a lack of translation invariance, therefore stationary Wavelet Transform (SWT) algorithm is designed to improve this lack. Up samplers and down samplers present in the DWT are suppressed from the algorithm of SWT to accomplish this goal [2]. The sequences of the output signal have the same length as the input sequence because of the absence of a decimator. To avoid the translational variance problem created by decimation, zeros are embedded between every SWT filter coefficients. A set of level-dependent decomposition filters, h_i and g_i are used in the SWT, which are the h_0 and g_0 filters with $2^j - 1$ zeros between each discrete filter coefficients.

The course approximation and high frequency coefficients of SWT can then be calculated utilizing equations (1) and (2).

$$a_{j+1}^{SWT}(k) = \sum_n h_i(n-k)\, a_j^{SWT}(k) \qquad (1)$$

$$d_{j+1}^{SWT}(k) = \sum_n g_i(n-k)\, a_j^{SWT}(k) \qquad (2)$$

For two dimension signals, 2D-SWT is utilized. In this technique, the DWT is applied and both down-sampling in the decomposition and up-sampling in the reconstruction are removed. Figure 2 illustrates the Stationary Wavelet Transform decomposition method where I_i, G_i, H_i are a original signal, impulse response of lowpass and highpass filters , respectively[3] .

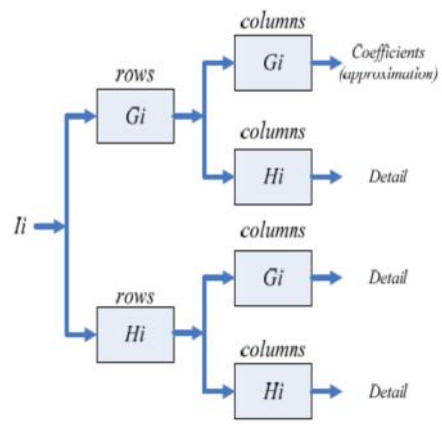


Figure 2: 2D SWT decomposition scheme [3].

4. Multiwavelet Transform (MWT)

Wavelet have particular attributes that make them valuable for some applications, for example, image compression and signal denoising. If two or more scaling function is found, this leads to the concept of multiwavelets. Multiwavelets have several properties such as short support, orthogonally; symmetry and vanishing moments. An ordinary wavelet can't have all attributes simultaneously [8]. Figure 3 shows diagram for two iterations of 1-D MWT.

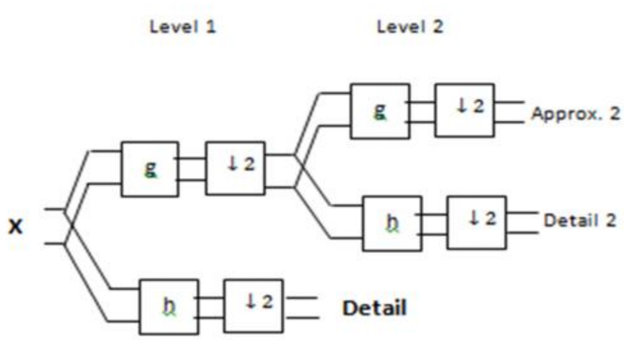


Figure 3: Diagram for a multiwavelet filterbank (two iterations).

Geronimo, Hardian, and Massopust proposed multifilter bank (GHM filter) [3]. The GHM basis submits a mix of orthogonality, symmetry, and compact support, which cannot be accomplished by any scalar wavelet basis. The GHM two scaling and wavelet functions satisfy the following two-scale dilation equations:

$$\begin{bmatrix} \emptyset_1(t) \\ \emptyset_2(t) \end{bmatrix} = \sqrt{2} \sum_k H_k * \begin{bmatrix} \emptyset_1(2t-k) \\ \emptyset_1(2t-k) \end{bmatrix} \quad (3)$$

$$\begin{bmatrix} \psi_1(t) \\ \psi_2(t) \end{bmatrix} = \sqrt{2} \sum_k G_k * \begin{bmatrix} \emptyset_1(2t-k) \\ \emptyset_1(2t-k) \end{bmatrix} \quad (4)$$

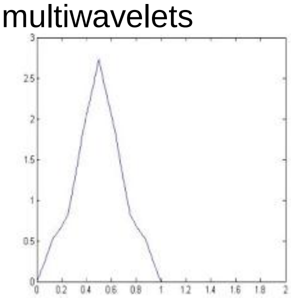
Where H_k for GHM system are four scaling matrices H_0, H_1, H_2, and H_3, [9],

$$H_0 = \begin{bmatrix} \frac{3}{5\sqrt{2}} & \frac{4}{5} \\ \frac{-1}{20} & \frac{-3}{10\sqrt{2}} \end{bmatrix} \quad H_1 = \begin{bmatrix} \frac{3}{5\sqrt{2}} & 0 \\ \frac{9}{20} & \frac{1}{\sqrt{2}} \end{bmatrix} \quad H_2 = \begin{bmatrix} 0 & 0 \\ \frac{9}{20} & \frac{-3}{\sqrt{2}} \end{bmatrix} \quad H_3 = \begin{bmatrix} 0 & 0 \\ \frac{-1}{20} & 0 \end{bmatrix}$$

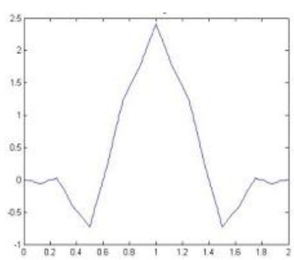
Also, G_k for GHM system is four wavelet matrices G_0, G_1, G_2, and G_3, [1],

$$G_0 = \begin{bmatrix} \frac{-1}{20} & \frac{-3}{10\sqrt{2}} \\ \frac{1}{10\sqrt{2}} & \frac{3}{10} \end{bmatrix} \quad G_1 = \begin{bmatrix} \frac{9}{20} & \frac{-1}{\sqrt{2}} \\ \frac{-9}{10\sqrt{2}} & 0 \end{bmatrix} \quad G_2 = \begin{bmatrix} \frac{9}{20} & \frac{-3}{10\sqrt{2}} \\ \frac{9}{10\sqrt{2}} & \frac{-3}{10} \end{bmatrix} \quad G_3 = \begin{bmatrix} \frac{-1}{20} & 0 \\ \frac{1}{10\sqrt{2}} & 0 \end{bmatrix}$$

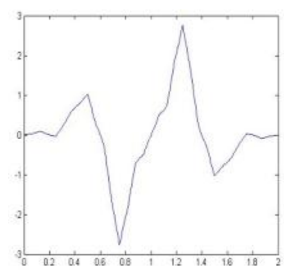
Figure 4 a , b , c , d shows the scaling and wavelet functions for the GHM multiwavelets



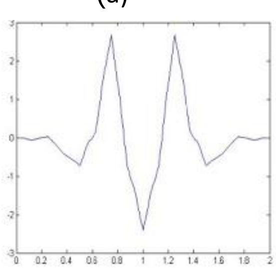
(a)



(b)



(c)



(d)

Figure 4 a) First scaling function
b) Second scaling function
c) First wavelet function
d) Second wavelet function

5. Stationary Multiwavelet Transform (SMWT)

Nason and Silverman (1995) introduced a notation of stationary scalar Wavelet transformation, and they gave out the algorithm of forward and reverse, which implies that low-pass filter and high-pass filter are interjected with zero. The stationary Wavelet can be decomposed without secondary extraction of the output coefficients of the filters. Figure 5 is a traditional multiwavelet decomposition process. A diagram of the proposed method is shown in Figure 6 [3].

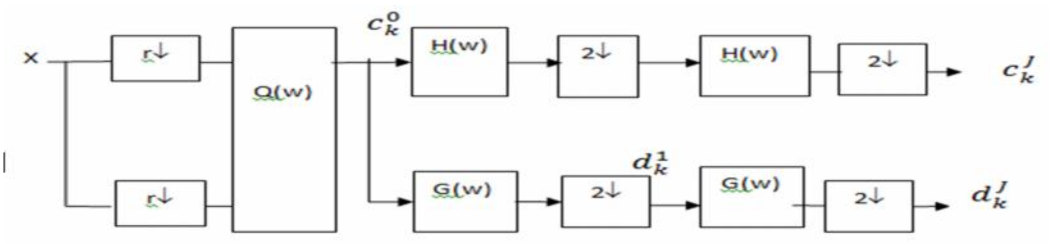


Figure 5: Structure of simple multiwavelet transform

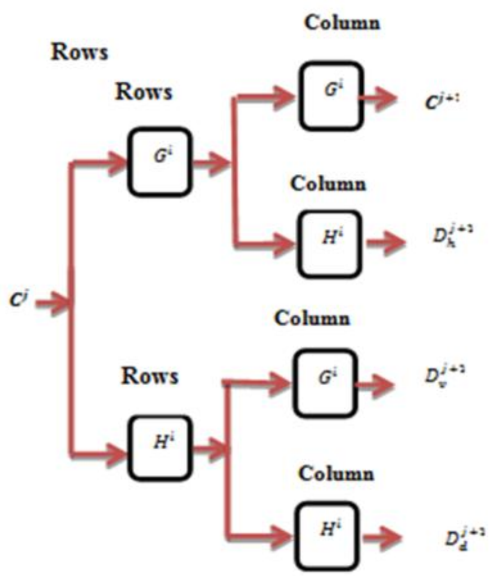


Figure 6: Structure of simple Stationary multiwavelet transform

The coefficients of the filter are matrix 2 by 2 and during the convolution step they must multiply by vectors (instead of scalars). Two input rows are needed for multifilter banks The most ideal approach to acquire two input lines from a original signal is to duplicate the signal. This system is called "Repeated Row" which presents oversampling of the information by a factor of 2.

$$\begin{bmatrix} X_k \\ \alpha X_k \end{bmatrix} \qquad \text{Where} \quad k = 1,2,3,\dots,N-1$$

The dimension of the input signal Xk is N points (N must be a power of 2) and processing the original signal is done by duplicating the row input stream with the same stream multiplied by a constant α. So the processing input vector is 2N.

Here α is constant, and from the preprocessing scheme of the GHM multifilter bank, α is equal to $\frac{1}{\sqrt{2}}$. It is found that this factor is very suitable for preprocessing in the application of the proposed transformed [10].

6. Artificial Neural Network (ANN)

The Artificial Neural Network (ANN) is a tool, which can be used to classify the ECG beats to an appropriate class according to their features. ANN learned with back propagation algorithm [6]. This type of neural network is known as a supervised network because it utilizes an actual output for each input pattern that guides the training process [11].

7. Data Selection

The MIT-BIH arrhythmia database is tested using the proposed method (SMWT-ANN). Three classes of EEG beats are tested by the proposed method, one of them is the normal beats class and the others are some of the heart arrhythmias. The number of beats used in the proposed work is 40 beats for each class and the number of samples in each beat is 256 samples [12].

8. Architecture of the Suggested SMW-ANN Classifier System

Figure 7 shows the general structure of the suggested SMWT-ANN classifier system. Function of each block is illustrated below:

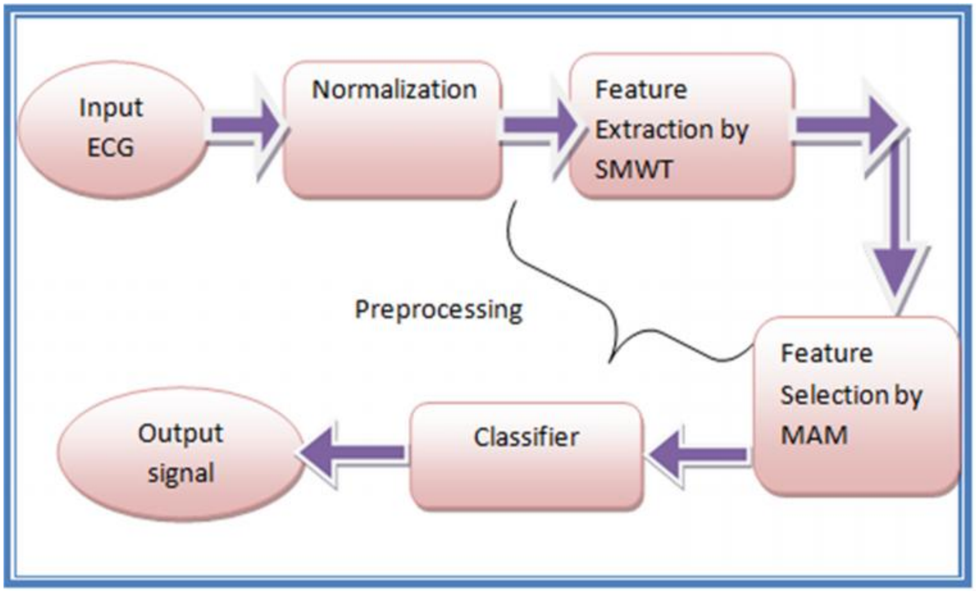


Figure 7: Block diagram of the Suggested SMWT-ANN Classifier System.

8.1 Normalization of ECG signals

Physiology conditions surrounding the accuracy of measurement systems and mental state are changed in heart rate. The effects of undesirable parameters are reduced by normalization of signal.
Normalization is one way to minimize the displacement in the amplitude and the time between all signals. Figure 8 demonstrates the difference in time and amplitude of the heart signals for the same person. This difference is due to tiredness or stress [12].

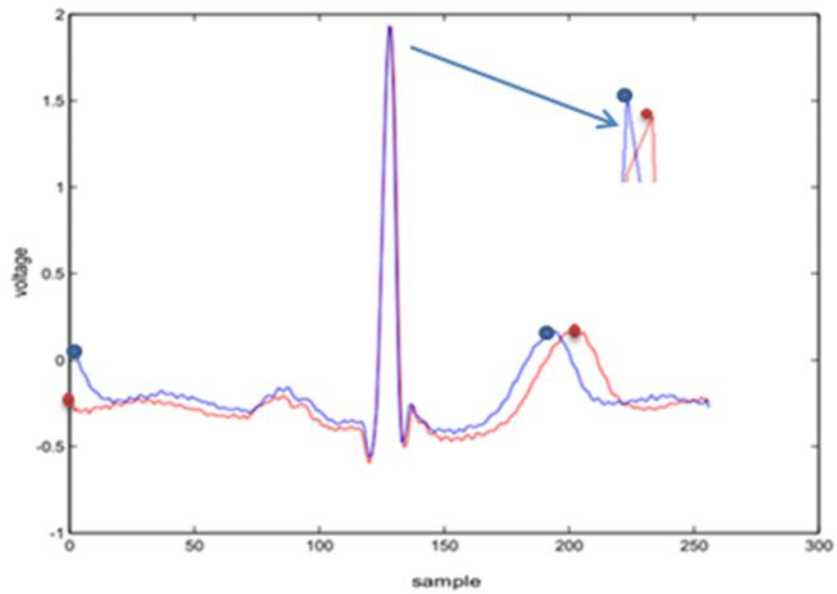


Figure 8: Two beats of the ECG signals with the difference in amplitude and time [12].

8.2 Feature extraction

ECG signals are huge data, but not huge information. It is impossible to apply any classification method directly to EEG signals. Feature extraction will be used to reduce representation set of components.

it is a special way of dimensionality reduction. If the components extracted are carefully chosen, it is normal that the elements set will separate the significant data from the original data in order to perform the end goal using this reduced representation instead of the full- size input [13].

8.3 A Proposed Computation Algorithm for Stationary Multiwavelet Transform

The general steps of computing 2-D Stationary Multiwavelet Transform are as follows:

1. For computing SMWT, the transformation matrix W, is used.
2. To compute a single-level 2-D SMWT, a general 2-D signal, for example, any 4x4 matrix is taken, and apply the following steps are applied:

a. The input signal is X

$$X = \begin{bmatrix} 6 & 2 & 3 & 13 \\ 5 & 11 & 10 & 8 \\ 9 & 7 & 6 & 12 \\ 4 & 14 & 15 & 1 \end{bmatrix}$$

b. For a 4x4 matrix input 2-D signal, X, creat a 4x4 transformation matrix, W, utilizing proposed multifilter bank coefficients.

$$W = \begin{bmatrix} H0 & H1 & H2 & H3 \\ H3 & H0 & H1 & H2 \\ H2 & H3 & H0 & H1 \\ H1 & H2 & H3 & H0 \\ G0 & G1 & G2 & G3 \\ G3 & G0 & G1 & G2 \\ G2 & G3 & G0 & G1 \\ G1 & G2 & G3 & G0 \end{bmatrix}$$

c. The raw processing is applied to the input signal X.

$$X = \begin{bmatrix} 6 & 2 & 3 & 13 \\ 5 & 11 & 10 & 8 \\ 9 & 7 & 6 & 12 \\ 4 & 14 & 15 & 1 \end{bmatrix} \xrightarrow{\text{Row Processing}} PR = \begin{bmatrix} 6 & 2 & 3 & 13 \\ \frac{6}{\sqrt{2}} & \frac{2}{\sqrt{2}} & \frac{3}{\sqrt{2}} & \frac{13}{\sqrt{2}} \\ 5 & 11 & 10 & 8 \\ \frac{5}{\sqrt{2}} & \frac{11}{\sqrt{2}} & \frac{10}{\sqrt{2}} & \frac{8}{\sqrt{2}} \\ 9 & 7 & 6 & 12 \\ \frac{9}{\sqrt{2}} & \frac{7}{\sqrt{2}} & \frac{6}{\sqrt{2}} & \frac{12}{\sqrt{2}} \\ 4 & 14 & 15 & 1 \\ \frac{4}{\sqrt{2}} & \frac{14}{\sqrt{2}} & \frac{15}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

d. Applying row transformation: [Z] = [W] * [PR]

$$Z = \begin{bmatrix} 17.96 & 6.64 & 7.21 & 16.23 \\ 4.05 & 11.45 & 9.95 & 8.55 \\ 8.76 & 13.85 & 12.44 & 13.01 \\ 7.95 & 8.55 & 8.05 & 9.45 \\ 10.6 & 12.86 & 12.3 & 12.3 \\ 6.55 & 11.95 & 13.45 & 2.05 \\ 10.74 & 14.7 & 16.12 & 6.5 \\ 15.45 & 2.05 & 2.55 & 13.95 \\ -0.95 & 0.45 & -0.05 & 0.55 \\ 5.72 & -1.48 & -0.84 & 3.81 \\ -1.05 & 1.56 & 2.05 & -2.55 \\ -0.35 & 4.87 & 5.79 & -3.11 \\ 2.55 & -2.05 & -1.55 & 1.05 \\ -0.55 & 0.05 & -0.45 & 0.95 \\ -5.65 & 8.34 & 7.42 & -2.89 \end{bmatrix}$$

e. Applying columns processing by transposing [Z] matrix.

$$Z' = \begin{bmatrix} 17.96 & 4.05 & 8.76 & 7.95 & 10.6 & 6.55 & 10.74 & 15.45 & -0.95 & 5.72 & -1.05 & -0.35 & 2.55 & -0.55 & -5.65 \\ 6.64 & 11.45 & 13.85 & 8.55 & 12.86 & 11.95 & 14.7 & 2.05 & 0.45 & -1.48 & 1.56 & 4.87 & -2.05 & 0.05 & 8.34 \\ 7.21 & 9.95 & 12.44 & 8.05 & 12.3 & 13.45 & 16.12 & 2.55 & -0.05 & -0.84 & 2.05 & 5.79 & -1.55 & -0.45 & 7.42 \\ 16.23 & 8.55 & 13.01 & 9.45 & 12.3 & 2.05 & 6.5 & 13.95 & 0.55 & 3.81 & -2.55 & -3.11 & 1.05 & 0.95 & -2.89 \end{bmatrix}$$

f. Preprocessing [Z'] to get column preprocessed matrix [PC].

$$PC=\left|\begin{array}{ccccccccccccccc}
17.96 & 4.05 & 8.76 & 7.95 & 10.6 & 6.55 & 10.74 & 15.45 & -0.95 & 5.72 & -1.05 & -0.35 & 2.55 & -0.55 & -5.65 \\
\frac{17.96}{\sqrt{2}} & \frac{4.05}{\sqrt{2}} & \frac{8.76}{\sqrt{2}} & \frac{7.95}{\sqrt{2}} & \frac{10.6}{\sqrt{2}} & \frac{6.55}{\sqrt{2}} & \frac{10.74}{\sqrt{2}} & \frac{15.45}{\sqrt{2}} & \frac{-0.95}{\sqrt{2}} & \frac{5.75}{\sqrt{2}} & \frac{-1.05}{\sqrt{2}} & \frac{-0.35}{\sqrt{2}} & \frac{2.55}{\sqrt{2}} & \frac{-0.55}{\sqrt{2}} & \frac{-5.65}{\sqrt{2}} \\
6.64 & 11.45 & 13.85 & 8.55 & 12.86 & 11.95 & 14.7 & 2.05 & 0.45 & -1.48 & 1.56 & 4.87 & -2.05 & 0.05 & 8.34 \\
\frac{6.64}{\sqrt{2}} & \frac{11.45}{\sqrt{2}} & \frac{13.85}{\sqrt{2}} & \frac{8.55}{\sqrt{2}} & \frac{12.86}{\sqrt{2}} & \frac{11.95}{\sqrt{2}} & \frac{14.7}{\sqrt{2}} & \frac{2.05}{\sqrt{2}} & \frac{0.45}{\sqrt{2}} & \frac{1.48}{\sqrt{2}} & \frac{1.56}{\sqrt{2}} & \frac{4.87}{\sqrt{2}} & \frac{2.05}{\sqrt{2}} & \frac{0.05}{\sqrt{2}} & \frac{8.34}{\sqrt{2}} \\
'.21 & 9.95 & 12.44 & 8.05 & 12.3 & 13.45 & 16.12 & 2.55 & -0.05 & 0.84 & 2.05 & 5.79 & -1.55 & -0.45 & 7.42 \\
\frac{21}{\sqrt{2}} & \frac{9.95}{\sqrt{2}} & \frac{12.44}{\sqrt{2}} & \frac{8.05}{\sqrt{2}} & \frac{12.3}{\sqrt{2}} & \frac{13,45}{\sqrt{2}} & \frac{16.12}{\sqrt{2}} & \frac{2.55}{\sqrt{2}} & \frac{-0.05}{\sqrt{2}} & \frac{0.84}{\sqrt{2}} & \frac{2.05}{\sqrt{2}} & \frac{5.79}{\sqrt{2}} & \frac{1.55}{\sqrt{2}} & \frac{-0.45}{\sqrt{2}} & \frac{7.42}{\sqrt{2}} \\
16.23 & 8.55 & 13.01 & 9.45 & 12.3 & 2.05 & 6.5 & 13.95 & 0.55 & 3.81 & -2.55 & -3.11 & 1.05 & 0.95 & -2.89 \\
\frac{16.23}{\sqrt{2}} & \frac{8.55}{\sqrt{2}} & \frac{13.01}{\sqrt{2}} & \frac{9.45}{\sqrt{2}} & \frac{12.3}{\sqrt{2}} & \frac{2.05}{\sqrt{2}} & \frac{6.5}{\sqrt{2}} & \frac{13.95}{\sqrt{2}} & \frac{0.05}{\sqrt{2}} & \frac{3.81}{\sqrt{2}} & \frac{-2.55}{\sqrt{2}} & \frac{-3.11}{\sqrt{2}} & \frac{1.05}{\sqrt{2}} & \frac{0.95}{\sqrt{2}} & \frac{-2.89}{\sqrt{2}}
\end{array}\right|$$

g. Transformation of input columns: [B]=[W]*[PC]

B=

20.6	8.867119	14.56	11.49756	15.96	11.55412	16.88	16.15446
4.072935	12.625	14.41569	8.475	13.13047	11.975	16.33417	-1.075
9.64	15.55635	19	11.87939	17.96	17.53625	21.4	3.11127
9.503515	9.525	12.51579	8.375	12.27537	11.675	13.73858	5.425
14.04	13.47745	17.84	11.97839	17.4	14.13456	18.72	8.442855
11.3636	6.775	11.81868	9.325	11.75626	1.625	5.444722	17.275
23.72	10.13234	16.6	12.72792	16.48	4.803326	11	20.35468
1544321	5.075	9.263099	7.825	10.86116	1.725	12.51579	12.375
0.125	-1.51674	0875	1721805	-0.925	-3.29158	-0.075	3.088521
-049851	2.745	-0.71428	-1.185	1.518744	4.14	0.24395	-417
0.125	1.193548	-1125	-2.13142	0.675	3.60978	0.325	-2.6269
0.253094	2.55	-2.08657	-3.68	1.212648	7.055	0.62579	-4.395
-0.325	1.771302	-4675	-1.35411	1.125	3.037024	-0.125	-3.45422
-073357	-0.45	1.971363	4.16	-0.31446	-4.905	0.95813	2.725
0.075	-1.4531	0925	1813729	-0.875	-3.35522	-0.125	2.994197
0.543988	-3.315	0.84449	2.235	-2.41417	-4.76	0.578292	737

8.4 Minimum Average Maximum Method (MAM)

The ECG signals are matrix (Xi, Yi) where i=1, 2, ..., M and j=1,2,…N. The first column Yi (i=1) in ECG data set is divided into 32 subsets, each subset consists of eight points. The parameters (maximum, average and minimum) are calculated for each subset and placed in a separate column. These processes are repeated for each column and each set. The final matrix of ECG signal is (32, 3*Y). The above procedure is shown in Figure 9.

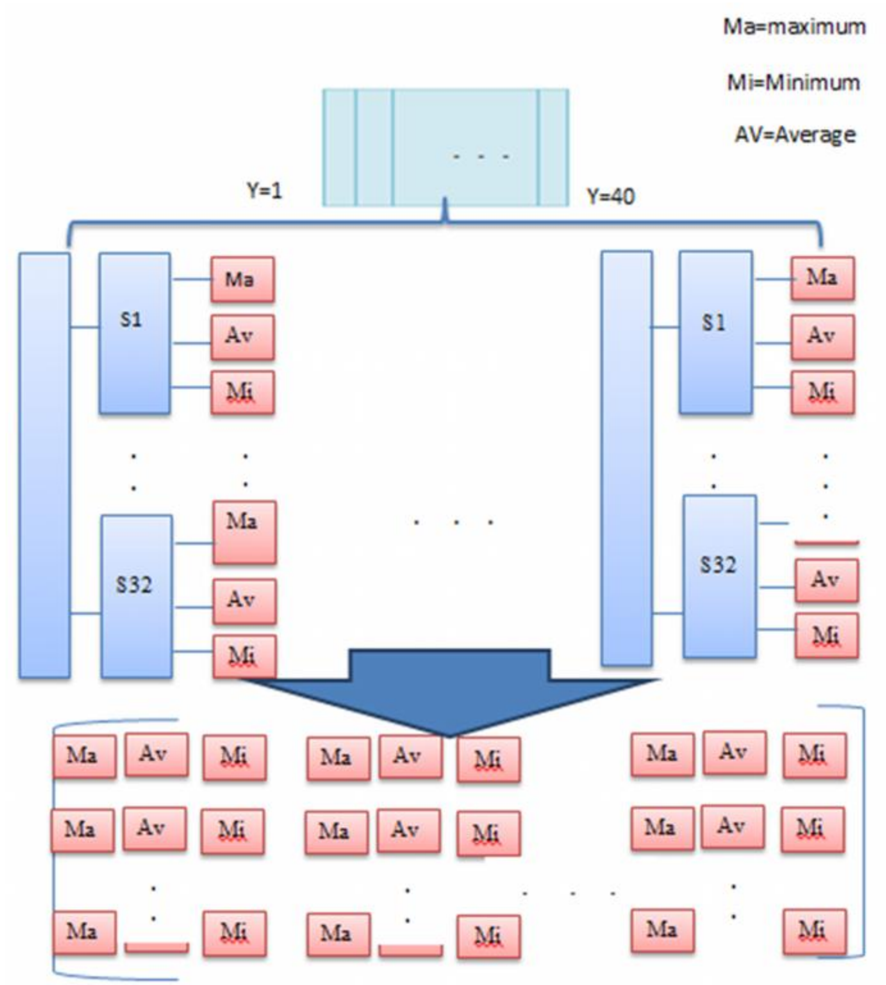


Figure 9: Block diagram of Minimum Average Maximum Method (MAM).

8.5 Artificial Neural Network Classifier

In this paper, ANN has three layers of processing element input layer, hidden layer, and output layer. Each layer consists from array of nodes; input node (ni), hidden nodes (nh) and output nodes (no). The inputs are x_1, x_2, ..,x_{ni} and desired outputs are d_1, d_2, …,d_{no} . Each feature vector will be fed to the ANN and the synaptic weights are adjusted so that E_k is minimized.

The weighted sum of the inputs to the hidden neurons are calculated and then transformed to y, the hidden-neuron output as given below:

$u_j = \sum_{l=1}^{n_i} a_{lj} x_l$ j=1, 2, …, n_h (5)

$y_j = \frac{1}{1+e^{-u_j}}$ j=1, 2, …, n_h (6)

Next, the weighted sum of inputs, v, to output neuron is calculated and transformed to z as given below:

$v_i = \sum_{j=1}^{nh} b_{ji} y_j$ i=1, 2, …, n_o (7)

$z_i = \frac{1}{1+e^{-v_i}}$ i=1, 2, …, n_o (8)

At this point, the desired output is presented to the network and MSE is calculated

$E = \frac{1}{2}(z_i - d_i)^2$ (9)

The online learning is used in this method. The weights are adjusted after each presentation of a training pattern.

9. Results & Discussion

The suggested work is performed using Matlab. Three classes of ECG are used to measure the performance of this study. The SMWT-ANN is used to analysis and classify the signal and then compared with conventional methods. Each beat is normalized. Features extraction is done by two methods that are SMWT and a (MAM).

In this paper, four methods have been applied to recognize ECG signal. These methods are PCA-ANN, SWT-ANN, MWT-ANN and SMWT-ANN.

The evaluation of the above methods was calculated in terms the accuracy of the classification and mean square error.

$$Accuracy = \frac{total\ Number\ of\ correct\ samples}{total\ Number\ of\ samples} * 100\% \quad (10)$$

The PCA-ANN gives the worst results because PCA is not scaled invariant. This means that if you change the scale of the data set, the obtained result is different. There are many statistical distributions in which mean and covariance don’t give relevant information of them. It can be shown from the results obtained there was the error for Training Set 0.33 and the error for testing set 0.66 and lower accuracy for both the training set and testing set are 33.33%. The SWT-ANN gave better behavior than the previous systems. Since the scaling function coefficients carry most important information of the signal. These coefficients can be considered as the features of the signal as given in Table (1)

It can be shown from the results of classification that the error of using SMWT method is the minimum error among all the errors obtained. Thus the pattern recognition system using the SMWT transform as the orthogonal transform for features extraction is the most accurate system compared with other systems explained in this work.

The SMWT incorporates between properties of SWT and MWT. This making it stronger to extract the realistic features that represent the ECG signals than other methods and reduces the redundancy of information. The experimental work demonstrates that by using this transform the errors in the classification of ECG beats are very small.

10. Conclusions

1. SMWT-ANN decreases mean square error, therefore, it is superior in most respects to traditional techniques. The results are shown in the Table (1).
2. The proposed mixed method is a combination of SMWT and SM to achieve better representation of the signal.
3. SMWT offered a good distribution of the signal in frequency and spatial domain.
4. SMWT is a translation invariant compared MWT and WT. This attribute enhances classification performance and mean square error.
5. The preprocessing scheme of SMWT is by repeating the signal using repeated row processing and this makes it suitable for feature extraction.

Table (1): Comparison of ECG classification results

Classification methods	MSE for training set	MSE for testing set	Accuracy for training set (%)	Accuracy for testing set (%)
PCA-ANN	0.3364	0.6672	33.333333	33.333333
SWT-ANN	0.1202	0.2474	100	100
MWT-ANN	0.0014	0.0032	100	100
SMWT-ANN	8. 2595e-04	0.0014	100	100

References

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أستخلاص الميزّات والخواص و تصنيفها من اشارة القلب بلاعتماد على الشبكة المتعددة المويجات المستقرة و الشبكه العصبية الصناعية

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المستخلص

تم في هذا البحث الدمج بين الشبكة المتعددة المويجات المستقرة و الشبكه العصبية الصناعية لغرض تصنيف اشارة القلب. ان قاعدة البيانات MIT-BIH قد استخدمت لقياس أداء الطريقة المقترحة ومقارنة النتيجة مع التقنيات التقليدية. ان الطرق (SMWT) و (MAM) تم اقتراحها لاستخلاص الميزّات والخواص من الاشارة قبل تصنيفها بواسطة ANN. بما ان SMWT لها خاصية عدم التغير مع الزحف فأن هذا يعزز من أداء عملية التصنيف ويقلل من الخطأ. أن تكرار معالجة الأسطر الموجودة في هذا المخطط جعل الاسلوب المستخدم أكثر ملاءمة لأستخراج الميزات مقارنة مع SWT, MWT وPCA. ان الطرق (SMWT) و (MAM) تقلل من ابعاد الإشارة وتقلل من تعقيد دائرة التصنيف. أخيراً ان نتائج الطريقة المقترحة هي واقعية مقارنة مع MWT-ANN,SWT-ANN و PCA-ANN. النتائج التي تم الحصول عليها تؤكد تفوق الخوارزمية المقترحة على الاساليب التقليدية.SMWT-ANN حققت دقة تصنيف 100% و معدل خطأ بمقدار 0.0014.

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