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OPTIMIZED CLASSIFICATION OF DE-NOISED ECG SIGNAL

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Abstract— **ECG signal is a physiological signal mainly used for the diagnosis of abnormalities in the functioning of the heart. There are limitations in detecting the nonlinearities due to the presence of noises in the ECG signal. In our work, the de-noised signal coefficients obtained from different de-noising methods are optimized for reducing the error and redundancy, and are then classified as normal or abnormal signals. The ECG signal is obtained from the PhysioBank dataset and the MIT-BIH arrhythmia database. The two methods used are the Stationary Wavelet Transform (SWT) and the Discrete Wavelet Transform (DWT). The optimization is done using Cuckoo Search (CS) algorithm and the classification is performed by Feed Forward Neural Network using back propagation (FFBP). The performances are evaluated in terms of standard metrics namely, Mean Square Error (MSE) and Signal to Noise Ratio(SNR). The results suggest that although SWT performs better than other de-noising techniques, the two methods correctly classify the given ECG signal of a monitored patient as a normal or abnormal signal.**

Keywords— Feed Forward Neural Network with Back Propagation (FFBP); Stationary Wavelet Transform (SWT), Discrete Wavelet Transform (DWT), Variational Mode Decomposition (VMD), Cuckoo Search Algorithm (CS

I. INTRODUCTION

ECG signal is a physiological signal from the clinical point of view for detecting abnormalities in the heart functioning. Telemedicine nowadays is gaining importance and there is a need to transmit bio signals through communication links. Signals are corrupted with noise when there is disturbance in the transmission link. Various noises associated with ECG signals are, electrode pop or contact noise, power line interference, motion artifacts etc. Due to these noise factors, diagnosis is made difficult for ECG signal. So the noise needs to be removed. The frequency of ECG signal is in the range of 0.05Hz to 125Hz.

DWT is a widely used techniques for de-noising the ECG signal. Many research works propose the use of different sets of wavelet coefficients and thresholding techniques of the DWT [1]. The signal decomposes to the basic functions in the Wavelet Transform. The decompositions of the ECG signal are analyzed and corrected using thresholding techniques. Thresholding techniques include Hard, Soft, Sigmoid thresholding etc. SWT is a wavelet transform algorithm designed to overcome the lack of translational invariance of the DWT. The stationary wavelet transform will not decimate (down sample) the input by two at every level unlike the DWT [2].

Feed Forward Neural Networks and unsupervised learning are generally used in literature related to ECG signal de-noising and Classification. Mohammad Reza Homaeinezhad et. al in 2011 explained the fuzzy classification of ECG signal in Discrete Wavelet-based Fuzzy Network. Architecture for ECG Rhythm by Martin Lagerholm et al in the year 2000 proposed the clustering of the ECG signal using Hermite functions. FFBP is the best method shown in the Analysis of ECG Signal and Classification of Heart Abnormalities Using Artificial Neural Network in IEEE 2016. N.Maglaveras, T.Stamkapoulos et. al have used neural networks and non-linear transformations for classification, in the year 2001. S. Osowski, T.H.Linh have used fuzzy hybrid neural networks and in the year 2000, P. de Chazal, B. G. Celler et. al have used Wavelet Coefficients for the Classification. The optimization techniques such as Cuckoo Search (CS) algorithm, Particle Swarm Optimization(PSO) and Artificial

Bee Colony (ABC) technique are exploited for learning the parameters of adaptive filtering required for optimum performance. CS algorithm yields better performance in terms of SNR, MSE and ME according to Ritika Thakur, et. al, in 2014. In this work, the DWT, SWT and peak detection are used to extract features, and the CS Algorithm is used for optimization purpose and the FFBP neural network is used for classification.

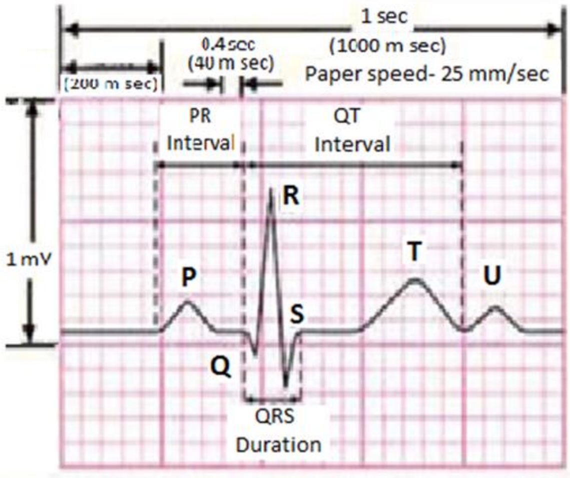

Fig. 1. ECG Signal Representation

II. METHODOLOGY AND DESCRIPTION

Two methods are adopted to de-noise the signals. In the first method, de-noising is done by DWT. Then it is optimized by CS Algorithm and classified using FFBP. In the second method, the de-noising of the ECG signal is done by using SWT which is then optimized and classified. As ECG classification is critical during an operation, we are using three different methods for de-noising so that the signals de-noised by different methods show the same classification of the ECG signal. The block diagram of the proposed method is shown in Fig. 2.

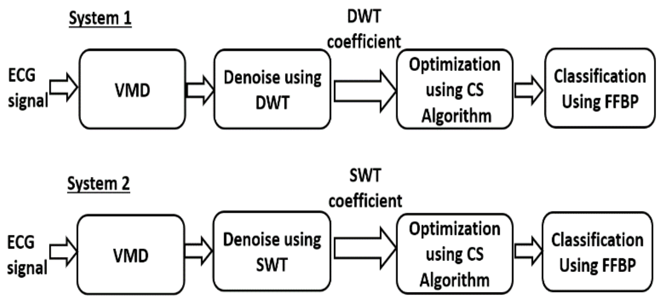

Fig. 2. Block diagram of the proposed system

III. DE-NOISING AND FEATURE EXTRACTION

All In this section we have used different methods to de-noise the signal and extract the features characterizing ECG signal [3]. In the first method, we apply DWT to the ECG signal after Variational Mode Decomposition (VMD). In the second case, SWT is used to de-noise the signal. The feature extracted for the two transforms are from the QRS part of the signal and it is used for the classification purpose.

The VMD is mainly used to generate discrete number of modes (u_k), that have the sparsity property while the input is reproduced, by decomposing a real valued input signal. In this decomposition method, the signal is decomposed into different modes [4]. Here we assume that each mode is compacted around a central pulsation (w_k). The center pulsation (w_k) is determined along with the decomposition. In order to assess the bandwidth of a mode, we propose the following scheme:

- The analytic signal associated is computed by means of the Hilbert transform, for each mode.
- Mix the frequency spectrum of the modes with an exponential tuned to the respective estimated center frequency to shift the spectrum.
- Estimate the bandwidth by using the squared norm of the gradient.

The constrained variational problem can be used to all the modes which is defined by:

$$\min\,(u\_k, w\_k\,) = \{\|\Sigma\partial t\left[\left(\delta(t) + \frac{j}{pi} * t\right) * uk\,(t)\right]\,\|2\} \quad ------------------(1)$$

Subject to,

$$\sum_k u_k = s ------------------(2)$$

where, u_k is the kth mode, s stands for the signal to decompose, w_k is a frequency, t is a time, δ is the Dirac distribution, and * denotes convolution. Higher values of k are used to indicate modes with lower frequency components.

The signal obtained from VMD [5] is de-noised using DWT. Soft thresholding is used as it does not sharply cut the signal as Hard thresholding. The Filter Bank (FB) implementation of DWT (up to two levels) is illustrated in Figure (3). The original signal (S) passes through a pair of low pass ($h(n)$) and high pass ($g(n)$) filters. These filters must satisfy some mathematical properties for perfect reconstruction. Then the outputs of each filter will be down sampled by a factor of two. Outputs of low pass $g(n)$ and high pass $h(n)$ filters are called approximation coefficients Ca and detail coefficients Cd respectively. Cd represents high frequency and Ca, the low frequency components of the signal. For the next level of decomposition in DWT, the approximation coefficients Ca will pass through the same low pass and high pass filters and then will be down sampled to obtain the next level of Ca and

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Cd and so on. Let 'h' denote the low pass and 'g' the high pass filter. The common notation is:

$$Y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k] \text{ ---------- } (3)$$

$$Y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k] \text{ ---------- } (4)$$

The results of the DWT are a series of coefficients in one approximation and J details. Here J is the number of the final decomposition level [6], the coefficients of which form an orthogonal basis. Inverse wavelet transform (IWT) is used for the reconstruction of the original signal.

The most important step in the process of decomposition is down-sampling. When a signal is decomposed, the signal length is halved every time it passes through the filter pair. The signal length is reduced to 1/2, 1/4, 1/8 ... of the original length, at level 1, 2, 3... and it allows to use same pair of filter in different levels. When a noisy signal is decomposed, the noise and signal manifest differently in the post-decomposition results, making it possible to separate them easily by applying a threshold to the different levels.

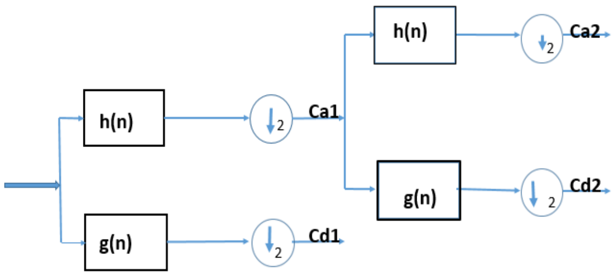

Fig. 3. Filter Bank implementation of DWT

The wavelet based de-noising procedure in general, involves three steps:

- Decomposition: For decomposing a mother wavelet and a maximum decomposition level J are chosen and the decomposition coefficients at each level are computed.
- Thresholding: The threshold values are computed for each level separately or for the whole set of the coefficients and the threshold is applied (in hard or soft process) to the coefficients at each level.
- Reconstruction of the signal is done with the modified coefficients.

According to the steps mentioned above, three parameters should be selected; maximum decomposition level, threshold values and mother wavelet. Proper mother wavelet can represent signal features in a few wavelet coefficients with high magnitude that can improve thresholding and consequently, de-noising performance [7]. For the selection of optimum mother wavelet cross-correlation function can be used. The optimum wavelet maximizes the cross correlation between the signal of interest and the mother wavelet. The level of Optimum decomposition of the wavelet depends on noise and signal frequency characteristics and may be obtained by the method of trial and error. Selection of the threshold values for each level is the most important part of the de-noising procedures. Small threshold values will result in noises in the reconstructed signal and the large values may eliminate some signal features.

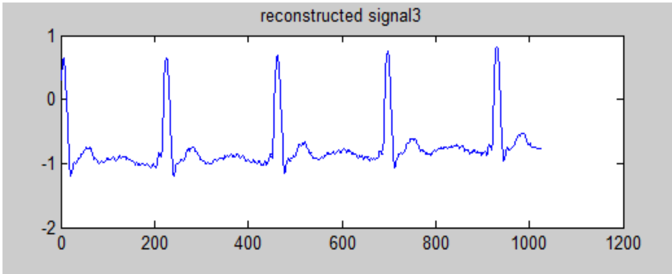

Fig. 4. De-noising using DWT

SWT is also used for signal de-noising [8]. The same procedure described for DWT is done for de-noising using SWT also. After applying VMD, the de-noising is done by SWT [9]. The coefficients are then optimized using the CS Algorithm. Then neural networks are for the classification purpose.

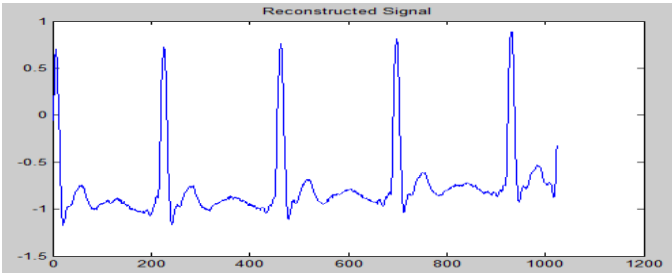

Fig. 5. De-noising using SWT

IV. OPTIMIZATION BY CUCKOO SEARCH ALGORITHM VIA LEVY FLIGHT

The CS Algorithm is used here for the optimizing the denoised coefficients [10]. Yang and Deb first introduced and proposed the Cuckoo search (CS) in (2010), Cuckoos have an aggressive strategy of reproduction: the female lay eggs in nests of other birds, if the host bird discovers that the eggs are not their own, they will throw it away or clear the nest. The new nests are built after abandoning a fraction of the worse nests. Always keep the solutions that have a better quality. Then keep the best solutions that come with a better quality. Finally rank all the solutions to obtain the current best solution.

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In CS Algorithm, instead of simple random walks, Levy fights are used where a class of non-Gaussian random processes are used. The stationary increments of the processes are distributed according to a Levy stable distribution. It is effective than the random walks applied to CS Algorithm. Lévy flights are Markovian stochastic processes. The individual jumps have lengths that are distributed with a PDF (probability density function) [10].

V. CLASSIFICATION USING FFBP

In this stage, an ECG signal is classified according to its extracted feature vector issued from the DWT coefficients by means of a Feed Forward Back Propagation neural network. The extracted signal's QRS portion is tested in the trained network and is found to be normal or abnormal. The ECG signal of a patient will be checked before and during an operation. The signal may be found to be normal before and changes might occur while the operation is going on. To check this, we are doing this classification. The network is already trained with some normal and abnormal signals of the person. When the de-noised test signal is given, it will be correctly classified as normal or abnormal. Also the classification is done using SWT [12]. Different methods of de-noising are used as the ECG signal varies from person to person and the classification result of the different methods should show the same result. In the subfield of data classification, neural network methods are found to be useful alternatives to statistical techniques such as those which involve regression analysis or probability density estimation. The training in back propagation includes the following steps:

- The results are produced at the output layer by the training data which is fed through the network.
- The error calculation is done at the output nodes based on the necessary changes to the weights and known target information. The weights are updated according to the local field generation.

The changes to the weights are determined as a function of the properties of the neurons to which they directly connect, until all necessary weight changes are calculated for the entire network, that lead to the preceding network layers.

VI. EXPERIMENTS AND RESULTS

In this work, we have used the MIT-BIH Arrhythmia Database and PhysioBank Database of ECG to evaluate the algorithm. MATLAB is the software used. We chose the data's are labeled 121,100,115,200,222 from MIT-BIH Database and rest from PhysioBank ATM which includes six normal and five abnormal signals for training the network. NPRtool in neural networks is used for classification purposes. The de-noised signal coefficients obtained from DWT and SWT, after optimization, are given as inputs to the neural network to test whether the signal is normal or abnormal.

The de-noised results of the three methods are shown in figures 4, 5 & 6 The DWT, SWT coefficients are then optimized using the CS algorithm for reducing the error and redundancy. The architecture of the neural network used for classification is as shown in fig.7.

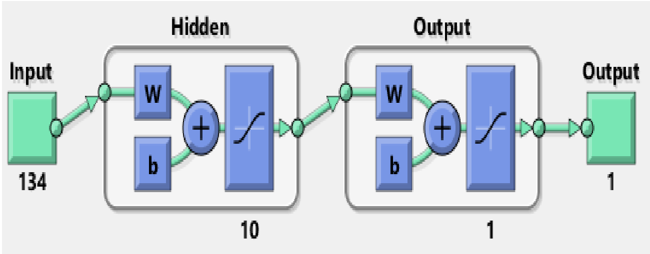

Fig. 6. Architecture of Neural Network

The architecture of neural network is same for DWT and SWT.

Table .1. Comparison of DWT, SWT After De-Noising

Parameters	DWT	SWT
SNR	15.3171	16.7449
PSNR	35.0334	37.8889
MSE	0.0165	0.0119

Table II below shows the results of de-noising with SWT-MSE with and without optimization using FFBP. The table shows the reduction in MSE after optimization.

Table .2. FFBP Result using SWT

SWT coefficients		
Iterations	***MSE-with CS***	***MSE- without CS***
13	4.814e-8	4.197e-7
10	3.562e-7	6.083e-6
9	6.929e-7	1.547e-5
8	1.37e-6	4.308e-5
7	2.622e-6	1.154e-4

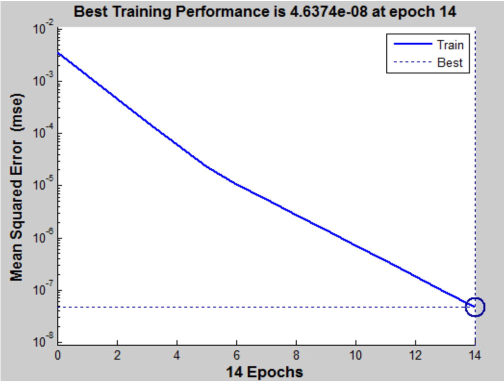

Fig. 7. Performance Plot of SWT with optimization

The Table 3 shows the results of de-noising with DWT - MSE before and after optimization using FFBP [13].

Table .3. FFBP Result using DWT

DWT coefficients		
Iterations	MSE-with CS	MSE- without CS
13	$6.915e^{-7}$	$3.617e^{-7}$
10	$4.187e^{-6}$	$3.648e^{-6}$
9	$7.954e^{-6}$	$9.111e^{-6}$
8	$1.382e^{-5}$	$2.392e^{-5}$
7	$2.757e^{-5}$	$5.925e^{-5}$

The number of input layers and hidden layers are 135 and 10 for SWT and DWT. Performance plots are obtained for these three methods. Optimization of the coefficients is done by CS Algorithm and performance plots are obtained before and after optimization using neural network. The signal obtained after de-noising and optimization is given to the trained neural network for classification. The network is trained with 6 normal and 5 abnormal signals. The two test signals given below are a normal and abnormal signal respectively and they are correctly classified

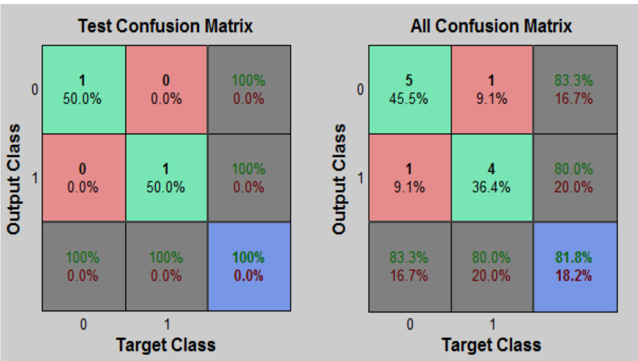

Fig. 8. Testing and All confusion matrix of different signals

The classification parameters are found to be

- Accuracy=82%
- Sensitivity=83%
- Specificity=80%.

VII. CONCLUSION

In this system, we are Classifying the optimized, de-noised signal coefficients obtained from three methods for further reduction of errors and redundancy. FFBP is used for classification purposes. The comparison of the SNR, PSNR, and MSE due to the three de-noising methods is found out and the optimization is done using cuckoo search algorithm. CS algorithm provides better MSE values compared to other optimization techniques. The MSE for the classification is found to reduce after optimization of the coefficients. The final performance shows that optimization and classification after de-noising by SWT provide better results for the tested signals. As the classification of ECG as normal and abnormal is important during an operation, we de-noise the signal using two different methods and verify that the classification result is the same even though de-noising is done using different methods. Future scope involves including improved de-noising methods in the system.

VIII. REFERENCES

[1] Wissam Jenkal, RachidLatif, (2016) "*An efficient algorithm of ECG signal denoising using the adaptive dual threshold filter and the discrete wavelet transform*", https://doi.org/10.1016/j.bbe.2016.04.001, Elsevier.

[2] Juhi Sharma, Prof. Neha Verma, (2016) "*ECG Signal De-Noising Techniques: A Review*", International Journal of Engineering Research and General Science Volume 4, Issue 1, January-February.

[3] E. Prabhakararao and M. S. Manikandan, (2016), "*On the use of variational mode decomposition for removal of baseline wander in ECG signals*," 2016 Twenty Second National Conference on Communication (NCC), Guwahati, (Pg 1-6), doi: 10.1109/NCC.2016.7561133.

[4] Goldberger AL, Amaral LA, Glass L, et al, (2000), "*PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signal*", Circulation, vol. 101, no. 23, (Pg215-220), doi:10.1161/01.cir.101.23.e215.

[5] Shemi P.M. and Shareena E.M., (2016), "*Analysis of ECG signal denoising using discrete wavelet transform*," 2016 IEEE International Conference on Engineering and Technology (ICETECH), Coimbatore, (Pg713-718), doi: 10.1109/ICETECH.2016.7569341.

[6] Ritika Thakur, Papiya Dutta, Dr. G.C. Manna, "*Analysis and comparison of evolutionary algorithms applied to Adaptive noise cancellation for speech signal*", International Journal of Recent Development in Engineering and Technology, vol. 3, no. 1, (pp.172-178).

[7] S. Li and J. Lin, (2009), "*The Optimal De-noising Algorithm for ECG Using Stationary Wavelet Transform*," 2009 WRI World Congress on Computer Science and Information Engineering, Los Angeles, CA, (Pg469-473), doi: 10.1109/CSIE.2009.999.

[8] E. B. Mazomenos et al., (2013), "*A Low-Complexity ECG Feature Extraction Algorithm for Mobile Healthcare Applications*," in IEEE Journal of Biomedical and Health Informatics, vol. 17, no. 2,(Pg459-469), doi: 10.1109/TITB.2012.2231312.

[9] L. E. Bouny, M. Khalil and A. Adib, (2017), "*ECG noise reduction based on stationary wavelet transform and zero-crossings interval thresholding*," 2017 International Conference on Electrical and Information Technologies (ICEIT), Rabat, (Pg1-6), doi: 10.1109/EITech.2017.8255255.

[10] Aswathy Velayudhan, Soniya Peter, (2015), "*Study of Different ECG Signal Denoising Techniques",* International Journal of Innovative Research in Computer and Communication Engineering, Vol. 3, Issue 8, August.

[11] T. Debnath, M. M. Hasan and T. Biswas,(2016), "*Analysis of ECG signal and classification of heart abnormalities using Artificial Neural Network*," 2016 9th International Conference on Electrical and Computer Engineering (ICECE), Dhaka, (Pg353-356), doi: 10.1109/ICECE.2016.7853929.

[12] U. Biswas, K. R. Hasan, B. Sana and M. Maniruzzaman, (2015), "*Denoising ECG signal using different wavelet families and comparison with other techniques*," 2015 International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), Dhaka, (Pg 1-6), doi: 10.1109/ICEEICT.2015.7307469.

[13] Therese Mahesh , Reji Jerin, Akil, K., Paulson Angel , Anjana, N. &Arunima LaL. (2020). "*Classification of De-noised ECG Signal to Monitor Stability of Heart*",Proceedings of International Conference AICERA 2019, Kerala,India doi 10.1201/9780429353628-36.