International Journal of Electrical and Computer Engineering (IJECE)
Vol. 12, No. 5, October 2022, pp. 4944~4950
ISSN: 2088-8708, DOI: 10.11591/ijece.v12i5.pp4944-4950

Electrocardiograph signal recognition using wavelet transform based on optimized neural network

Ali Talib Jawad[1], Dalael Saad Abdul-Zahra[2], Hassan Muwafaq Gheni[3], Ali Najim Abdullah[4]
[1]Department of Medical Instrumentation Technologies Engineering, Hilla University College, Babylon, Iraq
[2]Department of Medical Physics, Hilla University College, Babylon, Iraq
[3]Computer Techniques Engineering Department, Al-Mustaqbal University College, Hillah, Iraq
[4]Department of Medical Instrumentation Technologies Engineering, Hilla University College, Babylon, Iraq

Article Info

Article history:

Received Oct 18, 2021
Revised Jun 10, 2022
Accepted Jun 23, 2022

Keywords:

Electrocardiogram recognitions
Invasive weed optimization
Optimized neural networks
Patterns recognition
Wavelet transforms

ABSTRACT

Due to the growing number of cardiac patients, an automatic detection that detects various heart abnormalities has been developed to relieve and share physicians' workload. Many of the depolarization of ventricles complex waves (QRS) detection algorithms with multiple properties have recently been presented; nevertheless, real-time implementations in low-cost systems remain a challenge due to limited hardware resources. The proposed algorithm finds a solution for the delay in processing by minimizing the input vector's dimension and, as a result, the classifier's complexity. In this paper, the wavelet transform is employed for feature extraction. The optimized neural network is used for classification with 8-classes for the electrocardiogram (ECG) signal this data is taken from two ECG signals (ST-T and MIT-BIH database). The wavelet transform coefficients are used for the artificial neural network's training process and optimized by using the invasive weed optimization (IWO) algorithm. The suggested system has a sensitivity of over 70%, a specificity of over 94%, a positive predictive of over 65%, a negative predictive of more than 93%, and a classification accuracy of more than 80%. The performance of the classifier improves when the number of neurons in the hidden layer is increased.

Corresponding Author:

Ali Talib Jawad
Department of Medical Instrumentation Technologies Engineering, Hilla University College
Babylon, Iraq
Email: alitaleb54qq@gmail.com

1. INTRODUCTION

As a cost-effective and non-invasive method of observing heart function. The electrocardiogram (ECG) was commonly utilized [1]. The ECG signal reflects heart functionality, which helps the cardiologist diagnose cardiac problems. Cardiovascular disorders are the leading cause of death, the ECG field has advanced tremendously [2]. The ECG signal is used in various applications, including heart rate measurement, biometric identification, movement recognition, and anomaly diagnosis [3]. In general, ECG signals can be obtained by placing electrodes on the scalp with conductive gels [4]. The ECG is made up of potential fluctuations that are represented as an algebraic sum of cardiac fiber action potentials that can be computed from the body's skin surface [5]. The typical structure of normal ECG signals aids in the detection of heart abnormalities, which are referred to as heart disorders [6]. Abnormalities in the ECG signal indicate the presence of an illness. It may be feasible to diagnose the diseases by comparing tested signals with healthy control signals [7]. The importance of this research lies in developing the performance of a device by reducing the delay in processing by minimizing the input vector's dimension and, as a result, the classifier's complexity. The wavelet transform coefficients are used for the artificial neural networks (ANNs) training process and optimized by using the invasive weed optimization (IWO) algorithm. The classification accuracy is higher when using the wavelet coefficients with the IWO algorithm [8]. A huge amount of training data is required to train an ANN from scratch, which is computationally expensive [9]. A sufficient amount of training data is not available in many applications, hence synthesizing new realistic training data is necessary [10]. It is preferable to use existing neural networks that have been trained on huge data sets for jobs that are conceptually comparable [11]. Transfer learning is the process of exploiting existing neural networks. In this work the ANN is improved by using IWO algorithm, this optimization tries to optimize the error occurring during the training process of the ANN [12]. The ECG signal is analyzed using wavelet transform as a feature extraction method this algorithm used to choose best features for each ECG class in order to extract the best features [13]. Each class indicates a different type of cardiovascular illness [14]. The decreased vector is then fed into an optimized neural network as a train input. The previous studies Zahid *et al.* [15] in 2022 to limit the frequency of false alarms, a novel implementation of the 1D convolutional neural network (CNN) is combined with a verification model in this study. To create the 1D segmentation map of R-peaks from the input ECG signal, this CNN architecture consists of an encoder block and a corresponding decoder block, followed by a sample-wise classification layer. Once the suggested model has been trained, it can be used to detect R-peaks quickly and accurately in a single channel ECG data stream, or it can be utilized for real-time monitoring on a lightweight portable device. The model is validated using two open-access ECG databases. The proposed systematic technique achieves 99.30% F1-score, 99.69% recall, and 98.91 percent precision in CPSC-database, which is the best R-peak detection performance eve. By comparing with our work by using wavelet that minimizes the input vector's dimension and, as a result, the classifier's complexity and also improved the ANN by IWO algorithm.

Research by Chin *et al.* [16] in 2019, the goal of this research is to create a real-time and accurate QRS complex detector using a new method based on the Bayesian framework. To detect QRS complexes, we present a new technique consisting of two stages: variance-based detection (VBD) and maximum-likelihood estimation (MLE). Furthermore, simulations utilizing the MIT-BIH arrhythmia and QT datasets demonstrate the benefit of the proposed approach being easily transferrable to different databases by comparing our proposed work using wavelet and optimized neural network by minimizing the input vector's dimension and, as a result, the classifier's complexity. The coefficients of the wavelet transform are used for the training process of the ANN and optimized the training process by using the invasive weed optimization (IWO) algorithm the classification accuracy is higher when using the wavelet coefficients with the IWO algorithm. Wang *et al*. [17], in 2021 a proposed continuous wavelet transform (CWT) and convolutional neural network-based automatic ECG classification system (CNN). The 2D-scalogram composed of the aforementioned time-frequency components are decomposed using CWT to produce different time-frequency components, and CNN is used to extract features from the 2D-scalogram composed of the above time-frequency components. Four intervals of the time elapsed between two successive R-waves of the QRS signal on the electrocardiogram (RR) features are retrieved and merged with CNN features to input into a fully connected layer for ECG classification, as the surrounding R peak interval (also known as RR interval) is also useful for the diagnosis of arrhythmia. When tested in the MIT-BIH database, our technique gets an overall performance of 70.75%, 67.47%, and 68.76%. By comparing with our proposed work, the error in the training process of ANN is optimized by using the IWO algorithm, which improves system performance.

This paper is organized to present some sections. Section 2 present the research methodology which present the methods implemented for this work and the recognition system which used to classify the ECG signals and the calculations for the feature extraction by using wavelet and the classification by using the optimized neural networks. Section 3 is the simulation results for the ECG. Section 4 present the conclusions.

2. METHOD

In this paper, the proposed algorithm for the feature extraction and classification is as shown in Figure 1. The dataset for evaluating the suggested technique in the research is the well-known MIT-BIH arrhythmia database [18]. The ECG signal pre-processing contains denoising of the signal and heartbeat segmentations, R-R interval extractions [19]. After recording the ECG signal, The R-peak measurement is computed by founding zero-crossing points as the local maximum to determine the R-peak value and peak-to-peak magnitudes, signal offset, and R-peak position in the windowed ECG all affect feature extraction [20]. These impacts are caused by the patient's physiology, gender, and age, as well as the measurement system's characteristics [21]. The normalization reduces the influence of feature extraction methods on the peak-to-peak magnitudes and the signal offset [22]. Discrete wavelet transform (DWT) is used to de-noise ECG data after baseline corrections and normalizations at three, five, and eight levels.

By subtracting eight levels of de-noised signal from three levels of de-noised signal the noises like power line interfering and the electromyogram are cancelled [23]. To obtain QRS complexes, the level five de-noised signals are subtracted from level three denoised signals. On the resulting signal, a squaring operation is applied to augment the relatively high QRS frequency. A moving window integration filter is used to smooth the output of the preceding process, which includes many peaks during the period of a single QRS complex. The wavelet transform is then applied to the signal. The normalization process reduces the influence of the methods of features extraction on the peak to peak and signal offset [24]. When employing DWT to compute the compact of the signal data representation, we must decide how many of the best coefficients of the wavelet, to keep in order to adequately characterize the signal. The statistical parameters could be an effective way to describe the signal. All of the training data must be represented using matrices as a starting point. If there are two classes, they can be generalized to include greater than two classes, these are referred to as class 1 and class 2. The mean of all data set, as well as the overall data set mean, must be calculated next. As illustrated in the equation, the total mean can be computed by combining the separate data sets means:

$$\mu = (\rho_1 \times \mu_1) \div (\rho_2 \times \mu_2) \tag{1}$$

where

$$\mu_j = \frac{\sum_{j=1}^{n} a_j}{n} \tag{2}$$

where μ denotes the overall mean, a_i is a matrix that represents that class's data, ρ denotes the a priori class probability, and j denotes the class j mean. In a case with two classes of equal representation, the probability factor is 0.5, and n is the data points number. The criteria for class separability are formulated using the within-class and between-class scatter, this being the anticipated class variance. A variance matrix for the data sets j will be constructed using formula (3):

$$\mathrm{Var}_j = \frac{\sum_1^n (a_i - \mu_j)^2}{n} \tag{3}$$

where a_i is a matrix that represents that class's data. The within-class scatter (A_a) can now be calculated to be:

$$A_a = \sum_j (\rho_j - \mathrm{Var}_j) \tag{4}$$

A_a is the resulting within-class scatter, where each class's variance is adjusted according to the Apriori probability before merging them together. Where the between-class scatter (A_b) is calculated using (5).

$$A_b = \sum_1^n (a_i - \mu_j)^2 \tag{5}$$

The ratio of between-class scatter to within-class scatter, or the ratio of between-class scatter to within-class scatter, is the criterion that maximizes the ratio of between-class scatter to within-class scatter (crit).

$$\mathrm{cirt} = \frac{A_b}{A_a} \tag{6}$$

The wavelet coefficients that have a high criterion are those that can be employed for recognition. As a result, the parameters comprising the information essential for the recognition process can be detected. The proposed work is shown in Figure 1.

The statistics of a normal ECG signal are shown in Figure 2 which can be observed, only high-criterion components are used in recognition procedures because these points distinguish this class from others. Each class should have its unique features to distinguish it from other classes when using a neural network to classify them. There are two sorts of features in the N-class classification problem: shared features between two or more classes and independent features that belong to only one class. A network is proposed for each class in order to generalize the network and make it adaptable to new classes. The improved neural networks are used for the process of the recognition of the ECG signal [25]. The improved neural networks are trained using the back propagations algorithm, and the training process is optimized by using IWO, which was invented by Mehrabian and Lucas in 2006 [26]. IWO is a bio-inspired algorithm that simulates the natural behavior of seeds in colonization and finding suitable places for growth and reproduction. A modified version of IWO was used for training the ANN by adjusting the weights and biases of the ANN.

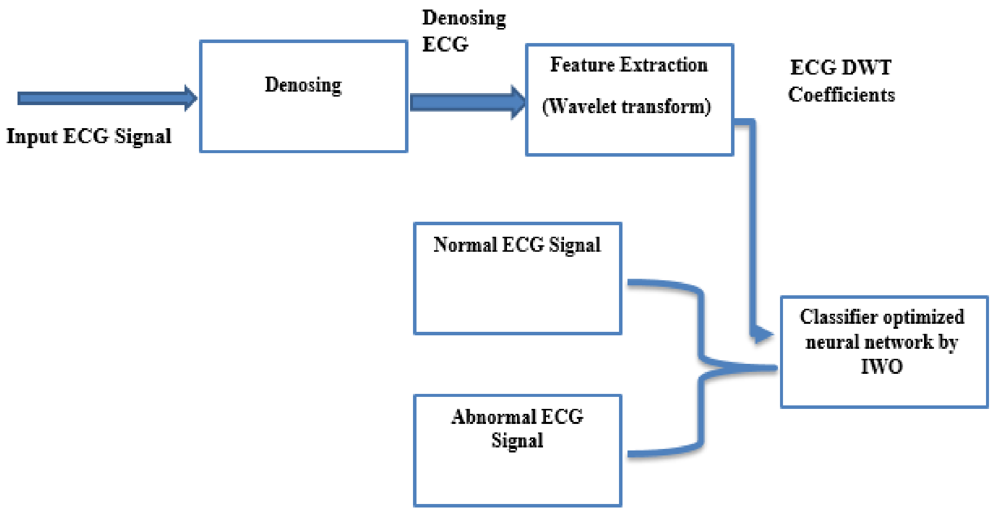

Figure 1. Proposed algorithm for ECG signal recognition

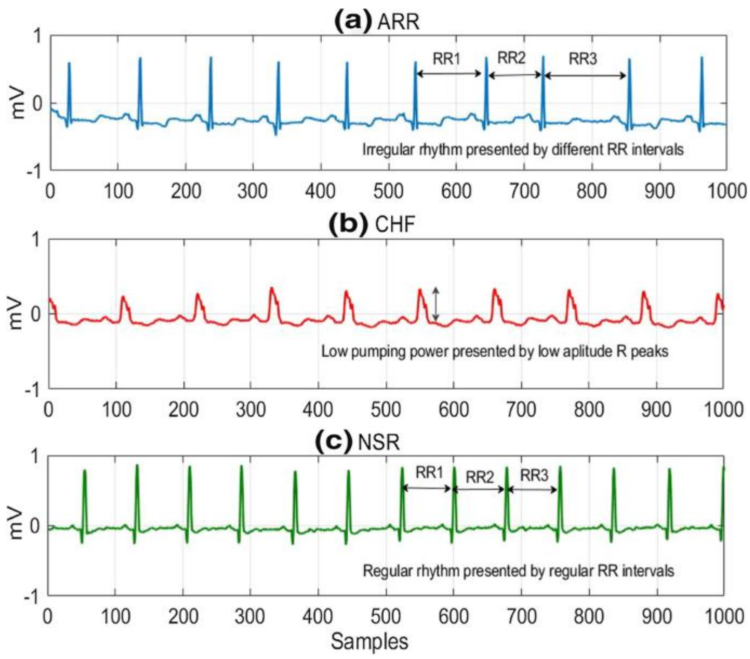

Figure 2. Representative each ECG category (a) ARR, (b) CHF, and (c) NSR

3. RESULTS AND DISCUSSION

The introduced recognition system is designed by using MATLAB 2020b estimated with 8-classes for the ECG signals; this data is taken from two ECG signals (ST-T and MIT-BIH database). The ECG classes: normal heart beats (NB), left and right bundles branches block (LBB), (RBB), also the paced beats (Pb), premature ventricular contractions (Vc), atrial premature beats (Ab), myocardial infarctions (Mi) and the ischemic heartbeats (I). The normal class is distinguished from other classes by three coefficients that make up the wavelet coefficients. The following parameters determine the recognition process's performance: positive productivity (Pb), sensitivity (Se), and total classification accuracy (TCA). The following are the definitions:

$$Se=\frac{Tbi}{Tbi+FNi} \quad (7)$$

$$Pb=\frac{Tbi}{Tbi+Fbi} \quad (8)$$

$$\mathrm{TCA}=\sum_{J=1}^{8}\frac{\mathrm{Tbi}}{\mathrm{Tq}} \tag{9}$$

where Tbi is the number of correct episodes classified of the class i^{th}, and the Fbi is the number of the correct episodes classified as another classes, FNi is the number of the correct episodes classified as other classes, and Tq is the number of the training sets of all beats. The method was also tested to determine the best attributes for reliably classifying ECG beats. For feed forward NN, the hidden layer neuron number was set at 400, and statistical parameters were calculated for various sets of training features. Tables 1-6 summarize the simulation findings and performance analyses in statistical parameters for various feature sets for different wavelet filter orders.

Table 1. Simulation results for ECG classification by using wavelet for DB1

	Tb	FN	Fb	Se	Pb
NB	73	11	16	0.893053	0.823344
LLB	71	17	11	0.912356	0.889050
RRB	74	12	20	0.888546	0.798787
Pb	72	16	16	0.834528	0.833519
Ab	76	12	14	0.892456	0.843636
Vc	73	6	24	0.911343	0.746943
I	68	22	13	0.785582	0.8636
Mi	74	14	15	0.888738	0.84906
TCA			80.9 %		

Table 2. Simulation results for ECG classification by using wavelet for DB2

	Tb	FN	Fb	Se	Pb
NB	81	11	9	0.899889	0.908889
LLB	82	16	5	0.94375	0.942943
RRB	83	3	16	0.983041	0.85376
Pb	81	7	13	0.921120	0.86230
Ab	80	6	14	0.93956	0.870216
Vc	84	8	11	0.932232	0.902476
I	86	3	15	0.986750	0.847244
Mi	82	2	18	0.99562	0.826429
TCA			83.5 %		

Table 3. Simulation results for ECG classification by using wavelet for DB3

	Tb	FN	Fb	Se	Pb
NB	90	6	6	0.937808	0.946640
LLB	88	4	12	0.976770	0.906607
RRB	88	7	9	0.944770	0.934895
Pb	90	4	8	0.977493	0.927325
Ab	84	8	12	0.901314	0.901404
Vc	83	13	9	0.889664	0.919081
I	86	6	11	0.964334	0.904634
Mi	86	12	10	0.878890	0.898786
TCA			86.7 %		

Table 4. Simulation results for ECG classification by using wavelet for DB4

	Tb	FN	Fb	Se	Pb
NB	86	6	11	0.934424	0.904743
LLB	84	6	13	0.963292	0.883686
RRB	85	7	11	0.933333	0.883616
Pb	82	5	13	0.933183	0.863784
Ab	83	4	15	0.963489	0.864170
Vc	86	9	7	0.923979	0.923914
I	83	10	9	0.921089	0.912093
Mi	83	11	7	0.903618	0.945343
TCA			84.9 %		

Table 5. Simulation results for ECG classification by using wavelet for DB5

	Tb	FN	Fb	Se	Pb
NB	87	7	9	0.946408	0.923834
LLB	86	9	8	0.932967	0.912915
RRB	87	6	11	0.9574746	0.874647
Pb	84	8	9	0.935917	0.907876
Ab	86	10	8	0.933425	0.933478
Vc	86	5	10	0.960357	0.875673
I	84	7	8	0.945086	0.937265
Mi	85	4	12	0.955651	0.885877
TCA			89.0 %		

Table 6. Simulation results for ECG classification by using wavelet for DB6

	Tb	FN	Fb	Se	Pb
NB	82	7	10	0.906707	0.887585
LLB	80	11	12	0.89663	0.896788
RRB	78	7	16	0.930413	0.831520
Pb	81	11	10	0.857267	0.896466
Ab	78	10	14	0.912542	0.867483
Vc	78	12	10	0.865758	0.896057
I	75	15	13	0.863470	0.893623
Mi	74	13	12	0.872488	0.872374
TCA			80.8 %		

4. CONCLUSION

In this paper, an optimized artificial neural network with a wavelet-based features extractions method is utilized for eight Variety types of ECG beats classifications into eight different categories. These beats of the ECG are taken from ST-T and MIT-BIH database. The number neurons in the hidden layers and the feature set that provide the best performance have been computed. When the number of hidden layer neurons was raised up to 400, classification performance improved. The classifier (optimized neural network) improved the TCA above 80% and the sensitivity above 70%, a positive predictive value of over 65%, a negative predictive value of more than 93%. This study the proposed classifier model demonstrated that it achieved high rates of the TCA and sensitivity and improved the values of specificity, positive and negative predictivity, all of which are required for a computer-assisted ECG diagnostic system. The normalizations processing, the features extraction, and optimized neural network by IWO are the three phases that lead to decision-making. The two ECG beats sets from two separate patients are used for the testing and training operations of ECG classifiers in order to generalize the classification process. The ability to interpret decision-making is advantageous to the optimized artificial neural network by IWO.

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BIOGRAPHIES OF AUTHORS

Ali Talib Jawad received the B.Sc. and M.Sc. degrees in electrical engineering from Babylon University, Babylon, Iraq, in 2015 and 2018, respectively. He is currently a lecturer at Hilla University College, Department. Of Medical Instrumentation Technologies Engineering Babylon, Iraq. His research interests include the applications of artificial intelligence, control system, communications, the biomedical field, and robotics. He can be contacted at email: alitaleb54qq@gmail.com.

Dalael Saad Abdul-Zahra received the B.Sc Mathematical from Babylon University, Babylon, Iraq, in 2015 and M.SC. Mathematical (Factional Analysis) from Kufa University, Najaf, Iraq, in 2020, I am currently working at Hilla University College as an assistant teacher in the Department of Medical Physics Interested in studying topics related to applied and pure mathematics, rubber engineering and some special interests in computers and basic programming languages. She can be contacted at email: dalael20175@gmail.com.

Hasan Muwaffaq Gheni is a lecturer at Al-Mustaqbal university college/Department of Computer Techniques Engineering. His BA in Electrical Engineering from Babylon university in 2016. Worked as electrical maintenance and control engineer in addition to his position as a quality control (QC) engineer in different sites in many companies (Al-Tekamal Company and Plastic Factory). After that, he joined UTHM in Malaysia to achieve his master s degree in Electrical Engineering. His Master s degree in Electrical Engineering/communication and Electronics department from UTHM University of Malaysia in 2019. He is employed at Al Mustaqbal university College in 2019/10 as a Lecturer Assistant for Microprocessor Architecture and Electromagnetic Fields currently, Ph.D. student in Babylon university Department of Electrical Engineering/Communications and Electronics. His research interest is optical communication, IoT, Wireless sensor Network. He can be contacted at email: hussein_awadh@mustaqbal-college.edu.iq.

Ali Najim Abdullah born in Babylon, Iraq on Oct 17, 1992. In 2014, he had got his bachelor's degree in the electrical engineer sciences, at the University of Babylon in Babylon, Iraq. In 2017, he had got a master's degree in the communications and electronics engineering sciences at the University of Babylon. He is currently a PhD student in the communications and electronics engineering sciences at the University of Babylon in Babylon, Iraq. His works studies and interests are focused on the design, implementation, and performance evaluation of Radio direction-finding system to create the best performance, which is required for the system improvements, confirming to locate and track the desired target at a specific frequency, under the supervision of Dr Laith Ali Abdul-Rahaim, Professor in Electrical engineering department at the same University. He can be contacted at email: alin@hilla-unc.edu.iq.