Pattern Recognition Application in ECG Arrhythmia Classification

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Abstract: In this paper, we propose a pattern recognition algorithm for arrhythmia recognition. Irregularity in the electrical activity of the heart (arrhythmia) is one of the leading reasons for sudden cardiac death in the world. Developing automatic computer aided techniques to diagnose this condition with high accuracy can play an important role in aiding cardiologists with decisions. In this work, we apply an adaptive segmentation approach, based on the median value of R-R intervals, on the de-noised ECG signals from the publically available MIT-BIH arrhythmia database and split signal into beat segments. The combination of wavelet transform and uniform one dimensional local binary pattern (1-D LBP) is applied to extract sudden variances and distinctive hidden patterns from ECG beats. Uniform 1-D LBP is not sensitive to noise and is computationally effective. ELM classification is adopted to classify beat segments into five types, based on the ANSI/AAMI EC57:1998 standard recommendation. Our preliminary experimental results show the effectiveness of the proposed algorithm in beat classification with 98.99% accuracy compared to the state of the art approaches.

1 INTRODUCTION

One of the primary cause of sudden death globally is cardiovascular disease. The improper life style by having an unhealthy diet, tension and stress, tobacco consumption and insufficient exercise leads to cardiovascular disease. Atrial and ventricular arrhythmias are concurrent side effects arises from cardiovascular disease. Arrhythmia is abnormal changes in the heart rate due to improper heart beating which causes failure in the blood pumping. The abnormal electrical activity of the heart can be life threatening. Arrhythmias are more common in people who suffer from high blood pressure, diabetes and coronary artery disease.

Electrocardiograms (ECGs) are the recordings of electrical activities of the heart. Each heart beat in an ECG record is divided into P, QRS and T waves which indicate the atrial depolarization, ventricular depolarization and ventricular repolarisation, respectively. Electrocardiograms are used by cardiologists to detect abnormal rhythms of the heart. Cardiologists must deal with challenges in the diagnosis of arrhythmia due to the effect of noise in ECG signals and the nonstationary nature of the heart beat signal. Automatic interpretation of ECG data using time-frequency signal processing techniques and pattern recognition approaches could be helpful to both cardiologists and patients for improved diagnostics (Thomas et al., 2015; Elhaj et al., 2016).

Although in the past few years, several computer-aided methods for early prediction of the risk of cardiovascular disease have been investigated, it is still an extremely challenging problem. There are many pattern recognition techniques in the literature to recognize and classify ECG beats. Particle swarm optimization (PSO) and radial basis functional neural network (RBFNN) were employed in the proposed beat classification algorithm in (Korurek and Dogan, 2010). In (Khoshnoud and Ebrahimnezhad, 2013), an accuracy of 92.9% was obtained where linear predictive coefficients (LPC) were adopted as beat features and normal and abnormal beat types were classified using probabilistic neural networks. In (Inan et al., 2006), beats are classified with an accuracy of 95.16% using the combination of time–frequency features, using wavelet transform, time domain information and the use of an artificial neural network (ANN) as a classifier. In (Martis et al., 2013a) a combination of a linear DWT feature extraction and principal component analysis (PCA), as dimensionality reduction technique, and neural

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network classifier leads to 98.78% classification accuracy between normal and abnormal beats. In (Kadambe and Srinivasan, 2006), normal and abnormal time domain features, P, QRS and T waves from American Heart Association database were classified with the accuracy of 96%, 90% and 93.3%, respectively, by discretizing the wavelet basis function using an adaptive sampling scheme. Adaptive parameters of wavelet non-linear functions and the relative weight of each basis function were estimated using a neural network. An accuracy of 99.65% for arrhythmia recognition was reported in (Yu and Chen, 2007) using wavelet transform and a probabilistic neural network. However, a small subset of MIT-BIH ECG database (only 23 records) was employed for evaluation. In order to classify ECG beats, the authors in (Ebrahimzadeh and Khazaee, 2009) adopted statistical features from Lyapunov exponents and wavelet coefficients power spectral density (PSD) values of eigenvectors and achieved a 94.64% accuracy for eight records from MIT-BIH arrhythmia database. Due to the effect of noise, and the nonstationary nature of ECG signal, nonlinear techniques appear to be more effective in extracting distinctive and hidden characteristics of ECG signals. In (Martis et al., 2013b), higher order spectra (HOS) bi-spectrum cumulants and PCA dimensionality reduction approach were adopted to represent ECG signals and feed-forward neural network and least square support vector machine (SVM) were used for classifying different types of beats with an accuracy of 93.48%. In (Khalaf et al., 2015), a cyclostationary analysis was proposed as a feature extraction approach to reduce the effect of noise and also to reveal hidden periodicities of ECG beats where spectral correlation coefficients were utilised as statistical signal characteristics and passed through SVM for classification; this results in an accuracy of 98.6% for 30 records of the MIT-BIH Arrhythmia database. Authors in (Oster et al., 2015) proposed a switching Kalman filter technique for arrhythmia classification, and automatic selection of beat type. This method also includes a beat type for unknown morphologies "X-factor" which incorporates a form of uncertainty in classification for the case of indecision on the beat type. The classification F1 score of the algorithm on MIT-BIH arrhythmia database was 98.3%. Employing the fusion of linear and nonlinear features has benefits the advantages of handling noise and a more effective description of the signal. In (Elhaj et al., 2016), a combination of linear (PCA of DWT coefficients) and nonlinear (high order statistics, cumulants and independent component analysis) features were proposed for heart beat representation. An accuracy of 98.91% was achieved using the fusion of SVM and radial basis function classifiers to classify five types of arrhythmia. The combination of fourth and fifth scale dual-tree complex wavelet transform (DTCWT) coefficients, AC power, kurtosis, skewness and timing information were adopted in (Thomas et al., 2015) as QRS characteristics. Multi-layer back propagation neural network was proposed to classify five types of ECG beats of MIT-BIH Arrhythmia database with the accuracy of 94.64%.

As discussed, encouraging results on the arrhythmia classification have been obtained in previous research. However, more applicable and fully automatic techniques with high accuracy and low complexity need to be developed. In particular, developing automatic computer aided segmentation of ECG signal into heart beats is very important as the first stage in beat classification. In previous research (Thomas et al., 2015; Khalaf et al., 2015), R peaks were located using an annotated file which makes the techniques semi-automatic. In contrast, in the approach proposed in this paper, R peaks are detected automatically based on a parabolic fitting algorithm. Moreover, a novel adaptive segmentation technique used in our work reduces the probability of beat misclassification and the risk of misdiagnosis due to the interference of adjacent beats which may occur when a constant beat size was used as in previous works (Martis et al., 2013a; Elhaj et al., 2016). As well, the chosen feature extraction technique has significant role in the accuracy of diagnosis. By discovering hidden patterns and extracting distinctive features from the ECG signal, which are less sensitive to noise, the accuracy of arrhythmia classification can be improved without requiring very complicated classifiers. Uniform 1-D local binary pattern (LBP), used in our work, has the advantage of less sensitivity to noise and effectiveness in extracting hidden and salient information from non-stationary ECG signals and due to low computational complexity, it can be employed in real-time applications (Kaya et al., 2014).

The proposed arrhythmia recognition approach in this paper is based on beat classification by adopting the fusion of wavelet transform and uniform 1-D LBP feature extraction of ECG signal and extreme learning machine (ELM) classification. The ECG signal is pre-processed to remove the unwanted effect of noise. Then, the de-noised signal

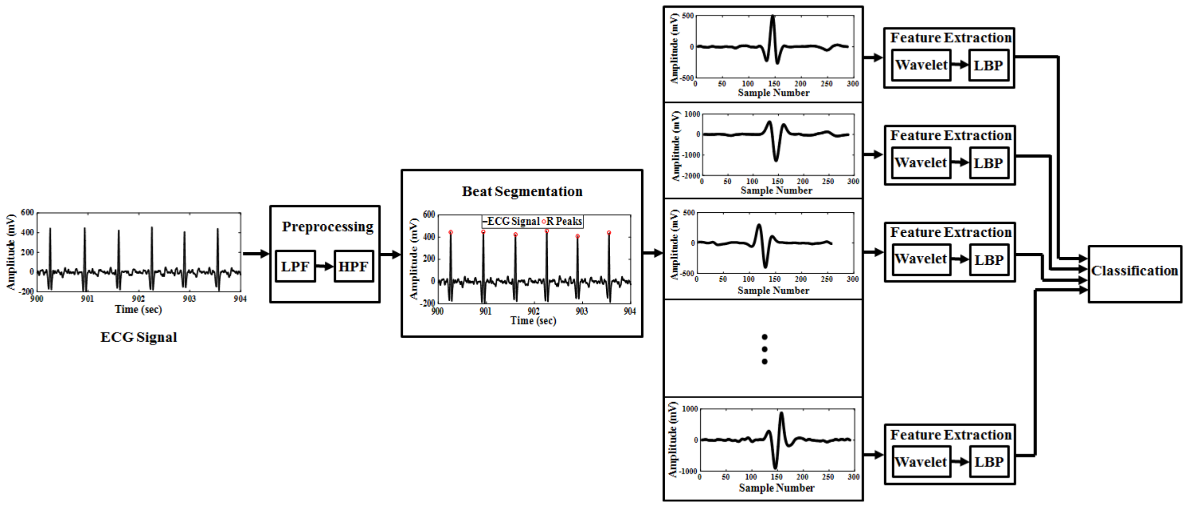

Figure 1: Block diagram of the proposed arrhythmia recognition and classification algorithm.

is divided into heart beats using the proposed adaptive segmentation technique in this paper, which is based on the detected R peaks and the median value of R-R intervals. Each segment of the ECG signal is transformed into time-frequency space by applying digital wavelet transform (DWT). Wavelet coefficients of signal go through a one-dimensional version of LBP which is a histogram-based signal descriptor and extracts hidden and distinctive characteristics of a signal. By transforming the feature space into histograms, the dimensionality of the feature space is reduced from the number of signal samples to the number of histogram bins. In this paper, we just keep uniform patterns which contain useful information about the one-dimensional signal, such as sudden changes, edges, end of lines and corners. The beat segments are divided into training and testing sets. The extracted features of training set are fed to an ELM classifier for the training procedure. The remaining feature vectors are used to test the beat classification algorithm. Figure 1 shows the block diagram of the proposed algorithm. The rest of paper is organized as follows: Section 2 describes the adopted ECG database and Section 3 provides mathematical details of the pre-processing techniques. Section 4 explains the proposed beat segmentation approach. Section 5 and 6 discuss feature extraction and classification techniques and Section 7 provides an evaluation through experimental results. Finally, the paper is concluded in Section 8.

2 MATERIALS

In this paper, we consider the ECG signals which are available online from PhysioNet that offers free web access to a large-scale dataset of recorded physiologic signals. The MIT-BIH arrhythmia database (Moody and Mark, 2001; Goldberger et al., 2000) is used to evaluate the arrhythmia recognition and classification technique which has been proposed in this paper. There are 48 ECG records, with the length of a little more than 30 minutes, in the MIT-BIH collection and the sampling frequency of each ECG signal is 360 Hz. Twenty-three of recordings were routine clinical ECGs selected from 4000 ambulatory records at Boston’s Beth Israel Hospital and the remaining 25 ECG signals were collected from the same set to include other less common significant arrhythmia types that may not be represented well in a small randomly selected group. Each beat in the ECG signal shows one cycle of electrical activity of the heart. The irregular heart rhythms are considered as ectopic beats. The entire MIT-BIH database is grouped into five beat types based on the ANSI/AAMI EC57:1998 standard recommendation (Martis et al., 2013a). The five classes include normal beats (N), fusion beats (F), supra-ventricular ectopic beats (S), ventricular ectopic beats (V) and unknown or unreadable beats (U) as shown in Fig 2. In this paper, we adopted the entire 48 ECG records in the database including (90,580) N, (2973) S, (7707) V, (1784) F and (7050) U beats (110094 beats, totally).

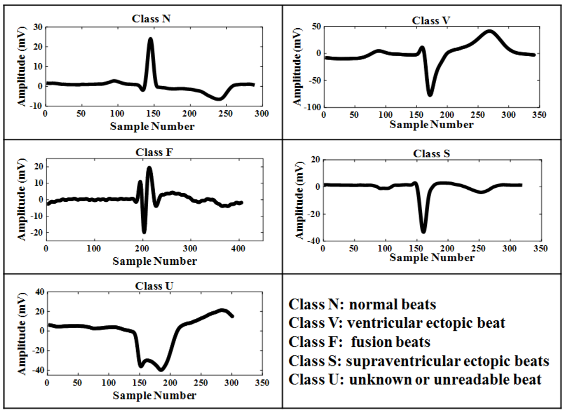

Figure 2: Five categories of ECG beat classes based on the ANSI/AAMI EC57-1998 standard.

3 PREPROCESSING

The effect of noise on the ECG signal reduces the accuracy of recognition of arrhythmia in the ECG records and therefore, the precision of diagnosis of cardiovascular disease will be decreased. Various categories of noise are associated with the ECG signal, such as powerline interference, device noise, muscle noise, motion noise, contact noise and quantization noise (Elhaj et al., 2016). In order to increase the accuracy of disease detection, pre-processing is required to be applied on the ECG signal to reduce the effect of noise and improve the signal to noise ratio. In this paper, we applied a digital elliptic band-pass filter with passband of 5-15 Hz (maximizes the QRS energy), which is constructed by cascading a low-pass and high-pass filters, to remove muscle noise and baseline wander (Pan and Tompkins, 1985) as follows.

3.1 Low-pass Filter

The adopted low-pass filter has the following transfer function and amplitude response, respectively (Pan and Tompkins, 1985).

$$H(z) = \frac{(1-z^{-6})^2}{(1-z^{-1})^2}, \tag{1}$$

$$|H(\omega T)| = \frac{sin^2(3\omega T)}{sin^2(\frac{\omega T}{2})} \quad \text{where T is sampling period} \tag{2}$$

3.2 High-pass Filter

The transfer function of the high-pass filter is based on the subtraction of the output of a first-order low-pass filter from an all-pass filter as follows (Pan and Tompkins, 1985).

$$H(z) = z^{-16} - \frac{(1-z^{-32})}{(1-z^{-1})}. \tag{3}$$

The proposed high-pass filter has the following amplitude response.

$$|H(\omega T)| = \frac{[256 + sin^2(16\omega T)]^{0.5}}{cos(\frac{\omega T}{2})}. \tag{4}$$

4 BEAT SEGMENTATION

In order to recognize arrhythmia, we had to compute a beat classification by dividing each ECG signal into beat segments and classify different types of beats. The segmentation process consists of R peak detection and isolation of beats based on the duration of R-R intervals.

4.1 R Peak Detection

R peaks are the largest deviation of ECG signals from the baseline. The proposed algorithm for R peak detection in this work is based on the parabolic fitting algorithm (Jokic et al., 2011). By adopting two polynomial functions (PFs) of degree 3, we modelled the R peak. A signal x of length M is defined as follows.

$$x\,(m){:}\; x\,(1), x\,(2), \dots, x\,(M) \tag{5}$$

where $x\,(i)$ is the i^{th} sample of the signal. The approximation of signal x using the polynomial function $\hat{x}$ of order d is denoted by the following equation.

$$\hat{x}\,(m) = c_0 + c_1\, m + c_2\, m^2 + \cdots + c_d\, m^d, \quad where \quad m = 1, 2, \dots, M. \tag{6}$$

By minimizing the least square error (the square of l_2 norm of the residual), we can calculate the c_k coefficients as follows.

$$er^2 = \|\hat{x}\,(m) - x(m)\|_2^2 = \sum_{m=1}^{M} (\hat{x}\,(m) - x(m))^2, \tag{7}$$

$$\frac{\partial er^2}{\partial c_k} = 0. \tag{8}$$

In order to find R peak, a differentiator is first used to highlight the high inclines of the ECG signal. Then, the PFs are fitted from the Q peak to the R peak (through the ascending R leg) and from R peak to the S peak (through the descending R leg) (Jokic et al., 2011).

4.2 Segmentation

After detection of the R peaks we need to split ECG signal into beat segments. The segmentation technique which is proposed in this paper starts from each R peak and separates beats by choosing some samples from the left and right side of the R peak without inclusion of the former or latter beats. In previous work in the literature (Thomas et al., 2015; Elhaj et al., 2016) a constant number of samples are selected from both signal sides. Therefore, the length of all beat segments is equal. However, due to the non-stationary and aperiodic nature of ECG signal, beat lengths for all of the ECG records are not equal-sized. Therefore, determining a constant size for all beats may lead to inclusion of adjacent beats in each segment. In this paper, in order to reduce the effect of beat interference, we employ a novel adaptive segmentation approach. For each ECG record we calculate the consecutive R-R intervals and find the median value of R-R durations for each ECG signal as the adaptive beat duration. Therefore, from each R peak, we select the number of samples equal to the half of the beat duration from the left and right sides of the R peak.

5 FEATURE EXTRACTION TECHNIQUES

In this section, we describe how we find the distinctive characteristics of ECG beats to feed to classification stage for beat recognition. The cascade combination of wavelet transform and uniform 1-D LBP is applied on beat segments to extract sudden variances and sparse hidden patterns from signal.

5.1 Wavelet

Discrete wavelet transform is a viable and powerful feature extraction technique to analyse ECG signals locally in multi-resolution manner in time and frequency domain simultaneously and separate the signal frequency sub-bands. A signal can be displayed with different scaling and wavelet basis functions (Emadi et al., 2012). DWT extracts the approximation (low frequency components) and detailed coefficients (high frequency components) as shown in Fig 3 (A_i and D_i are approximation and detail coefficients and $i = 1, 2 \; and \; 3$). A continuous wavelet transform is generated by a series of translations and dilations of mother wavelet $\varphi(.)$ as follows (Ródenas et al., 2015).

$$\varphi_{\alpha,\beta}(t) = |\alpha|^{-\frac{1}{2}}\varphi\left(\frac{t-\beta}{\alpha}\right) \quad (9)$$

where, α and β are scaling and shift parameters, respectively. DWT is the sampled version of continuous wavelet as follows.

$$\varphi_{\alpha,\beta}[n] = 2^{-\frac{\alpha}{2}}\varphi[2^{-\alpha}\, n - \beta]. \quad (10)$$

The wavelet transform of a signal, $x\,[n]$ of length N, is the correlation between the wavelet function $\varphi_{\alpha,\beta}[n]$ and signal as shown by the following set of wavelet coefficients (Ródenas et al., 2015).

$$CW[\alpha,\beta] = \sum_{n=1}^{N} x\,[n]\varphi_{\alpha,\beta}[n]. \quad (11)$$

In this paper, we use 8 level wavelet decomposition and adopt the approximation and detail coefficients as the extracted features. Therefore, the size of wavelet features for each beat, depending on the beat size, is different.

5.2 1-D LBP

Two-dimensional local binary pattern (2-D LBP) is one of the most successful feature extractors, which extracts texture features of the 2-D images by comparing each signal sample (image pixel) with its neighbour samples in a small neighbourhood. There is no training requirement which makes the feature extraction fast and easy to integrate into the new data sets. Furthermore, due to the application of

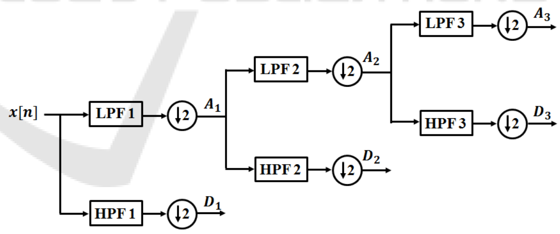

Figure 3: Three-level wavelet decomposition.

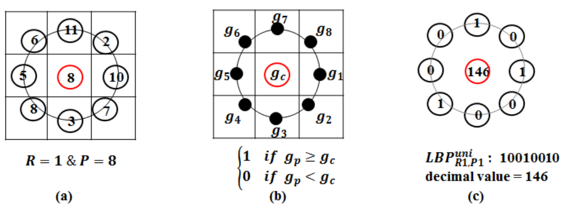

Figure 4: 2-D LBP for a sample point of a 2-D signal: a) choosing P neighbours on the neighbourhood of radius R around a centre sample point, b) comparing signal values for centre and neighbour points and c) creating the binary pattern and associated decimal value for the centre sample.

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histograms as the feature sets, the image-size dimension of the feature space can be reduced to the number of histogram bins (Ahonen et al., 2004). R is the radius of the neighbourhood and P is the number of neighbour samples which are compared with the centre pixel as shown in Fig 4. If the value of the neighbour sample is greater than or equal to the centre sample, a 1 is assigned to that neighbour and if it is less than the centre pixel a 0 is assigned to that sample. Therefore, we have a P-bit binary pattern for each pixel at (r, c) location and the decimal value (DV) associated with the binary pattern is calculated as follows.

$$DV(r,c) = \sum_{k=1}^{P} G(g_k - g_c)\,.\,2^{P-1}, \qquad (12)$$

$$G(u) = \begin{cases} 1 & if \;\; u \geq 0 \\ 0 & if \;\; u < 0 \end{cases}. \qquad (13)$$

Decimal values are used to make the histogram for the 2-D signal. Therefore, the size of feature vector which is extracted from the 2-D image is equal to the number of histogram bins (2^P). In order to reduce the size of features and remove redundant information, we ignore non-uniform patterns due to the fact that considerable amount of discriminating information (important local textures such as spots, line ends, edges and corners) is preserved by taking only uniform patterns into consideration (Ahonen et al., 2004). The binary pattern is uniform if there are at most two bitwise transitions from 0 to 1 or 1 to 0. Each histogram has $P(P-1)+2$ bins for uniform and 1 bin for all non-uniform patterns, in total there are $P(P-1)+3$ bins. Therefore, the computational complexity is also reduced (Nikan and Ahmadi, 2015).

The one-dimensional version of LBP can be adopted to extract distinctive characteristics from ECG signals. The same procedure is applied on each sample point of the signal by comparing P/2 neighbours from right and left side of centre sample to create the P-bit pattern as shown in Fig 5 (Kaya et al., 2014). In this paper, the uniform 1-D LBP with neighbourhood size of 8 points is applied on wavelet coefficients from the previous section. Therefore, a histogram of 59 bins (based on the above formulations $P(P-1)+3 = 8(8-1)+3 = 59$ bins) is created as the feature vector for each beat segment. This technique not only discovers local sudden variances and hidden patterns from ECG signal but also has the advantage of having less sensitivity to noise, extracting sparser characteristics, and is computationally effective. Furthermore, all feature vectors regardless of the beat size, have equal length of feature sets.

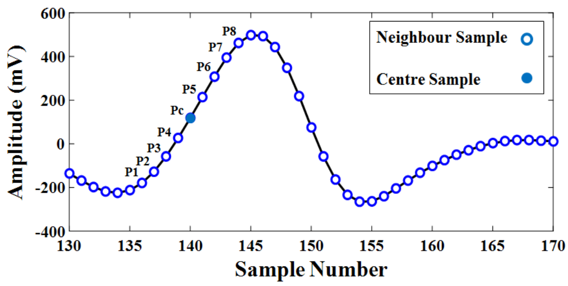

Figure 5: Neighbouring around one sample point of ECG signal for 1-D LBP feature extraction.

6 CLASSIFICATION

In this section, we describe our approach for training a classifier to learn the set of arrhythmia classes from a set of the extracted features from ECG beat segments. We then use the remaining features for testing the classifier to predict the class labels of beat segments; we apply 10-fold cross validation (to keep consistency with reference works). The feature set of all ECG beat segments is divided into two randomly selected subsets for training and validation, for 10 times, and the classification approach is applied every time to predict the arrhythmia class labels for the test set. Each time, 90% of the dataset is devoted to the training subset and the rest forms the testing subset. The final accuracy is the average of 10 folds. We employ an extreme learning machine as the proposed classification approach. Feed-forward neural networks are used extensively as classification strategies in medical pattern recognition applications due to their capability in approximating the nonlinear mappings in the data. In order to tune the weights and biases of the network, traditional learning mechanisms such as gradient decent method are employed. However, due to very slow iterative tuning by a gradient decent technique and its convergence into local minima, feed-forward neural networks suffer from slow learning and poor scalability. Extreme learning machine (ELM), as a learning algorithm for single hidden layer feed-forward neural network (FF-NN), is a faster technique. An ELM classifier is generalized single hidden layer neural network with random hidden nodes and determined hidden layer weights without iterative weight tuning (Huang et al., 2006). For N distinct training samples, the single hidden layer FF-

NN with N_h random hidden neurons, L input and K output nodes are modelled as follows.

$$\sum_{j=1}^{N_h} \bar{\lambda}_j F_j(\bar{x}_i) = \sum_{j=1}^{N_h} \lambda_j F(\bar{w}_j . \bar{x}_i + \mu_j) = \bar{o}_i, \quad where\ \ i = 1, 2, \dots, N \tag{14}$$

where, $\bar{x}_i = [x_{i1}, x_{i2}, \dots, x_{iL}]^T$ and $\bar{y}_i = [y_{i1}, y_{i2}, \dots, y_{iK}]^T$ are input and output nodes, $F(.)$ is the activation function of network, μ_j is threshold of j^{th} hidden node and $\bar{w}_j = [w_{j1}, w_{j2}, \dots, w_{jL}]^T$ and $\bar{\lambda}_j = [\lambda_{j1}, \lambda_{j2}, \dots, \lambda_{jK}]^T$ denote the weight vectors between the j^{th} hidden node and the input and output nodes, respectively. N samples can be approximated to have zero error means such that,

$$\sum_{j=1}^{N_h} \lambda_j F(\bar{w}_j . \bar{x}_i + \mu_j) = \bar{y}_i \tag{15}$$

where, (15) can be denoted as follows.

$$H\Lambda = Y \tag{16}$$

where, $\Lambda = \left[\bar{\lambda}_1{}^T, \bar{\lambda}_2{}^T, \dots, \bar{\lambda}_{N_h}{}^T\right]^T$ and $Y = \left[\bar{y}_1{}^T, \bar{y}_2{}^T, \dots, \bar{y}_N{}^T\right]^T$ and H is the hidden layer matrix, the l^{th} column of which is the output of l^{th} hidden node. It is proven in (Huang et al., 2006) that if $F(.)$ is infinitely differentiable, then we can assign random values to the weights and biases and the required hidden layer nodes is $N_h \leq N$. Therefore, in the ELM technique, rather than tuning the weights and biases iteratively in gradient descent method, they are randomly assigned in the beginning of learning. Then, H is calculated and output weights are obtained through the following minimum norm least squares solution of (16),

$$\hat{\Lambda} = H^{\dagger} Y \tag{17}$$

where, $H^{\dagger}$ is the Moore-Penrose generalized inverse of H (Huang et al., 2006).

7 EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed algorithm for arrhythmia recognition and classification, cross validation is applied on the entire MIT-BIH arrhythmia database (110094 beat segments). Sensitivity and precision of classification of each beat type are calculated using true positive (TP), false positive (FP) and false negative (FN) as follows and shown in Table 1.

$$Sensitivity\% = \frac{TP}{TP + FN} \times 100, \tag{18}$$

$$Precision\% = \frac{TP}{TP + FP} \times 100. \tag{19}$$

Table 2 shows the total accuracy of the proposed arrhythmia classification approach compared to the previous works in the literature, using the following equation.

$$Accuracy\% = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{20}$$

where, TN is the true negative value of the classification. As shown in Table 2, our proposed method outperforms other reference techniques in the accuracy of beat classification. In the presented work, we adopted the same dataset as what was employed in the studies that are used for comparison, except for the work in (Khalaf et al., 2015), were only 30 ECG recordings were adopted which is much smaller than the 48 recordings in our study.

Our proposed algorithm is fully automatic, compared to the semi-automatic techniques in (Thomas et al., 2015; Khalaf et al., 2015). Based on

Table 1: Sensitivity and Precision of the proposed algorithm for classifying each beat type.

Beat Class	Sensitivity %	Precision %
N	97.86	98.50
V	96.20	98.63
F	92.73	96.35
S	90.50	94.06
U	78.66	82.36

Table 2: Comparison of the accuracy of different algorithms for arrhythmia classification.

Method	Total Accuracy %
DTCWT+Morphological-ANN (Thomas et al., 2015)	94.64
PDHI-SVM/RBF (Elhaj et al., 2016)	98.91
SC-SVM (Khalaf et al., 2015)	98.60
DWT+PCA-NN (Martis et al., 2013a)	98.78
Proposed algorithm	98.99

the results in Table 2, the classification accuracies in (Martis et al., 2013a) and (Elhaj et al., 2016) are very close to the result of our proposed approach. However, the proposed adaptive segmentation method in this paper reduces the interference of adjacent beats, which is caused by using fixed beat size as in (Martis et al., 2013a) and (Elhaj et al., 2016). Our proposed technique outperforms those approaches by 232 and 89 less misclassifications, respectively.

8 CONCLUSIONS

The proposed arrhythmia classification approach introduces a novel adaptive beat segmentation method based on the median value of the R-R intervals which reduces the misclassification due to the inclusion of adjacent beats in each segment. Moreover, applying uniform 1-D LBP on the wavelet coefficients not only reduces the dimensionality of feature space to 59 bins, which makes the proposed algorithm computationally effective, but also extracts local sudden variances and sparser hidden patterns from the ECG signal and has the advantage of having less sensitivity to noise. ELM classification leads to 98.99% accuracy of beat classification of ECG records in the MIT-BIH arrhythmia database, based on the ANSI/AAMI EC57:1998 standard recommendation, which outperforms the performance of the state of the art arrhythmia recognition algorithms in the literature. These types of algorithms create opportunities for automatic methods that can be applied to ECG readings to help cardiologists assess the risk of arrhythmias that may result in sudden cardiac death. This, given the shortage of cardiologists, can enhance our ability to screen people at risk.

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