Research Article

J Wave Autodetection Using Analytic Time-Frequency Flexible Wavelet Transformation Applied on ECG Signals

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As a new important index of the electrocardiogram (ECG) of ventricular bipolar play, J wave plays an increasingly significant role in the clinical diagnosis. The existence of J wave hints at potential crisis of fatal disease and even death. Nowadays, however, it can hardly meet the clinical needs where the diagnosis of J wave variation only depends on experience of clinicians. Therefore, a new technique which is capable of detecting J wave using analytic time-frequency flexible wavelet transformation (ATFFWT) is proposed in this paper. We have used ATFFWT to decompose the processed ECG signals into the desired subbands. Further, Fuzzy Entropy (FE) is computed from each subband to capture more hidden and meaningful information. Feature scoring method is applied to select optimal feature set. Finally, the extracted features are fed to Least Squares-Support Vector Machine (LS-SVM) classifier. The 10-fold cross validation is used to obtain reliable and stable performance and to avoid the overfitting of the model. Our proposed algorithm has achieved accuracy of 97.61% for Morlet Wavelet (MW) kernel in comparison to 97.56% for Radial Basis Function (RBF) kernel. The developed effective algorithm can be used to design an expert system to aid clinicians in their regular diagnosis.

1. Introduction

Nowadays, cardiovascular diseases (CVDs) cause nearly one-third of all deaths worldwide. CVDs remain a leading cause of health loss for all regions of the world and a major barrier to long-term sustainable development of mankind [1]. Nearly 17 million people die due to cardiovascular diseases globally every year [2]. J wave is regarded as a new important index of the electrocardiogram (ECG) of ventricular bipolar play, and it plays an increasingly significant role in the clinical diagnosis of cardiovascular diseases. A series of diseases or conditions that can produce J waves in the ECG continues to rise [3].

The J wave, also referred to as an Osborn wave, is a deflection immediately following the QRS complex of the surface ECG, which is usually partially buried inside the QRS, often appearing as a J-point elevation; it represents the end of depolarization and the start of bipolarization [4]. The presence of J wave may lead to early repolarization syndrome (ERS), pericarditis, idiopathic ventricular fibrillation (IVF),

Brugada syndrome (BrS), and even sudden unexplained nocturnal death syndrome [4]. From a mechanistic point of view, these syndromes should be referred to as the J wave syndromes [4]. J wave and J wave syndrome are high-risk early warning indicators of sudden cardiac death [5]. The appearances of prominent J waves in the ECG have long been reported in cases of hypothermia and hypercalcemia [6]. More recently, accentuation of the J wave has been associated with life-threatening ventricular arrhythmias. Although typical J waves usually are accentuated with bradycardia or long pauses, the opposite has also been described [5, 7]. J waves are often seen in young males with no apparent structural heart diseases, whereas intraventricular conduction delay is often observed in older individuals or those with a history of myocardial infarction or cardiomyopathy [5, 7].

J wave is mixed in the normal ST segment, coupled with the small amplitude, existence of noise, and baseline wander. Accordingly, the diagnosis of J wave variation and minute changes in the ECG signals only depends on the clinicians' experience, which can not meet demand at present

FIGURE 1: Steps used for automatic J wave detection.

clinical, and is also apt to be misdiagnosed. Therefore, it is pretty essential and necessary for us to analyze J wave from the perspective of computer aided method with advanced digital signal processing techniques and machine learning algorithms, which can help to capture the subtle and hidden information in the ECG signals and realize the accurate and automatic diagnosis of J wave. Such an automated system will provide tremendous assistance to the clinicians in their routine screening of cardiac patients [8–12]. In literature, although the method of processing ECG signals has been very mature, methods of detecting J wave signals from ECG signal were relatively less and the detection precision is undesirable. The authors in [13] proposed the method based on locating a break point in the descending limb of the terminal QRS. They added new logic to Glasgow ECG analysis program to automate the detection of J wave. A technique based on digital 12-lead electrocardiogram is used in [14]. ECG signals were automatically processed with the GE Marquette 12-SL program 2001 version (GE Marquette, Milwaukee, WI). And the functional data analysis techniques were applied to the processed ECG signals. In [15], five features including three time-domain features and two wavelet-based features are defined; these features are found significantly different in discriminate J wave and normal classes. Thereafter, Principle Component Analysis (PCA) is used to reduce the dimension of these features. An approach for J wave autodetection based on SVM is proposed. Curving Fitting (CF) and wavelet transform (WT) are used for feature extraction from J wave and healthy ECG segments data in [16], which have shown effective variations for J wave and normal subjects. In [17], a novel J wave detection method based on massive ECG data and MapReduce is presented. The power spectrum and the cumulative probability of ECG signals are computed as features and Decision Tree (DT) is applied for classification.

Compared with the existing methods of J wave detection, the main contributions of this work are listed as follows: (1) we built a J wave detection expert system with FE entropy on the coefficient of ATFFWT as feature and LS-SVM as a classifier, and it owned high accurate rate; (2) we use lower number of features because feature scoring method is applied

(only entropy features) to obtain the desirable accuracy; the detection of J wave will be fast; (3) it is the first time that tenfold cross validation method is applied, which makes our algorithm more reliable and robust. The objective of present work is to develop a noninvasion marker for some cardiac diseases clinically that can automatically, accurately, and fast detect J wave. To achieve this, the ECG signals are segmented into beats firstly. Then, to cope with the nonlinear and nonstationary nature of ECG signals, analytic time-frequency flexible wavelet transformation (ATFFWT) is employed to decompose the signals in terms of subbands signals. Further, Fuzzy Entropy (FE) is computed on decomposed subband. Then, feature scoring method is performed on these FE to select more meaningful features and improve the classification performance. Finally, these clinically significant features are fed to Least Squares-Support Vector Machine (LS-SVM) classifier with different kernel functions. The followed steps of the proposed method are shown in Figure 1.

2. Materials and Methods

2.1. Data Acquisition and Preprocessing. In this work, the normal ECG signals (normal class) were recorded from 58 normal subjects, which are acquired from MIT/BIH Normal Sinus Rhythm (NSR) database [12] and Fantasia [12, 18]. From the MIT/BIH NSR dataset, we have used 18 subjects (5 males and 13 females). From the Fantasia dataset, we have obtained the ECG records of 40 subjects (20 young and 20 old). The ECG signals with J wave (abnormal class) of 15 patients (10 males and 5 females) are obtained from Shanxi Dayi Hospital; the sampling frequency is 257 Hz. The age of all the subjects varies from 20 to 71 years. ECG signals of lead II were applied in our study. All ECG signals we used were initially inspected by experienced cardiologists. To avoid the inclusion of noise, artifacts, and baseline wander, the digitized ECG signals were preprocessed by using eight levels' Daubechies 6 (db6) basis function of wavelet [8].

2.2. Beats Segmentation. In order to segment the ECG signals into single beats, R-points should be detected firstly. In the

TABLE 1: Total number of beats used in this work.

Type	Number of beats
J wave	25,468
Normal	169,426
Total	194,894

present study, Pan-Tompkins algorithm is carried out on each preprocessed ECG signal to detect R-peaks [8, 19]. Then ECG beats are segmented or selected through the detected R-points [20]. We chose 64 samples before the R-point and 105 samples after R-point for each ECG beat. Hence, there is a segment of 170 samples for one ECG beat, and it consists of P, QRS, T, and U waves. The number of ECG beats segmented for J wave and normal in this work are shown in Table 1.

2.3. Decomposition of the Beats Based on ATFFWT. Wavelet transform (WT) is a powerful mathematical tool for processing nonstationary signal [10]. WT and its various improved methods are still playing a significant role in the signal processing field, because it enjoys fine time-frequency concentration and multiresolution analysis property. However, WT and some of its improved methods are suffering from a number of limitations and shortcomings. For instance, the continuous WT (CWT) suffers restricted computational efficiency, the discrete WT (DWT) suffers from the limitation of having constant time-frequency covering at all scales, and it also suffers shift-variance and poor resolution at its high frequency subbands [21]. These limitations are addressed by a newly introduced time-frequency analysis tool called ATFFWT [11], which has desirable properties such as shift-invariance, flexible time-frequency covering, and tunable oscillatory bases [11]. It has been applied to the weak fault features detection in rotating machinery [21] and the diagnosis of coronary artery disease using HRV signals [9]. ATFFWT is realized by the iterated filter bank (IFB) which consists of one low-pass channel and two high-pass channels; one of these high-pass channels analyzes “positive frequencies,” while the other analyzes “negative frequencies” [11]. J th level decomposition of ATFFWT can be achieved by using IFB [11].

Frequency response of the low-pass filter can be given by the following mathematical equations [11]:

$$H(\omega) = \begin{cases} \sqrt{pq}, & |\omega| < w_p \\ \sqrt{pq}\theta\left(\frac{\omega - w_p}{w_s - w_p}\right), & w_p \leq \omega \leq w_s \\ \sqrt{pq}\theta\left(\frac{\pi - (\omega - w_p)}{w_s - w_p}\right), & -w_s \leq \omega \leq -w_p \\ 0, & |\omega| > w_s, \end{cases} \quad (1)$$

where p and q are up and down sampling parameters for low-pass filter, respectively. w_s and w_p represent the stop band and

pass band frequencies of the low-pass filter and are shown as [11]

$$w_p = \frac{(1 - \beta)\pi}{p} + \frac{\varepsilon}{p}, \quad (2)$$

$$w_s = \frac{\pi}{q}.$$

The other used filter is the high-pass filter and can be defined mathematically as [11]

$$G(\omega) = \begin{cases} \sqrt{rs}\theta\left(\frac{\pi - (\omega + w_0)}{w_1 - w_0}\right), & w_0 < \omega < w_1 \\ \sqrt{rs}, & w_1 \leq \omega \leq w_2 \\ \sqrt{rs}\theta\left(\frac{\omega - w_2}{w_3 - w_2}\right), & w_2 \leq \omega \leq w_3 \\ 0, & \omega \in [0, w_0) \cup (w_2, 2\pi), \end{cases} \quad (3)$$

where r and s are up and down sampling parameters for high-pass filter, respectively. The other parameters are described as follows [11]:

$$w_0 = \frac{(1 - \beta)\pi}{r} + \frac{\varepsilon}{r},$$

$$w_1 = \frac{p\pi}{qr},$$

$$w_2 = \frac{\pi - \varepsilon}{r}, \quad (4)$$

$$w_3 = \frac{\pi + \varepsilon}{r},$$

$$\varepsilon \leq \left(\frac{p - q + \beta q}{p + q}\right)\pi.$$

In this work, the transition band $\theta(\omega)$ is chosen as [11]

$$\theta(\omega) = \frac{[1 + \cos(\omega)]\sqrt{2 - \cos(\omega)}}{2} \quad \omega \in [0, \pi]. \quad (5)$$

The parameters p , q , r , s , and β provide flexibility to control wavelets with the attractive quality-factor (Q -factor) Q , dilation factor d , and redundancy factor R . β and ε are the nonnegative constants. These parameters are not independent of each other and are given as [11]

$$Q \approx \frac{2 - \beta}{\beta},$$

$$d \approx \frac{p}{q},$$

$$\beta \leq 1, \quad (6)$$

$$R \approx \left(\frac{r}{s}\right) \frac{1}{1 - d},$$

$$R > \frac{\beta}{1 - d}.$$

The perfect reconstruction filter bank can be achieved by satisfying the following condition [11]:

$$\begin{aligned} |\theta(w)|^2 + |\theta(\pi - w)|^2 &= 1, \\ 1 - \frac{p}{q} \leq \beta \leq \frac{r}{s}. \end{aligned} \quad (7)$$

Hilbert transform pairs of the wavelet bases can be obtained owing to this type of separation of positive and negative frequencies. These characters make ATFFWT flexible by allowing one to control the Q-factor, redundancy, and dilation factor [11]. Recently, it has been applied for characterization of coronary artery disease [22, 23], myocardial infarction ECG signals [23], and detection of congestive heart failure using heart rate variability (HRV) signals [24]. Matlab toolbox of ATFFWT method is available at <http://web.itu.edu.tr/ibayram/AnDWT/>.

2.4. Nonlinear Feature Extraction from the Detail Coefficients. Fuzzy Entropy is extracted as nonlinear feature from the each beat segment from the standard ECG signals. Therefore, Fuzzy Entropy is computed on the real value of detail coefficients at each level. As an improvement of the sample entropy algorithm, the similarity measures are fuzzed by Fuzzy Entropy (FE) using an exponential function. The steps for the calculation of the FE are as follows [25].

(1) The sampling sequences of length N are extracted from the detail coefficients:

$$\{u(i) : 1 \leq i \leq N\}. \quad (8)$$

(2) A set of m -dimensional vectors refactored and generated in sequential order $X_i^m = \{u(i), u(i+1), \dots, u(i+m-1)\} - u^0(i)$ ($i = 1, \dots, N-m$). $u^0(i)$ represents the mean value and can be defined as [25]

$$u^0(i) = \frac{1}{m} \sum_{j=0}^{m-1} u(i+j). \quad (9)$$

(3) The distance d_{ij}^m between the sequences X_i^m and X_j^m is defined as the largest difference, and it can be expressed as

$$\begin{aligned} d_{ij}^m &= d[X_i^m, X_j^m] \\ &= \max_{k \in (0, m-1)} \{|u(i+k) - u^0(i) - u(j+k) - u^0(j)|\} \quad (10) \\ &\quad (i, j \in [1, N-m], j \neq i). \end{aligned}$$

(4) The similarity degree D_{ij}^m between the sequences X_i^m and X_j^m is computed by applying the fuzzy function as follows [25]:

$$D_{ij}^m = \mu(d_{ij}^m, n, r) = \exp\left(-\frac{(d_{ij}^m)^n}{r}\right), \quad (11)$$

where μ , n , and r stand for the fuzzy function, the gradient, and the width of the exponential function boundary, respectively.

(5) The function $Q^m(n, r)$ is defined, and it is shown as follows [25]:

$$Q^m(n, r) = \frac{1}{N-m} \sum_{i=1}^{N-m} \left(\frac{1}{N-m-1} \sum_{j=1, j \neq i}^{N-m} D_{ij}^m \right). \quad (12)$$

(6) Finally, FE can be computed according to the formula as follows [25]:

$$\begin{aligned} \text{Fuzzy En}(m, n, r, N) &= \ln[Q^m(n, r)] \\ &\quad - \ln[Q^{m+1}(n, r)]. \end{aligned} \quad (13)$$

FE more easily identifies the abnormal activities in the signal. Therefore, it is applied to discriminate nonfocal and focal electroencephalogram signals [26], characterize the surface electromyogram signals [25], and diagnose epilepsy [27].

2.5. Features Selection Based on Feature Scoring. Feature selection is widely used in pattern classification and regression to remove the redundant and uncorrelated features in feature space, thus reducing the computational load and improving the classification performance [28]. In this investigation, we employed a feature scoring algorithm to choose the optimal set. This algorithm is also known as mutual information based feature scoring [28]. In this algorithm, score value is calculated for each feature to reflect its usefulness. The larger S^q , the higher the dependency between the feature values and the class labels. The score value of each feature is evaluated according to the following formula [29, 30]:

$$S^q = \sum_{x^q} \sum_y P(x^q, y) \log \frac{P(x^q, y)}{P(y)P(x^q)}. \quad (14)$$

The feature matrix $X \in R^{p \times q}$ consists of p number of beat samples and q number of feature attributes. We gave the class label vector y , $y \in R^p$ for the feature matrix. The values of y are 1 and -1 corresponding to the class label of normal class and J wave class. The score value of q th feature in the feature vector x_p is calculated by using the probability of q th feature $P(x^q)$ and the probability of class level $P(y)$. In this work, the FE feature vectors and the new feature vectors obtained using feature scoring are fed to LS-SVM.

2.6. Classification Based on LS-SVM. The LS-SVM [31], an excellent binary classifier derived from SVM, has successful application of pattern recognition and nonlinear function fitting. However, some problems exist in SVM such as the parameter selection for hyperplane, and the size of matrix is greatly influenced by the number of training samples in Quadratic Programming (QP) problem solving, resulting in the huge solution dimension. Therefore, the improved method LS-SVM makes up for the limitation of SVM. They minimize the classification error by constructing a hyperplane in higher dimensional space and maximize the

TABLE 2: p values of features computed from each level of ATFFWT decomposition for J wave and normal classes.

Features	Level 2	Level 3	Level 4	Level 5	Level 6
FE p value	8.328×10^{-19}	3.943×10^{-19}	1.791×10^{-19}	1.293×10^{-19}	4.531×10^{-18}

TABLE 3: Mean (μ) and standard deviation (σ) of features computed from each level of ATFFWT decomposition for J wave and normal classes.

Level of decomposition	Features	J wave class ($\mu \pm \sigma$)	Normal class ($\mu \pm \sigma$)
Level 1	FE _{D1}	0.2787 ± 0.0370	0.2254 ± 0.1098
Level 2	FE _{D2}	0.2638 ± 0.2549	0.2396 ± 0.0723
Level 3	FE _{D3}	0.3081 ± 0.2995	0.2602 ± 0.0259
Level 4	FE _{D4}	0.2807 ± 0.0578	0.2340 ± 0.1492
Level 5	FE _{D5}	0.1032 ± 0.0216	0.0984 ± 0.0743

distance of any one of the classes. The classification decision function of LS-SVM is defined mathematically as [31]

$$J = \text{sign} \left[\sum_{m=1}^M \alpha_m \omega_m K(z, z_m) + b \right], \quad (15)$$

where $K(z, z_m)$ represents a kernel function, α_m denotes the Lagrangian multiplier, z_m is the M th input vector, ω_m is the target vector, and b represents bias term. In this work, we selected Radial Basis Function (RBF) and Morlet Wavelet (MW) as the kernel function.

The expression of the RBF kernel is given as [32]

$$K(z, z_m) = e^{-\|z - z_m\|^2 / 2\sigma^2}, \quad (16)$$

where σ is the kernel parameter and it controls the width of the RBF kernel function. MW kernel can be represented as follows [33, 34]:

$$K(z, z_m) = \prod_{n=1}^D \cos \left[v_0 \frac{z^n - z_m^n}{l} \right] e^{-\|z^n - z_m^n\|^2 / 2l^2}, \quad (17)$$

where D is the dimension of the feature set and l denotes the scale factor of MW kernel. LS-SVM is widely used in the diagnosis of diabetes [35], analysis of the heart sound signals [36], and classification of focal EEG class [37, 38], seizure class [26, 39], and glaucoma using fundus images [40].

3. Results and Discussion

In this present study, we have segmented ECG signals into beats. Then, to extract features, the ECG beats are employed to ATFFWT decomposition method to obtain a series of subbands signals. The plots of real values of coefficients are shown in Figures 2(a) and 2(b) for J wave and normal classes, respectively. These subband signals are obtained from ATFFWT-based decomposition of the ECG beats. In Figure 2, CN is the decomposition detail coefficient and CO stands for the magnitude of the coefficient. L1a and L1b are described as detail coefficients of first level. Similarly, L2a and L1b, L3a and L3b, L4a and L4b, and L5a and L5b represent second-level, third-level, fourth-level, and fifth-level detail coefficients, respectively. The parameters of ATFFWT are selected by way

of trial and error experimentation to reach the maximum classification accuracy. In the present study, the values of the parameters are $p = 5$, $q = 6$, $r = 1$, $s = 2$, and $\beta = 0.8(r/s)$ [9, 21]. Therefore, $d = 5/6$, $Q = 4$, and $R = 3$. The high Q -factor denotes that desirable frequency analysis of ECG signals is acquired. In order to select the desirable decomposition level, p values from subbands at different levels of ATFFWT-based decomposition are computed using Kruskal-Wallis test [41]. It should be noted that the lowest p value indicates the best discrimination ability of the feature. The lowest p values are observed at the fifth level of decomposition, as can be seen in Table 2. There was no significant improvement when the decomposition is increased from fifth to sixth level. Accordingly, we select fifth level of decomposition for analyzing J wave and normal ECG signals.

FE is computed from detail coefficients, and the parameters demanded to compute FE are also chosen by trial and error experimentation, thus getting maximum classification accuracy; the values of the parameters m , n , and r are selected to be 5, 2, and 0.3 separately [27]. Mean (μ) and standard deviation (σ) of the features computed from various levels of ATFFWT decomposition for J wave and normal classes are offered in Table 3, and we can observe from the table that, for J wave classes, μ and σ of the FE features have higher values at each decomposition level as compared to normal classes. Boxplots for FE at various levels of decomposition are depicted in Figures 3(a)–3(e). Feature scoring method is employed for selection, thus removing irrelevant and redundant features, and search for the optimal feature subset. In this work, the dimension of the feature vector is five, and it derives from the FE computation of 5 levels subbands. The score value of each feature evaluated using feature scoring method is shown in Figure 4. It can be observed that FE_{D1}, FE_{D4}, and FE_{D5} have higher score values than those of FE_{D2} and FE_{D3} features.

Accuracy (ACC), sensitivity (SEN), and specificity (SPE) are computed at each level of decomposition and are tabulated in Table 4. It is obviously seen that the significant improvement in classification performance occurs at second level of decomposition. The average accuracy, average sensitivity, and average specificity of classification are found to be 97.56%, 95.69%, and 95.78% for RBF kernel and 97.61%, 97.76%, and 95.82% for MW kernel functions, respectively.

FIGURE 2: Plots of real coefficients of ATFFWT decomposition: (a) normal class and (b) J wave class.

FIGURE 3: Boxplots for features at each decomposition level of normal ECG and J wave: (a) Level 1, (b) Level 2, (c) Level 3, (d) Level 4, and (e) Level 5.

TABLE 4: Classification performance of LS-SVM classifier using different kernel functions.

Feature number	Kernel function	ACC (%)	SEN (%)	SPE (%)
All features	RBF	96.73	95.18	95.17
	MW	96.79	95.47	95.29
Feature selection	RBF	97.56	95.69	95.78
	MW	97.61	97.76	95.82

FIGURE 4: Score value of each feature using feature scoring.

FIGURE 5: Plots showing performance measures versus the number of folds for LS-SVM classifier for kernel function: (a) RBF; (b) MW.

We can also observe that after using feature selection method the values of average accuracy, average sensitivity, and average specificity are higher compared with using all features. The values of the kernel parameters we selected are $\sigma = 0.9$ for RBF kernel and $l = 1.1$ and $v_0 = 0.35$ for MW kernel. In order to gain a stable and reliable classification performance of LS-SVM, tenfold cross validation technique is applied to avoid the possibility of overfitting of the model [42, 43]. That is, the dataset of features is divided into 10 subsets randomly and consists of one testing subset and nine training subsets. The performances are averaged after ten iterations. ACC, SEN, and SPE for tenfold cross validation method can be seen in Figures 5(a) and 5(b) for RBF and MW kernels, respectively.

Currently, however, only few research teams have studied the automatic detection and classification of J wave from the perspective of signal processing and machine learning.

In [13], a method for automated detection of J wave is performed. Their method is based on locating a break point in the descending limb of the terminal QRS. New logic was added to Glasgow ECG analysis program to automate the detection of J wave. The high sensitivity of 90.5% and specificity of 96.5% are achieved using this method. A technique based on digital 12-lead electrocardiogram is proposed for the automated J wave detection in [14]. ECG signals were automatically processed with the GE Marquette 12-SL program 2001 version (GE Marquette, Milwaukee, WI). Thereafter, the functional data analysis techniques were applied to the processed ECG signals. The detection sensitivity and specificity are 89% and 86%, respectively. The two methods have no parameter of accuracy. In [15], a method for automated J wave detection and characterization based on feature extraction is developed. First, five features including

TABLE 5: Comparison of proposed method with other existing methods of J wave automatic detection.

Authors	Applied methods	Classification	ACC (%)	SEN (%)	SPE (%)
Clark et al. (2014)	Glasgow ECG analysis program with new logic		91.3	89.5	94.5
Wang et al. (2015)	GE Marquette 12-SL program 2001 version	Functional data analysis	89.6	88.45	87.8
Li et al. (2015)	Time-domain features and discrete wavelet transform (DWT)	Hidden Markov model (HMM)	93.35	91.32	92.2
Li et al. (2015)	Curve fitting and wavelet transform (WT)	SVM	92.58	93.21	93.87
Li et al. (2016)	Time-domain features, power spectrum, and cumulative probability	Decision tree (DT)	96.03	95.1	96.25
In the present work	ATFFWT and Fuzzy Entropy	LS-SVM	97.61	97.76	95.82

three time-domain features and two wavelet-based features are defined. Then, PCA is used to reduce the dimension of these features. Highest classification accuracy of 92.5% is attained using HMM. An approach for J wave autodetection is based on support vector machine [16]. CF and WT are used for feature extraction from ECG segments data. Also 92.5% classification accuracy is reported using SVM classifier. In [17], a novel J wave detection method based on massive ECG data and MapReduce is presented. The power spectrum and the cumulative probability of ECG signals are computed as features. Further, DT is applied to classify and recognize ECG signals. Lastly, they implemented the above process under the parallel programming model MapReduce to handle the massive ECG data and achieved an accuracy of 96.23%.

In the present work, we have developed a novel methodology for automatic detection of J wave. ATFFWT is applied to decompose the processed ECG signals into the desired subbands to capture the hidden useful information from ECG segment beats of 100 normal and 15 J wave subjects. We have used ATFFWT-based decomposition due to its desirable property; it is able to extract more meaningful information and is suitable for biomedical signals analysis. Furthermore, FE is computed on the decomposed subbands to fetch the information from detail coefficients at each level. FE can measure the similarity based on exponential function in the time series [25]. Feature scoring method is employed for selection, thus removing irrelevant and redundant features, and searching for the optimal feature subset. Finally, these clinically significant features are fed to a LS-SVM classifier with different kernel functions. We have observed an accuracy of 97.56% and 97.61% using RBF and MW kernel functions, respectively. Finally, to verify the effectiveness of our method, we have evaluated all methods with the latest collected data, and the summary of performance of other existing methods of J wave automatic detection is shown in Table 5.

4. Conclusion

An automated detection of J wave from ECG signals with high speed and accuracy is a great challenge task. In this study, a new technique is proposed to detect the J wave automatically using ECG segment beats. ATFFWT decomposition method and FE extraction are employed to catch the hidden information from ECG signals. Feature scoring method is used to optimize the classification performance. Highest classification performance is founded using LS-SVM classifier with tenfold cross validation procedure while training and testing. The limitation of this work is small dataset; we have used only 15 J wave subjects. Before the developed effective algorithm can be used to design an expert system to aid clinicians in their regular diagnosis, it needs to be tested using large dataset. And another limitation is that utilization of a fixed beat length is not always optimum because of fast and slow varying heart rhythms. Better methods of adaptive beat size segmentation are needed to study. In the future, the work could be extended in three aspects: (1) it would be of interest to develop an expert model for filter parameters p , q , r , s , and β optimization of ATFFWT; (2) it is highly desirable that the large dataset would be used to evaluate the proposed technique; (3) the method can be used for other biosignals application, such as electroencephalograph (EEG) and electromyogram (EMG).

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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