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Automated detection of atrial fibrillation in ECG signals based on wavelet packet transform and correlation function of random process

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ABSTRACT

Atrial fibrillation (AF) is a common cardiac arrhythmia in clinic. The traditional AF detection using visual inspection by trained physicians is an inefficient and burdensome task. In this paper, we introduce a novel method for the automated AF detection using two-lead electrocardiogram (ECG) signals. We use the wavelet packet transform (WPT) and the correlation function of random process theory to devise an efficient feature extraction strategy for physiological signal analysis, and construct the corresponding histogram. Then, multivariate statistical features based on the correlation among wavelet coefficient series are extracted from the corresponding histogram as the feature set, which is the input to artificial neural network (ANN) classifier for the detection. Moreover, various statistical analyses are performed and some parameter tuning strategies are formulated by fitting the receiver operating characteristic (ROC) curve to ensure the reliability and robustness of the work. To evaluate the classification performance of the algorithm, 10-fold cross-validation is implemented on the MIT-BIH AF database. Compared with some state-of-the-art algorithms, the numerical results prove that our proposed strategy yields superior classification performance. To the best of our knowledge, this is also the first application of random process theory for AF detection, providing great potential in medical diagnosis.

1. Introduction

Atrial fibrillation (AF), a common cardiac arrhythmia, endangers human health and causes a social burden, which is closely related to the occurrence of stroke, thrombus, even death. More than 6 million people have been affected in the United States and about 90 million people have AF around the world [1]. This trend is expected to increase significantly with age [2]. Therefore, it is essential for public health to combat the harm and prevalence of the disease. Conventionally, AF detection is diagnosed by visual inspection of electrocardiogram (ECG) signals by trained physicians, which makes artificial detection inefficient and subjective [3]. A large amount of ECG data have inevitably hindered the efficiency of AF detection. Hence, there is an urgent demand for an automated AF detection mechanism to analyze massive amounts of ECG data, facilitate diagnosis and lighten the burden on physicians [4].

The ECG is one of the most common and powerful tools for diagnosing atrial activity in clinical treatment, which mainly reveals the electrical action in the heart of human body [3,5]. The irregularity of RR intervals and absence of P-waves (replaced by rapid, irregular and disordered fibrillatory waves, called f-waves) are two main features of ECG data in AF [6]. Various algorithms based on these two features have been performed to automatically detect AF from ECG data. According to the absence of P-waves, Maji et al. [7] utilized empirical mode decomposition to analyze the denoised ECG signals for the corresponding intrinsic mode functions, and then some statistical parameters of P-waves were derived from these functions to perform classification. Padmavathi and Ramakrishna [8] measured some related coefficients based on the auto-regressive model of ECG signals and the support vector machine (SVM) as well as K-nearest neighbor (KNN) classifier was used to detect AF episodes. Pourbabaee et al. [9] developed a feature learning method using deep convolutional neural networks for the analysis of ECG data. At the same time, more schemes using the irregularity of RR intervals have also been initiated to classify AF signals. Dash et al. [10] performed a feature extraction scheme based on the complexity and randomness of RR intervals and computed three statistical features for AF signals analysis. Francisco et al. [11] employed the features from hybrid RR intervals and ECG data to perform classification. Still, Henzel et al. [12] extracted four statistical features based on RR intervals and combined the generalized linear model for the analysis of AF episodes. However, it is noted that almost all

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of these algorithms are involved in some pre-processing steps such as the detection of P-waves and/or R-peak, since if these parameters are not accurately measured, this may affect the algorithm performance.

Apart from the mentioned algorithms that are basically only based on time-domain or frequency-domain feature of ECG data, some superior algorithms have been proposed from the perspective of time–frequency feature in recent decades [13]. Also, the superior classification performances derived from these algorithms for medical diagnosis were yielded. Li et al. [14] developed an algorithm based on the multiscale features of wavelet transform (WT) to detect ECG characteristic points for the identification of characteristic waves. Faziludeen et al. [15] utilized WT to extract 25 features from each beat with 3 RR intervals features and SVM for the classification of three beat types. Asgari et al. [16] employed the log-energy entropy of continuous wavelet transform (CWT) coefficients and SVM for the analysis of AF episodes. Thomas et al. [17] combined the discrete wavelet transform (DWT) and dual tree complex wavelet transform (DTCWT) coefficients with four morphological features from the QRS complex waves to perform classification. Qiao and Zhou [18] employed the entropies of each node of the reconstructed ECG signal based on the wavelet packet transform (WPT) and WT to detect AF episodes. Daqrouq et al. [19] performed WPT to decompose the ECG signal into different sub-band signals and extracted features based on average framing percentage energy of wavelet coefficients to classify AF signals. Also, Shu et al. [20] implemented WPT and common spatial pattern strategy to extract features from ECG segments, then KNN was performed for classification.

Since some previous studies have achieved good classification results [19,20], based on WPT decomposition, we are mainly committed to the features derived from the correlation among wavelet coefficient series in random process theory [21]. For the analysis of ECG signals, correlation function and its corresponding metrics are employed to construct the feature set. After the extraction of relevant features, various statistical analyses such as histogram and hypothesis testing are performed to indicate the differences among the proposed features of normal sinus rhythm (NSR) and AF segments. Then, some parameter tuning strategies are also formulated by fitting the receiver operating characteristic (ROC) curve to ensure the robustness of the work. Additionally, we also use 10-fold cross-validation to evaluate the performance of the artificial neural network (ANN) classifier on the MIT-BIH AF database.

The outline of the paper is as follows. Section 2 describes the ECG data set, data pre-processing, WPT decomposition, feature extraction and ANN classifier. The numerical results are displayed in Section 3 and some related discussions are analyzed in Section 4. Section 5 summarizes the paper and layouts for future work.

2. Methods and materials

2.1. Data set

To verify the validity and feasibility of the proposed method, ECG signals from the MIT-BIH database established jointly by Massachusetts Institute of Technology (MIT) and Bess Israel Hospital (BIH) in 1980 were analyzed [22]. The database is publicly available in medical research, which mainly includes arrhythmia data set, AF data set, noise stress test data set and other data sets. Aiming at evaluating the classification performance of our proposed approach, we employed the AF data set to perform the numerical experiments. This data set mainly contains 23 two-lead ECG records of paroxysmal atrial fibrillation (PAF) from different patients, each record of which lasts about 10 h and the duration of all records are no more than 234 h. These records are sampled at 250 Hz with 12-bit resolution, and the bandwidth of signal is 0.1–100 Hz. In this paper, some ECG episodes containing AF and NSR from all 23 ECG records (such as record #04015) were employed to construct an experimental data set, and the results were finally verified and evaluated via 10-fold cross-validation.

2.2. Pre-processing

2.2.1. Segmentation and denoising

In the proposed algorithm, the pre-processing of ECG data is mainly comprise of two steps: segmentation and denoising. Each ECG episode is divided into segments for every 10 s, and each segment is equivalent to a window without overlapping. Then, a total of 56,832 AF segments and 84,724 NSR segments were obtained to train and test the proposed model. Meanwhile, ECG signals are usually mixed with diverse noises such as power-line interference, baseline drift, muscle noise and so on [23], so the 50 Hz notch filter, the 30 Hz low-pass digital filter and the 0.1 Hz Chebyshev high-pass filter were assembled to remove these noises for each segment. The filtered ECG segment will serve as the input to the next step.

2.2.2. Wavelet packet transform

It is well known that WT has been recently considered as an effective tool to analyze non-stationary time series signals like ECG signals, which decomposes the signal into weighted sums of wavelet base function at different scales [24,25]. A very essential ability of WT is to efficiently characterize local features in signals. Moreover, the output of signal decomposed by WT in different sub-bands is wavelet coefficients. They can directly provide more intrinsic physiological information in time-frequency domain of signal [26,27]. Meanwhile, based on the WT theory, WPT decomposition has gradually become a more sophisticated method for signal spectrum analysis, and it can be considered in combination with proper statistical strategy to efficiently analyze the time-frequency features and explore compositions of physiological signals [28].

Assuming that $S(t)$ decomposed by WPT is a set of discrete random signal, $d_l^p(t)$ is wavelet coefficients of the signal at decomposition level l and p is the serial number of node with $p = 0, 1, \ldots, 2^l - 1$ in the WPT decomposition tree. Then the wavelet coefficients can be computed as follows:

$$d_l^{2p}(t) = \sum_{n \in Z} h(n) d_{l-1}^p (2t - n), \tag{1}$$

$$d_l^{2p+1}(t) = \sum_{n \in Z} g(n) d_{l-1}^p (2t - n), \tag{2}$$

where $h(n)$ and $g(n)$ are the coefficients of low-pass and high-pass filter, respectively. In our work, each ECG segment was decomposed at the level $l = 5$, and a part of the WPT decomposition tree is shown in Fig. 1. An illustration of the normal ECG signal and AF signal and their WPT decomposition to some of the selected sub-bands (such as $Band_{51}$ and $Band_{52}$) from record #04015 are shown in Fig. 2.

2.3. Feature extraction

There is the medical knowledge that the correlation among wavelet coefficient series in ECG signals affected from the disorder of atrial activity will be decreased, and the pathological changes are actually reflected by the degree of correlation [29]. In fact, the correlation function is suitable for sequential data analysis and has superior ability to quantify specific characteristics in the random series, which also highlights the changes in atrial activity. Therefore, this can be regarded as an effective scheme for AF detection [30]. Also, based on the contribution rate of correlation and information gain, weighted sums and information entropy of corresponding metric are calculated to construct the feature set, respectively. In our proposed scheme, the detailed steps of feature

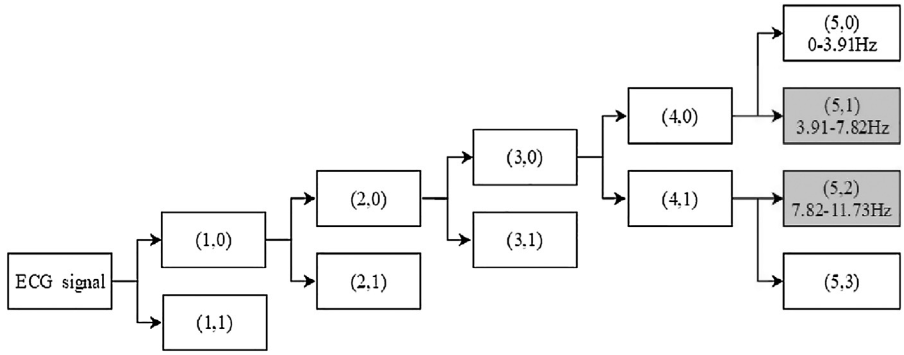

Fig. 1. A part of the tree-structure of a 5-level wavelet packet transform.

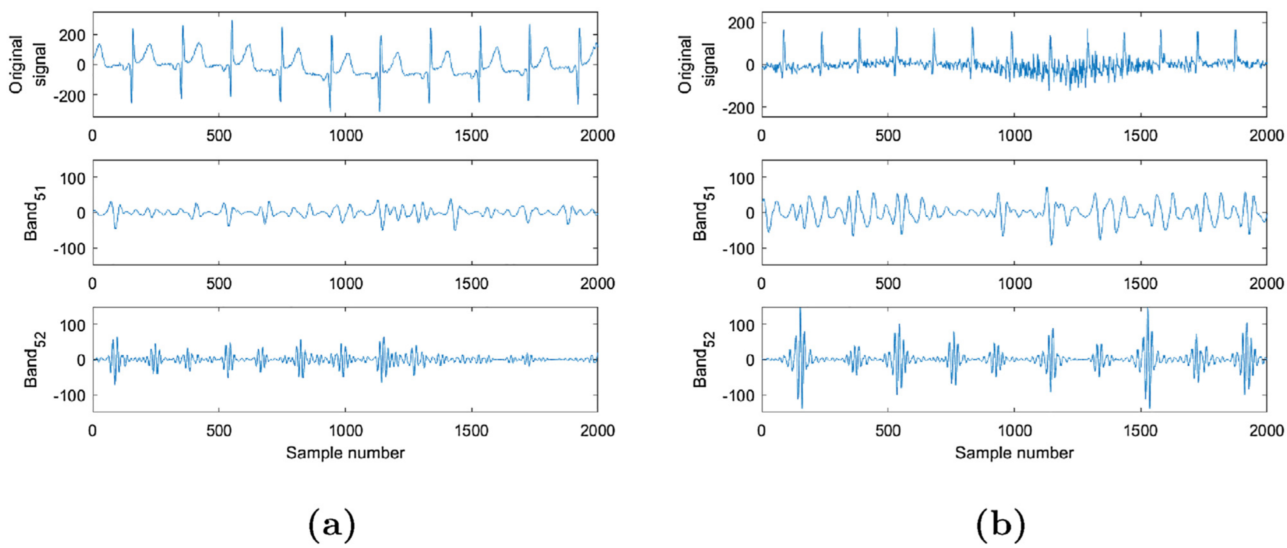

Fig. 2. Example of the WPT decomposition to ECG segments from record #04015 in the selected sub-bands. (a) Normal sinus rhythm; (b) atrial fibrillation.

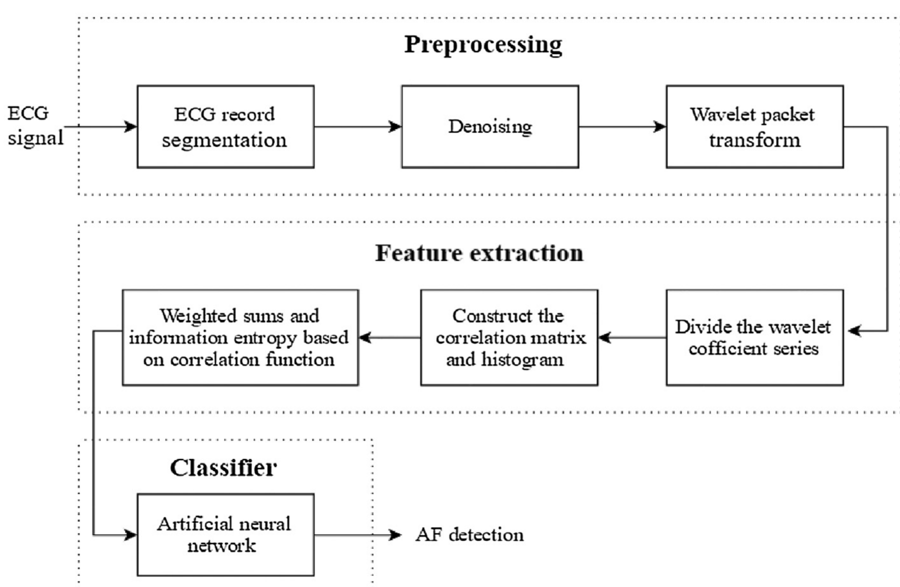

Fig. 3. The framework of the proposed algorithm for AF detection.

extraction are summarized as follows, and the formed framework of the algorithm for AF detection is shown in Fig. 3.

Step 1. Utilize WPT method to decompose the filtered ECG segment and obtain the wavelet coefficients from the selected sub-bands.

Step 2. Divide these coefficients series into n equal segments, and one of the segments is presented as $\overline{d}(t_i) = \{d^{(1)}(t_i), d^{(2)}(t_i), \ldots, d^{(m)}(t_i)\}$ with $i = 1, 2, \ldots, n$.

Step 3. Use these segments to compute the correlation matrix with $\tau = 0, 1, \ldots, n-1$, normalized as follows:

$$R_{\overline{d}} = \begin{bmatrix} B_{1,1} & \cdots & B_{1,1+\tau} & \cdots & B_{1,n} \\ \vdots & & \vdots & & \vdots \\ B_{i,1} & \cdots & B_{i,1+\tau} & \cdots & B_{i,n} \\ \vdots & & \vdots & & \vdots \\ B_{n,1} & \cdots & B_{n,1+\tau} & \cdots & B_{n,n} \end{bmatrix} \tag{3}$$

Step 4. Construct the corresponding histogram based on the normalized matrix.

Step 5. Calculate features from the histogram as follows:

$$W_B = \sum_{i=1}^{n} B_{i,i+\tau} n_{i,i+\tau}, \tag{4}$$

$$H_B = -\sum_{i=1}^{n} p_{i,i+\tau} \log p_{i,i+\tau}. \tag{5}$$

Step 6. Assemble the features as feature set for the ANN classifier.

In the above steps, $n_{i,i+\tau}$ is the number of $B_{i,i+\tau}$ in a given precision, and $p_{i,i+\tau}$ is the proportion of $n_{i,i+\tau}$ in total number. $\hat{B_{\overline{d}}}(\tau_0)$ is the estimation of correlation function of any two segments, which is actually a sequence of numbers with $\tau_0 = 0, \pm 1, \pm 2, \ldots, \pm(m-1)$, presented as follows:

$$\hat{B_{\overline{d}}}(\tau_0) = \frac{1}{m} \sum_{j=1}^{m} \overline{d}^{j}(t_i) \overline{d}^{(j+\tau_0)}(t_{i+\tau}), \tag{6}$$

then $\overline{B}_{i,i+\tau}$ is the mean value of this sequence,

$$\overline{B}_{i,i+\tau} = \frac{1}{2m-1} \sum_{\tau_0=-(m-1)}^{m-1} \hat{B_{\overline{d}}}(\tau_0), \tag{7}$$

and $B_{i,i+\tau}$ is the normalized value of $\overline{B}_{i,i+\tau}$, respectively.

In order to implement feature extraction scheme based on the correlation of coefficients series more efficiently, the mean value of correlation function sequence was utilized as the value can provide an exhaustive representation for the general tendency of correlation. Furthermore, it should also be noted that the main aim to normalize correlation matrix is to eliminate the influence from different dimensions of high-capacity data. By this way, the issue of comparability among data can be well resolved [31]. Meanwhile, the values of lower left or right upper part of normalized matrix are only required to construct the histogram due to the symmetry of this matrix.

2.4. Artificial neural network classifier

Developed by Hecht-Nielsen [32], the ANN classifier has gradually become a remarkable learning model. The classifier, connected by a large number basic neurons, has a more stronger generalization ability for new samples than other existing classifiers such as SVM, KNN and so on [33]. In our neural network structure, an output layer, a hidden layer and an input layer were trained to construct a 3-layers neural network structure for classification. Meanwhile, the dimension of feature vector determines the number of neurons in the input layer, which was set as 4. The number of output classes determines the number of neurons in the output layer, set as 2 due to the binary classification. So far, there is not a sound algorithm to select the number of hidden nodes. Most of them can only be obtained through sufficient experience or extensive experiments [34]. In our work, the number of hidden nodes was set as 10 through detailed experiments, the activation function of the hidden layer and output layer were set as Sigmoid function and Softmax function, respectively. The value of adaptive learning rate was 0.1 by setting mean square error no more than 0.001.

2.5. Performance evaluation

Ten-fold cross-validation was implemented to assure the credible classification performance of ANN classifier, which enhances the generalization ability of the model. The data set is randomly divided into 10 parts, nine of which are taken as the training set in turn, and the rest as the test set. Then we averaged the results of the 10 experiments for final classification performance. Three standard metrics are employed to reveal the effectiveness of this model. They are sensitivity (SEN), specificity (SPF) and accuracy (ACC) [35], given as follows:

$$SEN = \frac{TP}{TP + FN}, \tag{8}$$

$$SPF = \frac{TN}{TN + FP}, \tag{9}$$

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}, \tag{10}$$

where TP is true positive, indicating the number of AF signals correctly detected as AF signals; FN is false negative, indicating the number of AF signals mistaken as normal ECG signals; TN is true negative, indicating the number of normal ECG signals correctly detected as normal ECG signals; FP is false positive, indicating the number of normal ECG signals mistaken as AF signals.

3. Results

Keep in mind that both f-waves and P-waves are considered as the low-frequency waves and their bandwidths are mainly concentrated in 4–12 Hz [36,37]. Due to the sampling rate of 250 Hz and the bandwidth of each sub-band in ECG signals by WPT, $Band_{51}$ and $Band_{52}$ were selected as frequency interval for feature extraction [38]. Meanwhile, it is noted that the mother wavelet function with 'db4' was empirically performed in WPT, since we conducted a sea of selection experiments for mother wavelet function and also combined the characteristic of various waveforms from the Daubechies, Haar, Coiflet and Symlet wavelet families [39].

In order to visualize the constructed features, their corresponding bar charts were built to present the statistical distribution of $B_{i,i+\tau}$ in the selected sub-bands for twenty ECG segments of experimental data set during AF and NSR, respectively. As shown in Fig. 4a, these values in $Band_{51}$ or $Band_{52}$ are nearly distributed between 0 and 0.4 in AF, revealing a poor correlation among random coefficient series. However, Fig. 4b indicates that these values in NSR are mostly distributed between 0.5 and 0.8, revealing a stronger correlation than that in AF. Furthermore, another remarkable finding from the figure was that the numerical distribution in NSR is more dense than that in AF, thus revealing that ECG signals may carry more information in NSR with larger information entropy. Meanwhile, Fig. 5 also presents the statistical histogram for one of twenty segments in the selected sub-bands during AF and NSR,

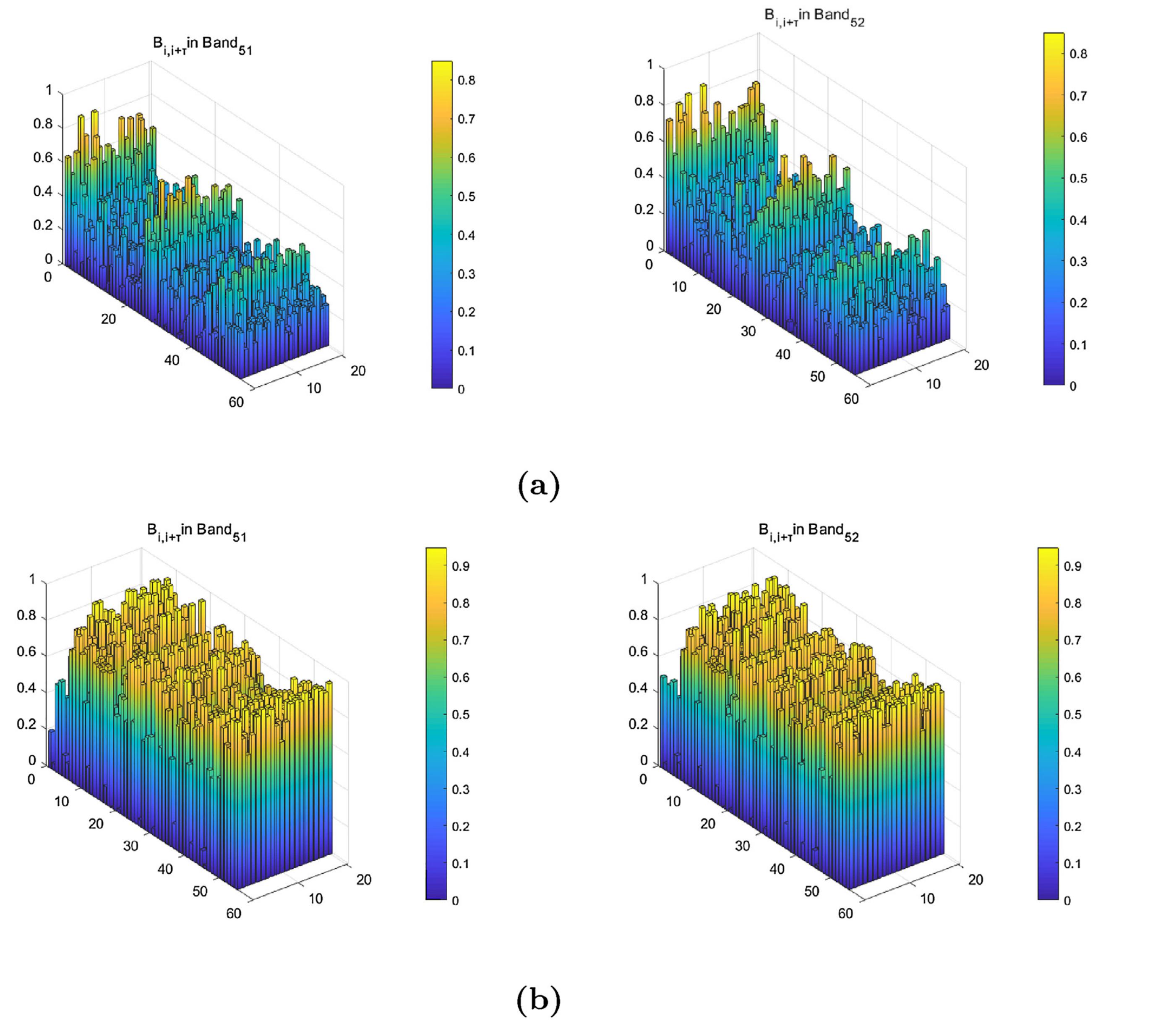

Fig. 4. The bar charts of $B_{i,i+\tau}$ in the selected sub-bands for twenty ECG segments of experimental data set. (a) AF; (b) NSR.

respectively, and its statistical values were rounded to two decimal places. Furthermore, almost the same numerical distributions as Fig. 4 were also obtained. Therefore, on the basis of these distributions, we can conclude that the disorder of atrial activity caused by AF makes the correlation among coefficient series decreased, and the periodicity of normal ECG signals maintains the close correlation in NSR. Thus, it is advisable to construct statistical features based on the correlation function of wavelet coefficients.

Faced with various classification problems, hypothesis testing is implemented to enhance the ability of identification feature in several categories. Hence, in order to indicate the statistical significance in the two proposed features, Mann-Whitney test was carried out for the comparison of data distribution. Meanwhile, the tests were employed at the 95% confidence interval. That is to say if the value of p is less than 0.05 such that the difference for classification is statistically significant, and then the constructed feature set is considered reasonable; otherwise, the selected feature will be removed from the feature set. In our work, we employed some ECG segments from record #04015 for the feature selection test.

Table 1
Statistical comparison of the constructed features and p-value.

	AF	NSR	p
W_B in $Band_{51}$	14.5 ± 3.07	27.4 ± 3.12	1.5381e−06
W_B in $Band_{52}$	13.1 ± 4.01	24.0 ± 2.84	4.1330e−06
H_B in $Band_{51}$	2.51 ± 0.01	2.79 ± 0.07	1.6387e−06
H_B in $Band_{52}$	2.62 ± 0.03	2.80 ± 0.07	4.6064e−06

The result of Mann-Whitney test and multivariate statistical features expressed as mean ± standard in the selected sub-bands are listed in Table 1. From the numerical results, we can clearly draw a conclusion that the differences in the proposed features among the AF signals and normal ECG signals are highly significant.

The box-plots of visual hypothesis testing were also performed to help us reveal the validity of features intuitively for the classification of NSR and AF segments. Then it can be clearly seen from Fig. 6 that the overall data distribution in NSR is almost higher than that in AF, and there are no outliers in the box-plots. All the results suggest that the constructed features can be considered as

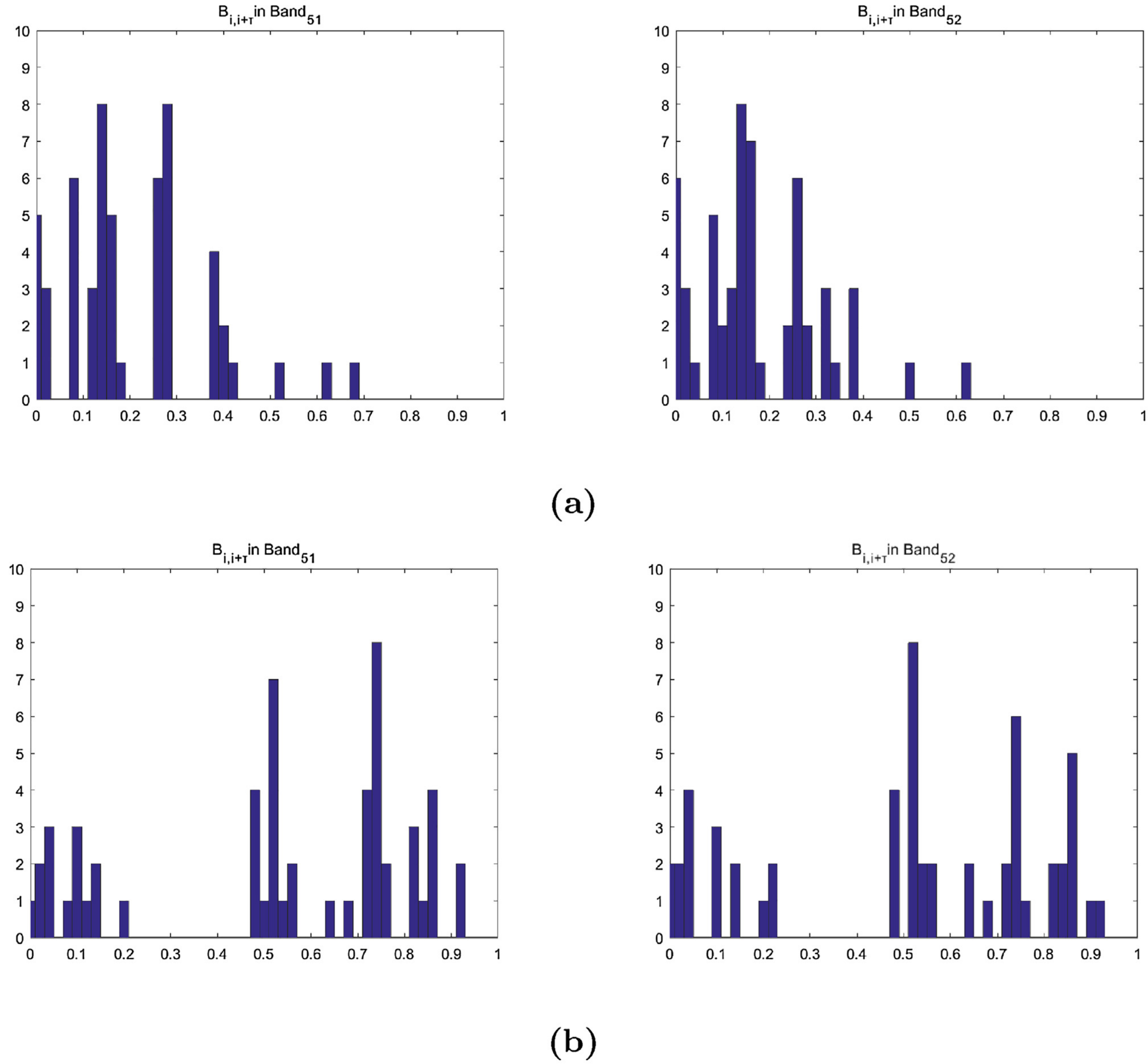

Fig. 5. Example of histograms of $B_{i,i+\tau}$ rounded to two decimal places in the selected sub-bands respectively. (a) AF; (b) NSR.

Table 2
Confusion matrix for the entire MIT-BIH AF data set across all 10-fold cross-validation.

Original/predicted	NSR	AF	ACC (%)	SEN (%)	SPF (%)
NSR	83764	960	98.8	98.9	98.7
AF	738	56093	98.8	98.7	98.9

Table 3
Results of the performance comparison of our proposed algorithm on the MIT-BIH AF database using different numbers of segments.

	ACC (%)	SEN (%)	SPF (%)
0	87.9	88.2	88.1
5	93.8	94.5	94.2
10	**98.8**	**98.7**	**98.9**
20	94.8	93.2	94.5

In the feature extraction stage, the wavelet coefficient series are divided into n equal segments (such as n = 0, 5, 10, 20). When n = 10, the proposed model achieves the best classification performance, outperforming other three cases.

significant judgements for automatic recognition of AF segments. Ultimately, based on the above features, the confusion matrix for the entire MIT-BIH AF data set across all 10-fold cross-validation is illustrated in Table 2. The high ACC of 98.8%, SEN of 98.7% and SPF of 98.9% were obtained. This result also demonstrates the high efficiency of our proposed algorithm strategy in AF detection. And all experiments were performed on a computer of Inter-core i5-5200U CPU@2.20 GHz with 12 GB RAM and MATLAB 2018a.

Fig. 7 compares the ROC curves for four cases of the number of segments in Section 2.3 (such as n = 0, 5, 10, 20). Then the area under ROC curve (AUC) is a powerful measure of classification performance. Also, the greater the AUC value, the better the classification performance. From these curves, it can be observed that the AUC value in n = 10 is larger than that of other three cases. Moreover, Table 3 also generalizes the results of all standard metrics of our proposed algorithm on the MIT-BIH AF database using different numbers of segments. Taking these results into account, we clearly come to the conclusion that in the case of n = 10, the classification performance of our algorithm outperforms other three cases. Note that the selected wavelet coefficients were divided into n equal

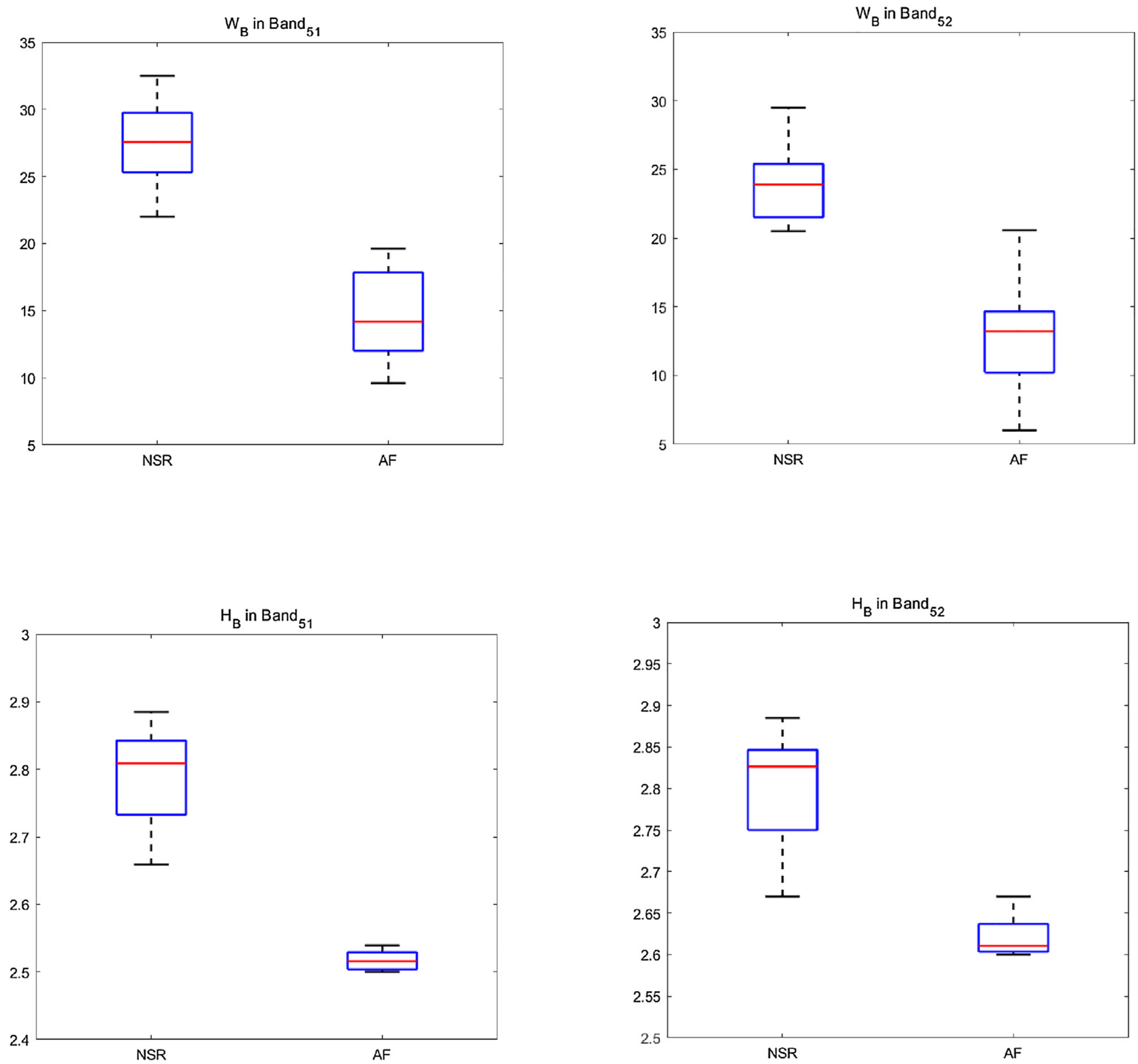

Fig. 6. The box-plots of features show the superior classification ability in the selected sub-bands.

segments without overlapping, this main purpose is to make these random coefficient series more specifically express the physiological or pathological information than without division. And one thing to be emphasized is that the case of $n = 0$ actually means the corresponding coefficient series was not divided, which is inferior to others divided in classification performance. Therefore, we can draw from Fig. 7 that dividing wavelet coefficient series properly to construct the feature set does significantly enhance the algorithm performance of the proposed strategy.

The advantage of ANN compared with other learning classification models is an essential factor for the ability of unsupervised self-learning [33,40]. One very critical step in ANN is parameter tuning such as the selection of number of hidden nodes, which has a direct impact on the result of experiment [41]. In our work, the number of optimal hidden nodes was determined by training the accuracy of experimental data set. Firstly, we set the initial number of hidden nodes as 2 and gradually increased to 13, then got the corresponding detection accuracy, and thus an approximate curve was fitted with the two variables. As shown in Fig. 8, when the number of hidden nodes is 10, the detection accuracy reaches the maximum of 98.8%. Meanwhile, with the optimal number of segments $n = 10$, the classification performances and results of the constructed ANN, SVM and KNN based on our proposed algorithm are presented in Fig. 9 and Table 4. It can be obtained from these data and curves that ANN performs best in classification performance for AF detection on the MIT-BIH AF database.

Table 4
Results of the performance comparison of our proposed algorithm on the MIT-BIH AF database using different various classifier with the number of segments $n = 10$.

Classifier	ACC (%)	SEN (%)	SPF (%)
SVM	97.2	97.8	97.4
KNN	96.3	95.4	96.1
ANN	**98.8**	**98.7**	**98.9**

In the classification stage, the classification performance of the constructed ANN, SVM and KNN based on the proposed algorithm are compared. When the number of hidden nodes of 10 and the optimal number of segments of 10, ANN performs best, outperforming other two classifiers.

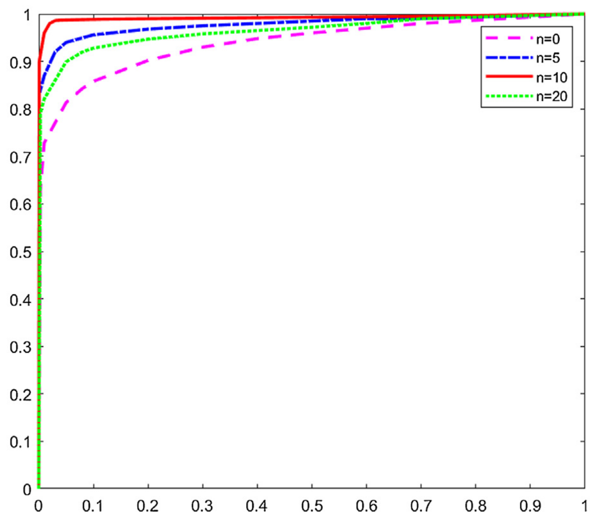

Fig. 7. Performance comparison of AF detection results for the ROC curves using different number of segments.

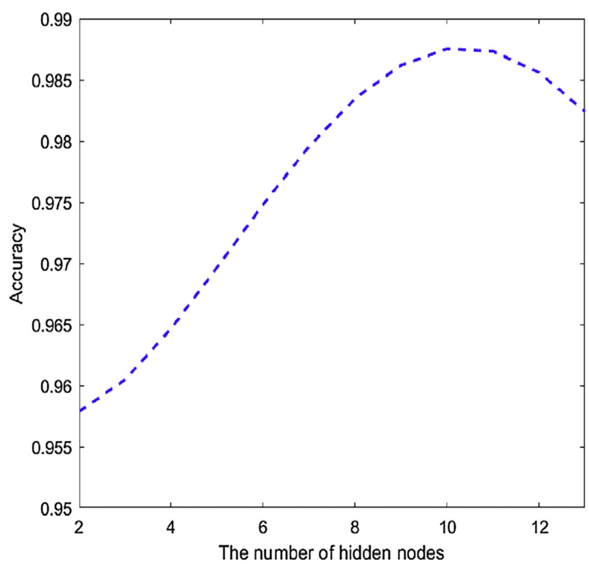

Fig. 8. Accuracy of different hidden nodes on the experimental data set in ANN.

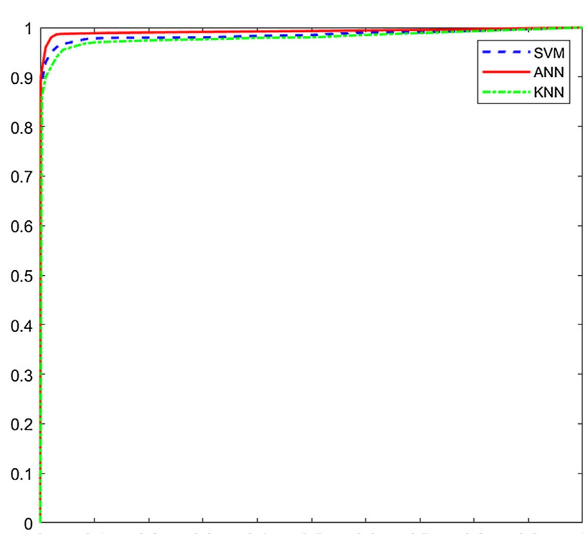

Fig. 9. Performance comparison of AF detection results for the ROC curves using different various classifier with the number of segments $n = 10$.

4. Discussion

4.1. Comparison of the proposed strategy with other existing algorithms

In this section, we compare and discuss our proposed strategy with other existing algorithms, indicating the classification performance of our proposed scheme through detailed tabular data. To reveal the superiority of our proposed algorithm, many algorithms based on absence of P-waves, irregularity of RR intervals, or other spectrum analysis methods are compared in this section. Meanwhile, the classification results, feature extraction strategies and classifiers of these algorithms are presented in Table 5. From the table, Maji et al. [7] performed a research on absence of P-waves for the classification of AF segments. Both Dash et al. [10] and Francisco et al. [11] combined irregularity of RR intervals with statistic characteristics as feature set to perform classification on the MIT-BIH AF database. If sensitivity and specificity are taken as the evaluation criteria, their values of above algorithms are nearly lower than ours. Meanwhile, it must be concerned that these methods do have some limitations that they demand the detection of P-waves and/or R-peak, and thus the detection efficiency of these parameters may largely affect the classification performance of methods. Moreover, they sometimes fail to perform well on the short ECG segments (less than a minute), especially for some schemes based on irregularity of RR intervals, which may lead to miss short-term AF segments [42].

It is noted that the time-frequency analysis of ECG signals has been widely concerned in recent years, and a remarkable advantage of this strategy is to focus on the local critical information carried by sub-band signal [43]. Decomposing ECG signals into several sub-bands for feature extraction is a direct and effective scheme indeed [44]. Asgari et al. [16] performed a work on AF detection based on CWT coefficients and its value of sensitivity and specificity is 97.0% and 97.1%, respectively. Thomas et al. [17] combined DWT and DTCWT coefficients with morphological features to perform classification and the average value of sensitivity and specificity is 88.60% and 96.18%, respectively. Similar to our method, Daqrouq et al. [19] also employed WPT and spectral analysis of sub-bands for classification, and obtained the sensitivity of 97.9%. However, the evaluation of specificity was not given in this paper. In [20], Shu et al. published a high classification performance with sensitivity of 99.64% and specificity of 99.71% on the MIT-BIH AF database, but this scheme employed many features.

From the above comparative research, an illustrious finding of our study was that our approach relatively yielded superior classification performance for AF detection on the experimental data set using 10-fold cross-validation. In addition to the superior classification results presented in Table 2, the proposed feature extraction strategy has been proved to provide a strong classification capacity to detect the short ECG segment of 10 s, and eliminates the detection requirement of some key parameters such as P-waves and/or R-peak. These advantages are superior to some algorithms proposed in [7,10,11].

Also, especially compared with the current-state of the art in some reported literatures such as [12,17,20], our scheme has the more solid and reliable medical basis that the more disordered atrial activity, the lower the correlation among wavelet coefficient series. In fact, it is easy to understand that the regularity of sinus rhythm can maintain a high correlation among the corresponding wavelet coefficients, while sudden atrial disorders significantly reduces this correlation. Hence, this can be considered as an essential reference for physicians to diagnose AF more accurately and quickly. And it should also be noted that our method does not need the complicated hyperparameter tuning and high hardware facilities such as GPU. Low computational complexity makes it easier

Table 5
Comparison of the classification performance of our proposed algorithm with the other algorithms on the MIT-BIH AF database.

Authors	Approach	Classifier	SEN (%)	SPF (%)
Maji et al. [7]	Absence of P-waves	Supervised classifier	96.0	93.0
Dash et al. [10]	Irregularity of RR intervals	–	94.4	95.1
Francisco et al. [11]	Irregularity of RR intervals	Fuzzy classifier	96	93
Asgari et al. [16]	CWT + log-energy entropy	SVM	97.0	97.1
Thomas et al. [17]	DWT, DTCWT + four morphological features	ANN	88.6	96.18
Daqrouq et al. [19]	WPT + percentage energy	ANN	97.9	–
Shu et al. [20]	WPT + common spatial pattern	KNN	99.64	99.71
This work	WPT + correlation function	**ANN**	**98.7**	**98.9**

to implement AF detection than some deep learning techniques. Meanwhile, to the best of authors' knowledge, the proposed strategy is a first attempt to combine machine learning technology with correlation function in random process theory for AF detection. It does open up a new direction for biological signal analysis.

Additionally, by dividing wavelet coefficient series properly to construct the feature set, the method validated by 10-fold cross-validation on the entire MIT-BIH AF database makes feature extraction more robust and discriminative. The novelty is particularly suitable and efficient in distinguishing AF segments in the massive ECG signals. Therefore, the main contribution of our research is to achieve automated AF detection using the proposed method for ECG signal analysis. This is expected to expand on the computer-aided diagnosis algorithm platform in the hospitals to enhance the efficiency of AF detection and alleviate the workload of cardiologists. The application contributes in reducing mortality and save life to some extent.

4.2. Limitations and enhancements of the study

PAF is one of the most common types of arrhythmia. The disease is not only sudden but sometimes lasts only a few seconds, which has been widely concerned by expert physicians in medical diagnosis. However, the length of ECG segment that can be detected is 10 s in our proposed method, and thus one need is to keep on enhancing the recognition rate for the shorter ECG segment. Another limitation of this study is that our work focuses on AF detection only. To enlarge the availability of our research, various types of heartbeat detection should be investigated. Since the generalization ability of the proposed algorithm are somehow restricted to the available samples, such that more larger and diverse database with variety of patients will be corroborated for a more robust classification model.

In addition, according to the work we have done and the obtained results, there are still some considerations to be further developed. For instance, how to continue to improve classification performance based on the proposed strategy and how to explore and make the best of more valuable medical basis for biological signal analysis are still challenging issues. Meanwhile, it can be inferred that our model may lead to a performance boost, as long as more scientific theoretical bases and comprehensive rhythm information can be utilized. Also, despite the fact that our proposed strategy is very promising, we are also firmly convinced that there will be a wide space by combining deep neural network such as recurrent neural network to detect AF. Finally inspired by random process theory, another future work will be expanded to more varied signals such as ventricular fibrillation signals or other arrhythmic signals.

5. Conclusion

In this paper, an automated approach for AF detection based on the correlation among wavelet coefficient series in ECG signals was proposed. Multivariate statistical features were extracted from the corresponding histogram, and classification was implemented by ANN. This method was commendably performed for the AF detection problem in clinical diagnosis and the reliability of the feature construction strategy was investigated. Compared with other existing methods, our proposed scheme yielded consistent enhancement in classification efficiency on the MIT-BIH AF database. The credibility and robustness of the work were also guaranteed by various statistical analyses and parameter tuning strategies. Moreover, our approach is not involved in tedious preprocessing steps such as the detection of R-peak and/or P-waves, and also provides a superior generalization ability to detect the ECG segment of 10 s. Considering the solid and credible medical basis, this method is easier to implement and considered as a promising reference for cardiologists to diagnose AF and improve the efficiency of disease detection. In future, based on random process theory, we will constantly investigate more high-performance algorithms for biological signal analysis and take into account the larger data sets and more diverse signals to provide more credible diagnosis and reduce mortality.

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Declaration of Competing Interest

None declared.

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