Australasian Physical & Engineering Sciences in Medicine (2019) 42:149–157
https://doi.org/10.1007/s13246-019-00722-z

SCIENTIFIC PAPER

Developing of robust and high accurate ECG beat classification by combining Gaussian mixtures and wavelets features

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Received: 28 July 2018 / Accepted: 7 January 2019 / Published online: 14 January 2019

Abstract

Electrocardiogram (ECG) beat classification is a significant application in computer-aided analysis and diagnosis technologies. This paper proposed a method to detect, extract informative features, and classify ECG beats utilizing real ECG signals available in the standard MIT-BIH Arrhythmia database, with 10,502 beats had been extracted from it. The present study classifies the ECG beat into six classes, normal beat (N), Left bundle branch block beat, Right bundle branch block beat, Premature ventricular contraction, atrial premature beat, and aberrated atrial premature, using Gaussian mixture and wavelets features, and by applying principal component analysis for feature set reduction. The classification process is implemented utilizing two classifier techniques, the probabilistic neural network (PNN) algorithm and Random Forest (RF) algorithm. The achieved accuracy is 99.99%, and 99.97% for PNN and RF respectively. The precision is 99.99%, and 99.98% for PNN and RF respectively. The sensitivity is 99.99%, and 99.81% for PNN and RF respectively, while the specificity is 99.97%, 99.96% for PNN and RF respectively. It has been shown that the combination of Gaussian mixtures coefficients and the wavelets features have provided a valuable information about the heart performance and can be used significantly in arrhythmia classification.

Keywords ECG beat · Arrhythmia · Gaussian mixtures · Wavelets · Principle component analysis · Features · Classification

Introduction

Electrocardiograph (ECG) beat detection, segmentation, and classification are vital and crucial for accurate diagnosis, and consequently, affect the treatment of patients in intensive care units (ICU) and cardiac care units (CCU) [1, 2]. Accurate detection of localization and precise segmentation algorithms of ECG beats were developed and validated with high level of performance. The current trend in the related literature is to optimize the classification performance of the acquired ECG signal, where the improved classifiers precision is reflected in the accuracy of patient's heart diagnosis and consequently decreases the mortality rate due to cardiovascular disorders. In Automatic ECG beat classification, the accuracy mainly depends on high accurate selection of the extracted features from each beat [2, 3]. In any classification system, noise filtration from the recorded ECG signal such are those due to motion, respiration, power line interference, and baseline wandering are common. Various methods for noise reduction were introduced in the literature [5–7].

ECG beat separation is crucial stage in features extraction which are exploited for the ECG signal analysis. The process of separating ECG beats is performed using the method proposed by Alqudah [3], which is based on calculating the cumulative area of the ECG trace, then resetting the cumulative area of the ECG trace to zero by finding a ten-consecutive point with approximately zero changes in between after removing all noises and using moving window technique [3].

After separating the ECG beats, the analysis is followed by implementing extraction of Gaussian mixtures modelling coefficients, and discrete wavelet transform (DWT) coefficients. The Gaussian mixtures model of the ECG beat is built after separating the beat into three main components; baseline, positive, and negative parts, then modeling each part as a sum of scaled and shifted Gaussians. Gaussian model provides a valuable morphological feature of the ECG beat under study. DWT analysis is mathematical tool to analyze the signal and extract information in frequency domain from biomedical signals, especially ECG signals. Wavelets analysis can provide information

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about both time–frequency plane and extend frequency analysis to the notion of scale as well [6].

The literature surveyed emphasized on low detection error rate in ECG beats segmentation and classification or in beats from cardiac-related signals as well, such as photoplethysmography (PPG) and arterial blood pressure (ABP). Also, the literature surveyed focus on combining current features rather than investigating new features and without reducing the classification complexity.

This paper proposes the mixture of Gaussian and DWT as a set of features to accurately classify the extracted ECG beats, available in the MIT-BIH database, using two types of classifiers. The proposed classifiers in this study are probabilistic neural network (PNN) and Random Forest (RF). The extracted features are then fed into the principal component analysis (PCA) algorithm to identify the most significant features, which are in turn fed into the classifiers. Finally, the accuracy, sensitivity, precision, and specificity of each classifier are evaluated to test and validate the performance of each classifier individually.

Methods

The proposed method consists of four main parts: (1) ECG preprocessing, (2) ECG beat segmentation, (3) ECG beat feature extraction, and (4) classification of ECG beat using different classifiers, and finally the comparison is made between the proposed techniques. The block diagram of the proposed methodology is shown in Fig. 1.

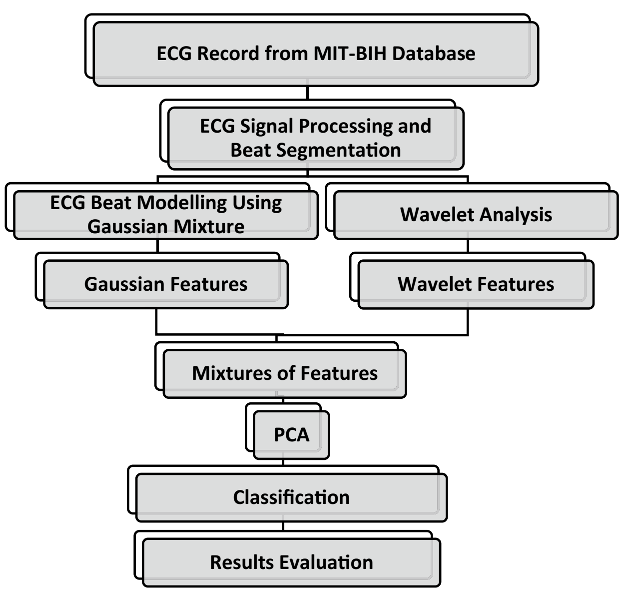


Fig. 1 Block diagram of the proposed method

Database

The present study used the MIT-BIH arrhythmia database for evaluating and validating the proposed methodology for ECG beats classification. This database contains 48 ECG recordings, each consists of 30 min segment selected from 24-h recordings of 48 patients [3, 7]. It is available in the MIT repository of (http://physionet.org/cgi-bin/atm/ATM) which contains different types of arrhythmias. In this study, the normal and arrhythmia beats are annotated based on AAMI standard. The present methodology is designed to classify the beats into six classes: normal (N), left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contraction (PVC), atrial premature beat (APB), and aberrated atrial premature (aAP) [7]. 10,502 beats have been extracted using the ECG beat segmentation method suggested by Alqudah [3], then these beats are split into training and test sets with ratio of 75% and 25% respectively. The distribution of beat arrhythmia types in the selected database is listed in Table 1.

ECG signal processing and beat segmentation

In this part, the preprocessing techniques on ECG signal from MIT-BIH database was performed. The ECG signal preprocessing is executed by applying Butterworth bandpass filter with frequency range of 0.1 and 100 Hz to eliminate the baseline wandering and the high-frequency noise. Next, moving average filter has been applied for smoothing the ECG signal [8–12]. Figure 2a, b show the ECG before and after the preprocessing techniques respectively.

For segmentation purposes, the ECG signal is initially normalized then passed to ECG beats segmentation algorithm which is based on using cumulative area as explained in the introduction part. Figure 3 shows an example of the segmented ECG beats using the approach of [3].

Table 1 Distribution of ECG records of six different ECG beats

Beat Type	Record Number
Normal	103, 113, 115, 123, 220, 234
LBBB	109, 111, 207, 214
RBBB	118, 124, 212, 231
aAP	113, 201, 202, 210, 213
APB	209, 222, 232
PVC	106, 116, 119, 200, 203, 208, 210, 213, 215, 221, 233

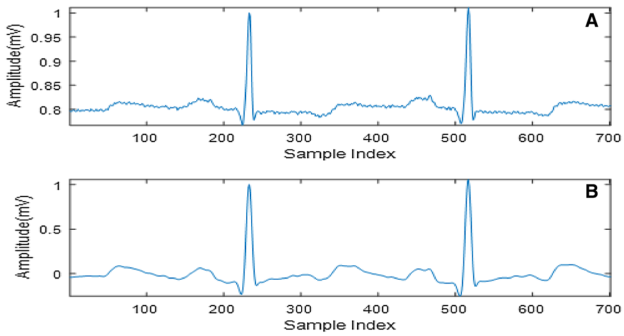


Fig. 2 ECG beat before and after preprocessing

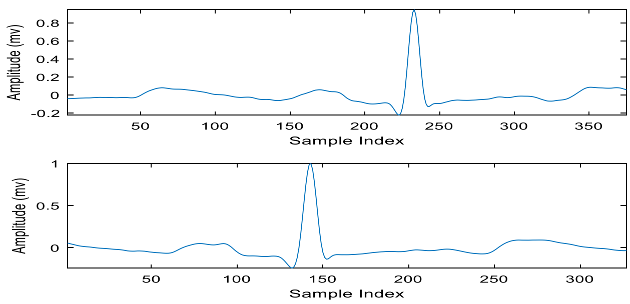


Fig. 3 Examples of segmented ECG beats

Gaussian mixtures features

Gaussian mixtures modeling features are morphological features, where each ECG beat is separated into three parts; baseline, positive, and negative parts for morphological features extraction. After that, each part is modeled using Gaussian mixtures modeling technique as a summation shifted and scaled Gaussian functions, as shown in Eq. 1 [3]. Figure 4 shows the block diagram steps of extracting features using gaussian modeling technique.

$$model(t) = \sum_{n=1}^{N} Gaussain_n = \sum_{n=1}^{N} W_n e^{-\left(\frac{t-S_n}{SC_n}\right)^2} \quad (1)$$

The number of used Gaussians in our proposed model is equal to N = 7.The number 7 was chosen because the gaussian models with this number of mixtures give the least root mean square error (RMSE) [3]. The W_n, S_n, and Sc_n values of seven gaussians of each part (positive, negative, and baseline) are stored in a vector. Next, for features extraction purposes, a statistical analysis is performed for each part (positive, negative, and baseline). The proposed statistical features are mean, standard deviation, energy, entropy, skewness, and variance [9, 13–16]. Consequently, each ECG beat will have 18 statistical gaussian based features set which are more informative than the raw Gaussian function coefficients.

Wavelet analysis feature

Wavelet analysis provides coefficients about the details of the signal. The detail coefficients D1 is the result of high-pass filter, where the approximation coefficients A1 represents the low-pass filter results. This kind of discretization of the wavelet has the form [17–19]. Figure 6 shows the decomposition of ECG beat into four levels and extracting the corresponding features from the required levels (D1, D2, D3, D4, and A4).

$$\Psi_{u,v}(t) = \frac{1}{\sqrt{u}} \Psi\left(\frac{t-u}{v}\right) \quad (2)$$

where $\Psi(t)$ is a window of finite length, v is window translation parameter, and u is the contraction parameter.

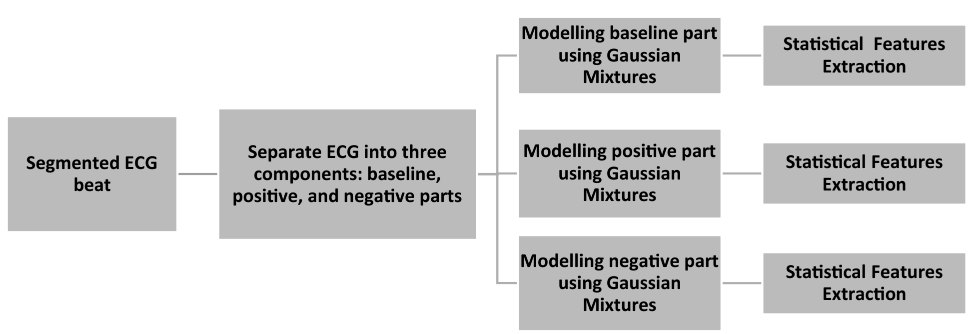
$$y(u, v) = \sum_{t=-\infty}^{\infty} y(t) \times \Psi_{u,v}(t) \quad (3)$$

Applying DWT on the signal y(t) gives the high-pass and low-pass filter outputs as follows:

$$z_{low}(t) = \sum_{k=-\infty}^{\infty} y(k) \times h(2t-k) \quad (4)$$

$$z_{high}(t) = \sum_{k=-\infty}^{\infty} y(k) \times g(2t-k) \quad (5)$$

Fig. 4 Block diagram of extracting features using Gaussian modeling



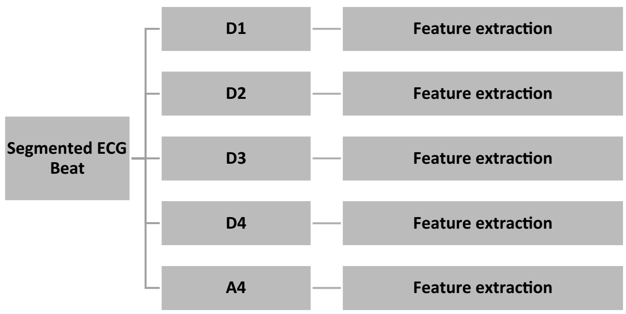


Fig. 5 Block diaram of extracting features using DWT

where $h(t)$ is the low pass filter kernel, $g(t)$ is the high pass filter kernel, and k is the shifting factor.

The high-pass and low-pass filters are applied at each level, the details and approximations coefficients are calculated. The details-signal is then separated again using low-pass and high-pass filters until the required resolution is achieved.

In the proposed methodology, each ECG beat is decomposed to 4 levels using db4 mother wavelet. The details coefficients at each level are named D1, D2, D3, and D4 as shown in Fig. 5. In addition to the last approximation coefficients, A4 is exploited in the proposed approach. Figure 6 shows the decomposition of the ECG beat. The extracted statistical features from each decomposed signal are; energy, variance, standard deviation, and waveform length.

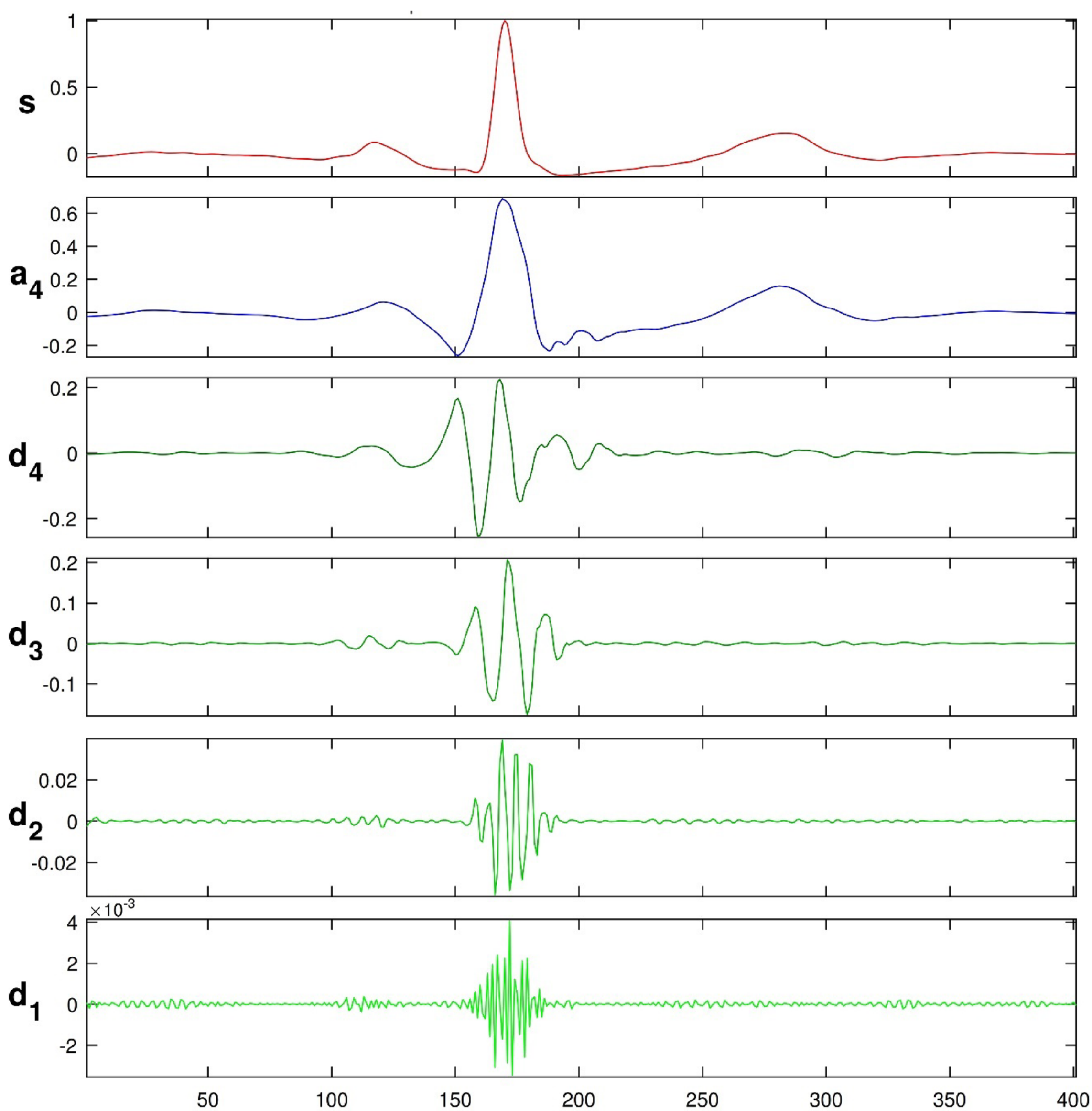


Fig. 6 The decmposition of ECG beat using 4 level DWT using db4 mother wavelet

Feature selection using PCA

PCA is a technique used to reduce the number and order of the extracted features [20]. The PCA technique uses the correlation matrix instead of the covariance matrix for features ordering and selection criteria. After implementing this operation and the calculation of eigenvalues and variances, a set of main components is obtained and arranged based on their ability to distinguish between classes [21]. The features in the present study are extracted from the two techniques (gaussian features and wavelet features) which are then fed into PCA for dimensionality reduction, where some of the extracted features are dependent/correlated to some extent on/to each other and therefore, and their contribution are ineffective on the accuracy of the proposed classifiers and their elimination will reduce the computational complexity.

Random Forest (RF) classifiers

Random forests (RF) classifier, first proposed by Breiman [22], is one of the most popular classification tools and excellent ensemble machine learning techniques. The main idea of RF classifier is to build classification trees, based on some randomly selected features from randomly selected samples with bagging strategy. The built trees are used to vote for a given input vector to get a class label. RF classifiers are constructed by many base learners, where each base learner is an independent binary tree adopting recursive partitioning. RF has many advantages; it provides higher accuracy than other classifiers, efficient on large-scale data, does not overfit, and can be easily applied in multi-class inputs. RF classifier has shown a superior performance in classification over other proposed methods since it was proposed.

Probabilistic neural networks (PNN)

Probabilistic neural networks (PNN) classifier uses Parzen windows to provide an estimation of the probability density functions (PDF) required in Bayesian rule step [23]. PNN consists of four main parts, the input, pattern, summation, and output parts. All four parts are fully interconnected, and the pattern parts are activated using an exponential function instead of a sigmoidal activation function which is usually used in other types of neural network. The pattern part function is used to compute the distances of the input vector to the training input vectors. When an input vector is generated, it will produce a vector with values that provide an indication about how close the input is to be a training input. The summation part sums the contributions of each inputs class and produces a single output, which is called a vector of probabilities. From the maximum of these probabilities, the output units produce a ‘1’ for that class and a ‘0’ for other classes using a complete transfer function.

Results

The PCA extracted significant features vector, is fed into RF and PNN as input, where at each time the seven most significant features are fed into the classifiers according to their PCA ordering.

The main problem in using the PNN is selecting the spread constant. Since the spread constant is used to determine the receptive field size of the PNN kernel, its misselection could cause PNN overfitting or underfitting. Therefore, the variation of accuracy over the spread constant is analyzed for spread constant selection. The analysis is done by testing the performance of the spread constant over the range 0.1 to 1 with step of 0.1 as shown in Fig. 7. Based on the output results, the spread constant 0.2 will be chosen in the PNN classifiers.

The performances of PNN and RF classifiers are described using the confusion matrix and statistical parameters. The confusion matrix represents the results of classification using a certain classifier. After calculating the statistical parameters, namely false positive (FP), false negative (FN), true positive (TP) and true negative (TN), the heartbeat classification effectiveness are compared using the four statistical indices: sensitivity, specificity, precision and accuracy. The performance evaluation results of RF and PNN classification for the six types of ECG beats arrythmia (N, LBBB, RBBB, PVC, APB, and aAP) using the full set of features are shown in Table 2. The confusion matrix of PNN and RF are shown in Figs. 8 and 9 respectively.

Comparison of feature effect on classification output

To investigate the efficiency of the extracted features, the PNN, and RF via three set of features (Gaussian and Wavelet) are demonstrated. Figure 10 illustrates the accuracy, sensitivity, specificity, and precision rates of PNN classifier. Figure 12. illustrates the accuracy, sensitivity, specificity, and precision rates of RF classifier. According to the results in Figs. 10 and 11, employing each feature separately will provide good classification rates (PNN: 98.83% for Gaussian, and 95.89% for Wavelet; RF: 97.36% for Gaussian, and 91.86% for Wavelet). While the combination of the Gaussian features with the Wavelet features gives higher rates (PNN: 99.99%; RF: 99.97%).

Finally, using the combination of two types of features, including Gaussians and Wavelets provides the highest

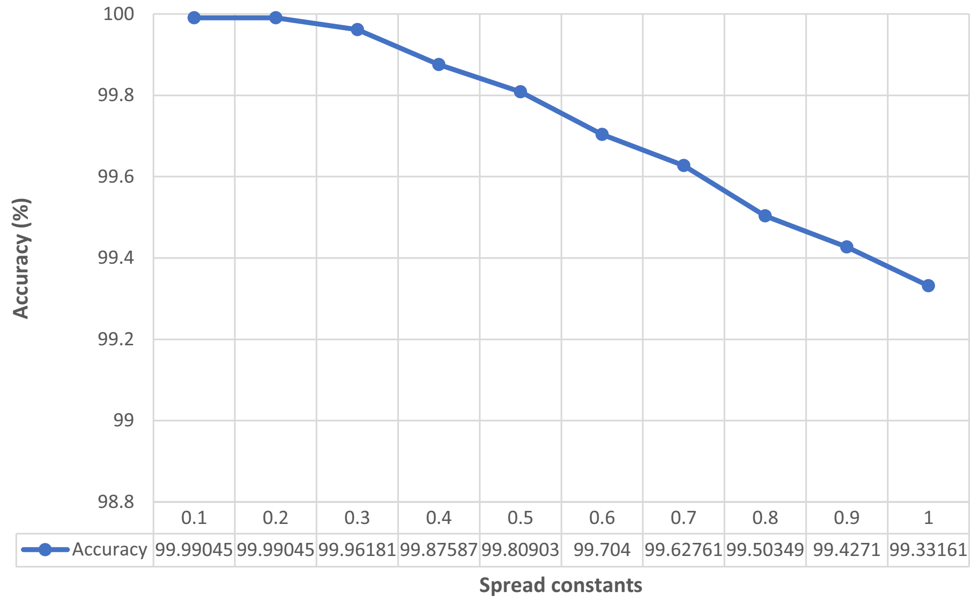


Fig. 7 Spread constant versus accuracy performance of PNN classifier

Table 2 Classification result of the features full set using RF and PNN

Classifier	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
Random Forest	99.97	99.98	99.81	99.96
PNN	99.99	99.99	99.99	99.97

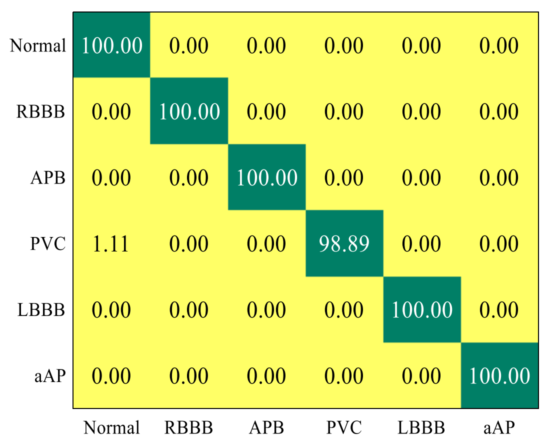


Fig. 8 The accuracy of classifying six types of beats probabilistic neural network (PNN) classifier

percentage of classification rates comparing with the rates using single set of features either the Gaussians or the Wavelets.

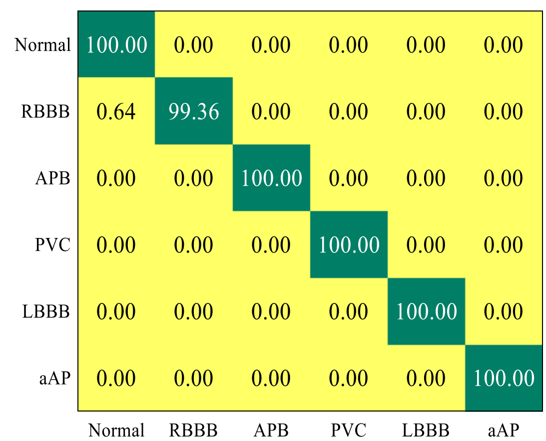


Fig. 9 The accuracy of classifying six types of beats using Random Forest (RF) classifier

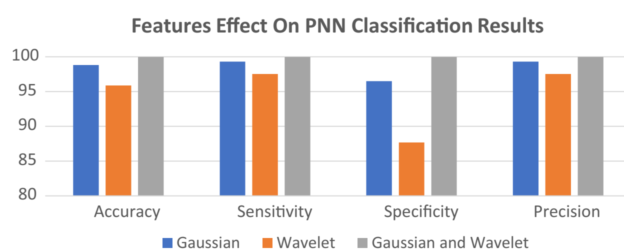


Fig. 10 Comparison the selected features effective on the PNN classification results

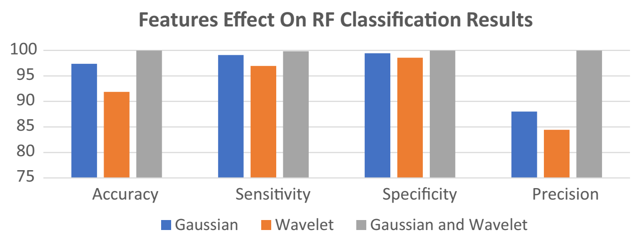


Fig. 11 Comparison the selected features effective on the RF classification results

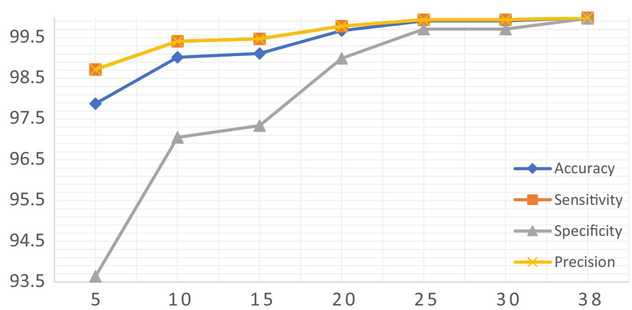


Fig. 12 The variation of performance measurements over selected number of features fed to probabilistic neural network (PNN) classifier

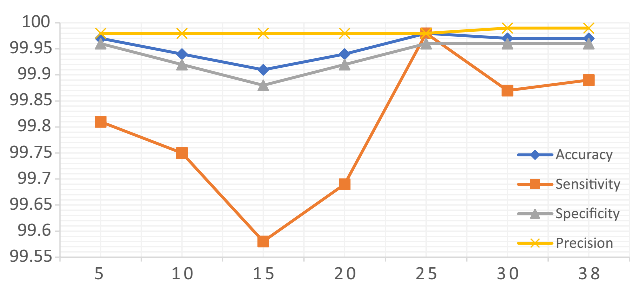


Fig. 13 The variation of performance measurements over selected number of features fed to RandomForest (RF) classifier

Comparison of PCA features ordering classification results

To compare the results of the proposed method, a different set of features ordered by PCA are selected. The total feature set length per ECG beat is 38. The selected features, 5, 10, 15, 20, 25, 30, and 38 in PCA order, are then fed into PNN and RF classifiers and the performance measurements are calculated and stored.

The results show that the accuracy, sensitivity, precision, and specificity for both PNN and RF forest classifiers are increased by including more features. Figures 11 and 12 show the calculated accuracy, sensitivity, precision, and specificity for PNN and RF classifiers using 5, 10, 15, 20, 25, 30, and 38 features in PCA order.

We can conclude from the results shown in Figs. 12 and 13 that the performance measurements increase rapidly and saturate at 25 features. Therefore, PCA technique reduces the number of features by 34.21% with small impact on the performance of both classifiers.

Discussion

The present study aimed to investigate the impact of gaussian mixtures features and their combinations with other features, on the accuracy of ECG beat classification. In the beat-based training scheme, our method achieved better classification results using two types of classifiers comparing to what is available in the literatures. PCA technique is used to reduce the number of features used in the classification process. The results show that the used classifiers still show high accuracy even when using few number of features.

Comparing the results of the proposed method with other methods in the literature are shown in Table 3. The listed research studies in Table 3 have used the same MIT-BIH arrhythmia database that we used in our study. It is noted that they used different number of classes, records, and features set. These factors can affect the performance of the used classification methods significantly. However, most of the listed methods in the literature have achieved high recognition rates, greater than 90%.

As we can notice from Table 3, the wavelet and morphological features are the most widely extracted features from the ECG beat, and the techniques of support vector machine (SVM) and neural network (NN) are the most used classifiers. In addition, most of these methods used the PCA for features dimensionality reduction and therefore, to increase the classifiers speed. It is worth noting that most of these classifiers classify the ECG beats into 6 main classes, while single method has 16 classes.

In general, the extracted features focused on both time and frequency domains, where time domain features include time difference between the main components of the ECG beat (P, R, Q, and S) positions, while in frequency domain the DWT and higher order spectrum (HOS) are used. All other features are morphological features where those features are the second most widely used features after those extracted from the DWT features.

The proposed system shows that both the new provided gaussian mixture feature or the used wavelets feature have high classification rates compared to other methods, while the combination of them provides higher classification

Table 3 Comparison between the related works and the proposed method

Reference	Features Set	Classifier	Feature selection	Classes	Accuracy (%)	
[10]	Morphological	Radial basis function neural network (RBFNN)	No	6	95.78	
[11]	Morphological and timing	Negative correlation learning (NCL), and mixture of experts (ME)	No	3	96.02	
[12]	DWT	Combining NN	No	4	96.94	
[13]	DWT, HOS, and independent component analysis (ICA)	Support vector machine radial base function (SVMRBF) and neural network (NN)	Yes	5	SVM	98.91
					NN	98.90
[14]	Morphological and timing	Modified Artificial Bee Colony (MABC)	No	7	99.30	
[16]	DWT (Frequency, Power, Entropy)	SVM	Yes	6	95.75	
[19]	HOS, Mixture Model, and R-R time	Ensemble learners	No	5	96.15	
				16	99.70	
[24]	Temporal, morphological, and empirical mode decomposition (EMD)	RBFNN and PNN	No	6	RBFNN	99.89
					PNN	99.54
[25]	Geometrical	SVM, k-NN, and BPNN	No	7	98.06	
[26]	DWT, and morphological	Linear Discriminant analysis	Yes	3	94.00	
[27]	Cross correlation	Neural network (NN)	No	3	95.24	
[28]	Low-dimensional Wavelet	SVM	Yes	6	99.70	
[29]	Hermit function, and coefficient and temporal	BBNN	No	5	97.00	
[30]	Mahalanobis distance	Neural network (NN)	No	2	95.14	
	Euclidean distance				81.83	
Proposed Method	Gaussian mixtures and DWT	PNN	Yes	6	99.99	
		Random Forest		6	99.97	

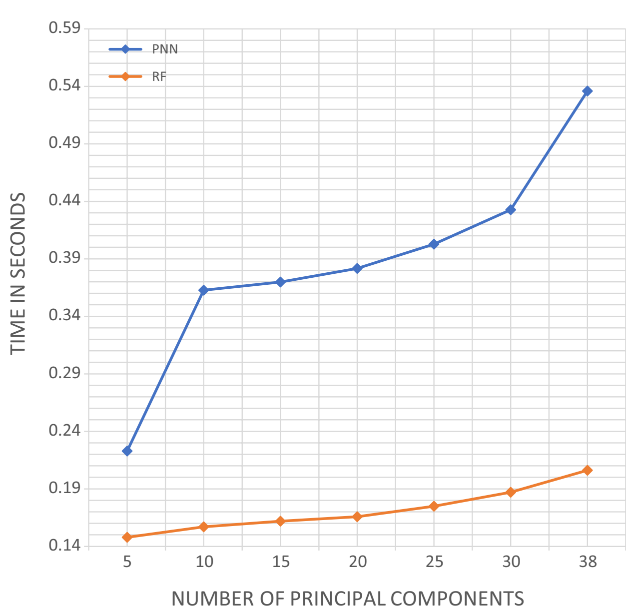


Fig. 14 Classification running time at different selected number of features

rates over other literature methods using PNN or RF classifier.

The system is tested for time consumption in n intel core i7-6700/3.4 GHz and 16.384 Gb of RAM desktop computer using MATLAB 2017b. The system shows that the time required for modelling and extracting the required features from each tested ECG beat is 1.6093 s. Figure 14 shows the time required for feature extraction, and classification using different principal components numbers.

Conclusion

A new method is proposed for classifying ECG heartbeats based on the beat's gaussian mixtures modeling and DWT coefficients. To enhance the classifiers performance, PCA technique is applied for feature dimension reduction, where the most significant features obtained from PCA are fed to the PNN and RF classifiers. Experimental results show that the proposed method achieve very high accuracy when normal with other five types of abnormal beats are classified, and therefore, the proposed method may be used effectively in cardiovascular diseases diagnosing and treatment. By comparing the proposed method with other methods in the literature, the present method is proven to be more effective and can provide a powerful tool for automatic ECG signal classification in daily ECG monitoring.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

1. Zadeh A, Khazaee A, Ranaee V (2010) Classification of the electrocardiogram signals using supervised classifiers and efficient features. Comput Method Progr Biomed 99(2):179–194
2. Yaghoobi M, Nam S, Gribonval R, Davies M (2013) Constrained overcomplete analysis operator learning for cosparse signal modelling. IEEE Trans Signal Process 61(9):2341–2355
3. Alqudah A (2017) An enhanced method for real-time modelling of cardiac related biosignals using Gaussian mixtures. J Med Eng Technol 41(8):600–611
4. Sarfraz M, Khan A, Li F (2014) Using independent component analysis to obtain feature space for reliable ECG Arrhythmia classification. In: 2014 IEEE international conference on bioinformatics and biomedicine (BIBM)
5. Kanaujia M, Srivastava G (2015) ECG signal decomposition using PCA and ICA. In: 2015 National Conference on Recent Advances in Electronics & Computer Engineering (RAECE)
6. Das M, Ari S (2014) ECG beats classification using mixture of features. Int Sch Res Not 2014:1–12
7. Goldberger A, Amaral L, Glass L, Hausdorff J, Ivanov P, Mark R, Mietus J, Moody G, Peng C, Stanley H (2000) PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. Circulation 101(23):e215–e220
8. Butt M, Akram U, Khan S (2015) Denoising practices for electrocardiographic (ECG) signals: a survey. In: 2015 international conference on computer, communications, and control technology (I4CT)
9. Afkhami RG, Azarnia G, Tinati M (2016) Cardiac arrhythmia classification using statistical and mixture modeling features of ECG signals. Pattern Recogn Lett 70:45–51
10. Korürek M, Doğan B (2010) ECG beat classification using particle swarm optimization and radial basis function neural network. Expert Syst Appl 37(12):7563–7569
11. Javadi M, Arani S, Sajedin A, Ebrahimpour R (2013) Classification of ECG arrhythmia by a modular neural network based on mixture of experts and negatively correlated learning. Biomed Signal Process Control 8(3):289–296
12. Güler I, Übeylı˙ E (2005) ECG beat classifier designed by combined neural network model. Pattern Recogn 38(2):199–208
13. Elhaj F, Salim N, Harris A, Swee T, Ahmed T (2016) Arrhythmia recognition and classification using combined linear and nonlinear features of ECG signals. Comput Method Progr Biomed 127:52–63
14. Dilmac S, Korurek M (2015) ECG heart beat classification method based on modified ABC algorithm. Appl Soft Comput 36:641–655
15. Roonizi E, Sameni R (2013) Morphological modeling of cardiac signals based on signal decomposition. Comput Biol Med 43(10):1453–1461
16. Arvanaghi R, Daneshvar S, Seyedarabi H, Goshvarpour A (2017) Classification of cardiac arrhythmias using arterial blood pressure based on discrete wavelet transform. Biomed Eng 29(05):1750034
17. Desai K, Sankhe M (2012) A real-time fetal ECG feature extraction using multiscale discrete wavelet transform. In: 2012 5th international conference on biomedical engineering and informatics
18. Seena V, Yomas J (2014) A review on feature extraction and denoising of ECG signal using wavelet transform. In: 2014 2nd international conference on devices, circuits and systems (ICDCS)
19. Kaur I, Rajni R, Marwaha A (2016) ECG signal analysis and arrhythmia detection using wavelet transform. J Inst Eng (India) Ser B 97(4):499–507
20. Song F, Guo Z, Mei D (2010) Feature selection using principal component analysis. In: 2010 international conference on system science, engineering design and manufacturing informatization
21. Mishra D, Dash R, Rath A, Acharya M (2011) Feature selection in gene expression data using principal component analysis and rough set theory. Adv Exp Med Biol 696: 91–100
22. Breiman L, Learning M (2001) Random forests. Mach Learn 45(1):5–32
23. Specht D (1990) Probabilistic neural networks. Neural Netw 3(1):109–118
24. Sahoo S, Mohanty M, Behera S, Sabut S (2017) ECG beat classification using empirical mode decomposition and mixture of features. J Med Eng Technol 41(8):652–661
25. Homaeinezhad M, Atyabi S, Tavakkoli E, Toosi H, Ghaffari A, Ebrahimpour R (2012) ECG arrhythmia recognition via a neuro-SVM–KNN hybrid classifier with virtual QRS image-based geometrical features. Expert Syst Appl 39(2):2047–2058
26. Llamedo M, Martínez J (2011) Heartbeat classification using feature selection driven by database generalization criteria. IEEE Trans Biomed Eng 58(3):616–625
27. Dutta S, Chatterjee A, Munshi S (2011) Identification of ECG beats from cross-spectrum information aided learning vector quantization. Measurement, 44(10):2020–2027
28. Qin Q, Li J, Zhang L, Yue Y, Liu C (2017) Combining low-dimensional wavelet features and support vector machine for arrhythmia beat classification. Sci Rep 7(1):6067
29. Shadmand S, Mashoufi B (2016) A new personalized ECG signal classification algorithm using block-based neural network and particle swarm optimization. Biomed Signal Process Control 25:12–23
30. Banerjee S, Mitra M (2013) ECG beat classification based on discrete wavelet transformation and nearest neighbour classifier. J Med Eng Technol 37(4):264–272