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Article

Meta-Heuristic Optimized Hybrid Wavelet Features for Arrhythmia Classification

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Abstract: The non-invasive evaluation of the heart through EectroCardioGraphy (ECG) has played a key role in detecting heart disease. The analysis of ECG signals requires years of learning and experience to interpret and extract useful information from them. Thus, a computerized system is needed to classify ECG signals with more accurate results effectively. Abnormal heart rhythms are called arrhythmias and cause sudden cardiac deaths. In this work, a Computerized Abnormal Heart Rhythms Detection (CAHRD) system is developed using ECG signals. It consists of four stages; preprocessing, feature extraction, feature optimization and classifier. At first, Pan and Tompkins algorithm is employed to detect the envelope of Q, R and S waves in the preprocessing stage. It uses a recursive filter to eliminate muscle noise, T-wave interference and baseline wander. As the analysis of ECG signal in the spatial domain does not provide a complete description of the signal, the feature extraction involves using frequency contents obtained from multiple wavelet filters; bi-orthogonal, Symlet and Daubechies at different resolution levels in the feature extraction stage. Then, Black Widow Optimization (BWO) is applied to optimize the hybrid wavelet features in the feature optimization stage. Finally, a kernel based Support Vector Machine (SVM) is employed to classify heartbeats into five classes. In SVM, Radial Basis Function (RBF), polynomial and linear kernels are used. A total of ~15000 ECG signals are obtained from the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database for performance evaluation of the proposed CAHRD system. Results show that the proposed CAHRD system proved to be a powerful tool for ECG analysis. It correctly classifies five classes of heartbeats with 99.91% accuracy using an RBF kernel with 2nd level wavelet coefficients. The CAHRD system achieves an improvement of ~6% over random projections with the ensemble SVM approach and ~2% over morphological and ECG segment based features with the RBF classifier.

Keywords: Arrhythmia classification; abnormal heartbeats; wavelets; meta-heuristics algorithm; neural network; signal classification

1 Introduction

An abnormal heart rhythm is called an arrhythmia and is due to a disturbance in the heart's system. The heart rhythm is measured by EectroCardioGraphy (ECG) from the human body surface. The most common symptoms are tiredness, dizziness, loss of consciousness, breathlessness and palpitations in the chest region. A rapid and effective assessment of ECG signal is required to avoid sudden cardiac death due to arrhythmia. A fast machine learning model is described in [1] for arrhythmia classification. Before feature extraction, a series of preprocessing steps, re-sampling, filtering, heartbeat detection, and two successive R (RR) waves calculation are performed. The logarithm of the raw RR interval is fed to a combination of ensembles for the classification using an echo state network.

A simple and efficient approach using statistical features for ECG signal classification is described in [2]. From the de-noised ECG signal, statistical features such as mean, skewness, variance and standard deviation are extracted and given to the Support Vector Machine (SVM) for normal/abnormal classification. The entire ECG signal is used for the classification. A Generalized Discriminant Analysis (GDA) based feature reduction is applied in [3] for arrhythmia classification. After preprocessing, fifteen linear and non-linear features are extracted from the interval of RR waves. These features are optimized using GDA, and an SVM classifier is used for the classification.

Wavelet transform based features are discussed in [4] for arrhythmia classification. The extracted wavelet features from the preprocessed signals are reduced by linear discriminant analysis and an SVM classifier is employed for the classification. Probabilistic Neural Network (PNN) based heartbeat classification is discussed in [5]. Features such as the power of the original and wavelet decomposed signals; coherence and morphological characteristics of each wavelet sub-band are extracted from the 2nd level wavelet decomposition. The extracted features are normalized before classification by PNN. The Independent Component Analysis (ICA) is integrated with the Back Propagation Neural Network (BPNN) for heartbeat classification in [6]. The combination of RR interval and ICA is used as features, with classifiers such as BPNN and PNN for classifying heartbeats in ECG signals.

A knowledge representation system is designed in [7] for arrhythmia classification. It encodes the ECG signal with two knowledge parts; hand encoding and machine encoding by an autoencoder, and then a Convolution Neural Network (CNN) is employed for the classification. The ECG signals are normalized by min-max normalization before encoding. A combination of morphological and ECG segment based features is utilized in [8] for arrhythmia classification. The morphological features such as amplitude, duration, heartbeat interval and ECG segment features from dynamic time wrapping and principal component analysis are extracted and an SVM classifier is used as a classifier.

A combination of CNN and Long Term Short Memory (LSTM) for arrhythmia classification is discussed in [9]. It has three convolution layers coupled with a max pooling layer to extract the features. The last layer is LSTM and a fully connected layer is employed for the classification. An ensemble SVM system is described in [10] for heartbeat classification. Before feature extraction, the segmented heartbeats are normalized. It uses RR intervals and random projections for the classification. Incremental broad learning is discussed in [11] for arrhythmia classification using the biased dropout technique. First, the ECG signals are de-noised and then morphological rhythm features are extracted.

Visual pattern features and morphological features are utilized for arrhythmia classification in [12]. A clustering based approach is used to extract the visual pattern features. Three different classification algorithms, SVM, BPNN and K-Nearest Neighbour (KNN) classifier, are employed for the classification. A kernelized fuzzy rough set is employed in [13] for heartbeat classification in a multi-label classification approach. The different heartbeats are mapped with the ECG features and optimized using a multi-objective optimization model. Log-linear and neural network models demand a lot of training data and effort, restricting their transfer to new interactions and domains.

Different frequency domain representations and their applications in the medical domain have been studied well recently. Though the frequency domain representation captures more information than the spatial domain, it also provides redundant information. Most systems directly use the information with the redundant data from the representation systems affecting the system's performance. To overcome this drawback, feature optimization is employed and hybridization is performed to increase efficiency. This paper provides hybrid wavelet features for arrhythmia classification using ECG signals. The primary goal of this work is to provide a high degree of accuracy between different heartbeats. The secondary goal is to combine spectral features other different wavelet filters to improve the discriminating power.

The rest of the paper is organized as follows: Section 2 provides details of the pattern recognition system; the CAHRD system applied to ECG signal classification. The clinical data used in this work are obtained from the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) database [14–16] and the CAHRD system's performance in this database is discussed in Section 3. Finally, a conclusion about using the CAHRD system for arrhythmia classification is provided in Section 4.

2 Methods and Materials

An ECG signal may be represented by the feature set $f = (f_1, f_2, \ldots f_N)$. The aim of the CAHRD system is to assign this set to one of the discrete heartbeats C_k. For the classes C_1 to C_k are to be disjoint, such that the feature set f belongs to only one type of heartbeat. Therefore, the form of any classification algorithm is $y(x)$. This function outputs a value (1 to k) to which the feature set is assigned. Using the known feature set from k classes of heartbeat signals, the function $y(x)$ is optimized during a training phase. Then, the performance of the classification algorithm is assessed in terms of sensitivity, accuracy and specificity using test data. In this work, only the case of $k = 5$ is considered. Fig. 1 shows the stages of the CAHRD system.

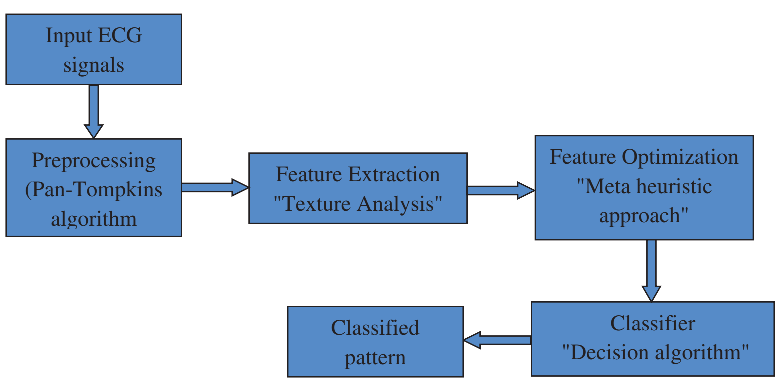


Figure 1: Stages of the CAHRD system

2.1 Preprocessing

To make the classification more accurate, the raw ECG signals obtained in a clinical environment need to be de-noised as they are mixed with much interference, such as baseline drift, power frequency and electromyography. The CAHRD system uses the well-known Q-wave, R-wave and S-wave (QRS) detection algorithm by Pan et al. [17]. At first, ECG signal's interference noises (60 Hz) are removed by a band pass filter algorithm composed of cascaded low and high pass filters. It is a recursive filter that eliminates muscle noise, removes T-wave interference and baseline wander. The transfer functions of the low-pass (Eq. (1)) and high pass (Eq. (2)) filters are defined in [17]

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

$$H(z) = \frac{(-1 + 32z^{-16} + z^{-32})}{(1 + z^{-1})} \tag{2}$$

After filtration, the QRS slope information is obtained from the differentiated filtered signal. The transfer function [17] used for this purpose is

$$H(z) = \frac{1}{8T}\left(-z^{-2} - 2z^{-1} + 2z^{1} + z^{2}\right) \tag{3}$$

In order to get nonlinear amplification of the derivative filter's output from Eq. (3), the signal is squared. It is defined by [17]

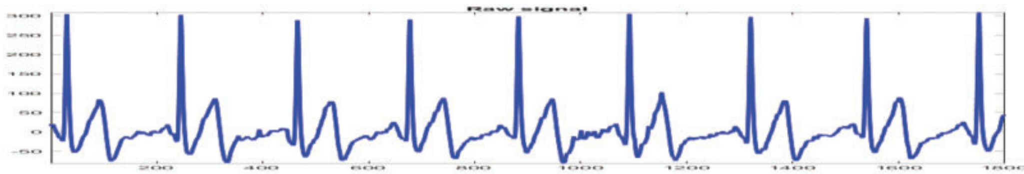
$$y(nT) = [x(nT)]^2 \tag{4}$$

To obtain the waveform feature information and R wave's slope, moving window integration is performed on the squared signal. Finally, the QRS signal is identified by adjusting the thresholds and RR interval limits. More information about the preprocessing steps can be obtained from [17]. Fig. 2 shows the preprocessing outputs from a sample ECG signal.

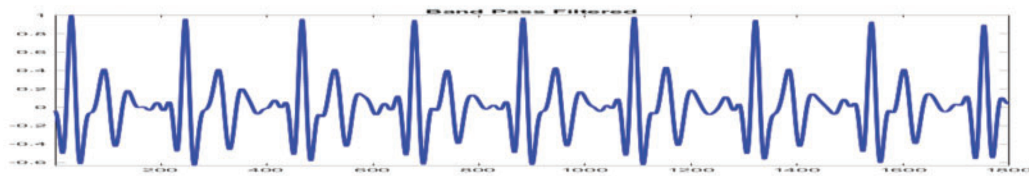
It is noted that all diagnostic information's available around the ECG signal's R peak. Thus, a portion of the signal before and after the R point is cropped for processing. The total length of the cropped signal is 200 points with 0.556 s. The cropped signal is then normalized to reduce the possibility of false decisions. The normalized ECG segment has a unit standard deviation and zero mean. The unit norm normalization for a signal (S) is defined as

$$S' = \frac{S - \mu}{\sigma} \tag{5}$$

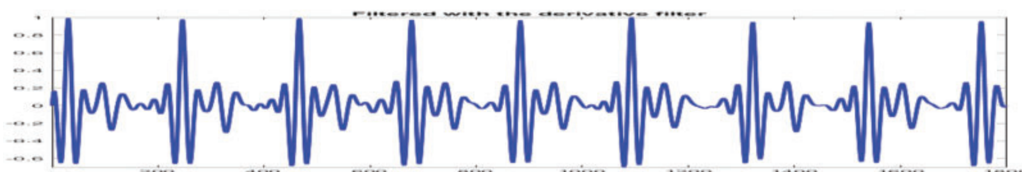
where μ and σ are the mean and standard deviation of signal S. The proposed hybrid features are extracted in the next stage of the CAHRD's system from the normalized ECG signal only.



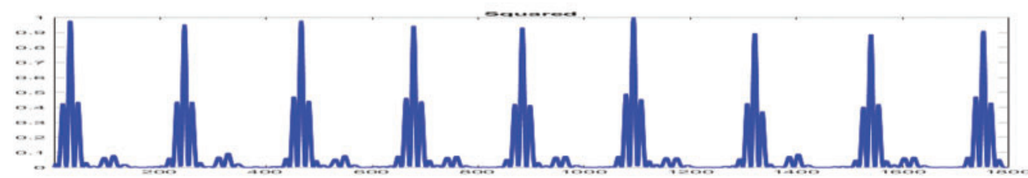
(a) raw signal



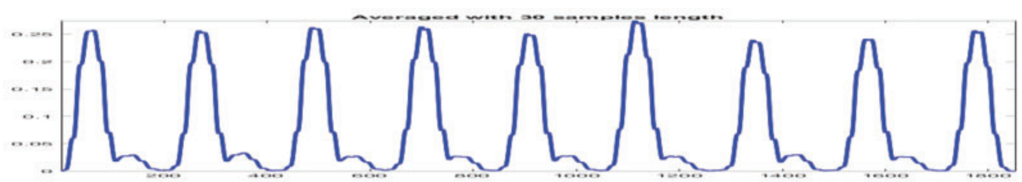
(b) band pass filtered output



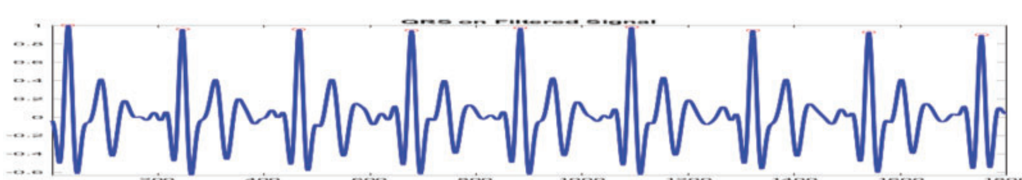
(c) derivative filter output



(d) squared signal



(e) moving window output



(f) QRS detection

Figure 2: Preprocessing outputs of CAHRD system

2.2 Feature Extraction

This stage facilitates the combination of spectral features from different wavelet families. The raw ECG signal is a temporal signal consisting of many frequency components. To get these components, the temporal ECG signal will be converted into a frequency domain via wavelets. A wavelet is viewed as a high and low pass filter that gives a low and high pass detail image [18]. What makes the wavelet unique from other spectral techniques is the aspect ratio of the window (support) which changes while the area under the window remains constant. Additionally, the wavelet is computationally inexpensive and less complex than other wavelet forms. The relation of a wavelet is [18]:

$$f(x) = \sum_{v_{finite}} \sum_{k} finite C_v \psi_{vk}(x) \tag{6}$$

where $\psi_{vk}(x) = 2^{\frac{\psi}{2}} \psi(2^v x - k)$. This alters the window size and the function is translated over integer values k which in turn shifts the energy localization to the next point on the signal. This integer translation defines the family of basis functions. The scaling of the variable x helps to increase the limited space spanned by the wavelet equation. The $2^{\frac{\psi}{2}}$ is for normalizing the basis. All the basis functions in ψ_i are scaled and translated versions of the mother wavelet (ψ_i) and the translation over the image in steps of size $2^v k$. A linear combination of all these step sizes gives a wavelet decomposition of the signal.

The scaling factor v in $\psi(2^v x)$ is a power of 2 which gives the desired cascaded octave bandwidth filter structure since the bandwidths of the frequency of the decomposed signal and centre frequencies must vary by octaves. C_{vk} are the coefficients computed by the wavelet transform. The proposed system uses three filters from different wavelet families such as 'db8', 'sym8' and 'bior3.3' [19] and their wavelet and scaling functions are shown in Figs. 3 and 4 respectively.

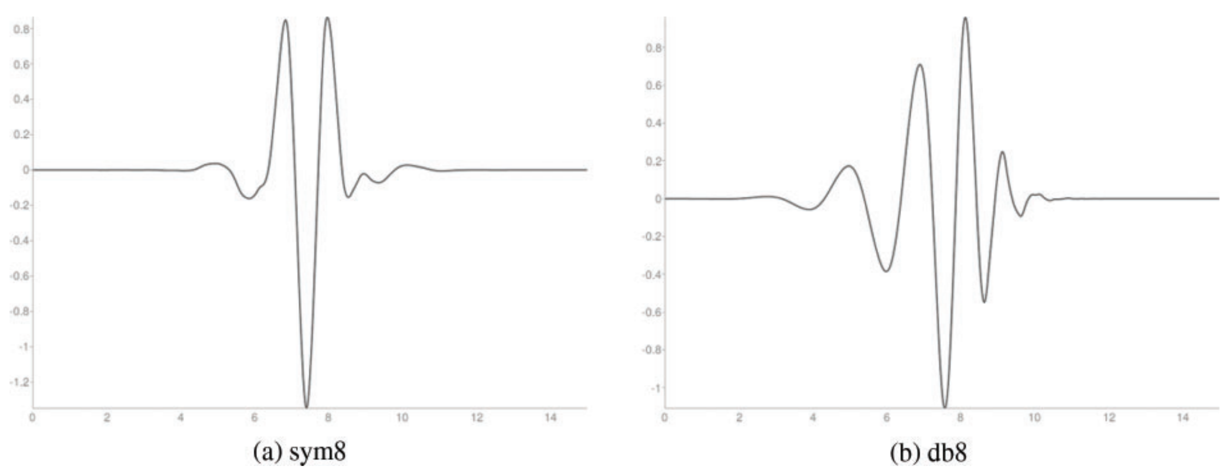
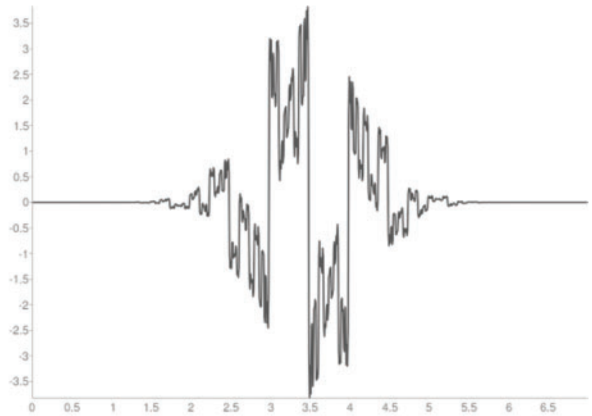


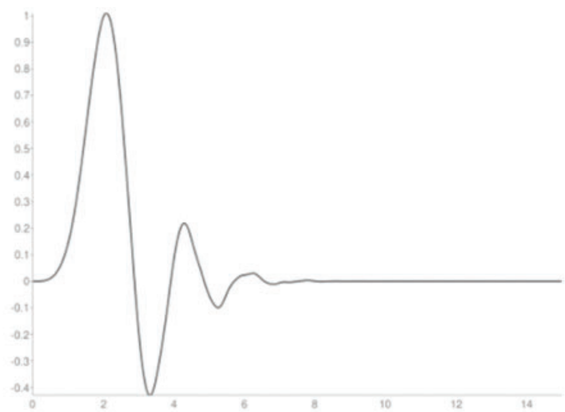
Figure 3: (Continued)



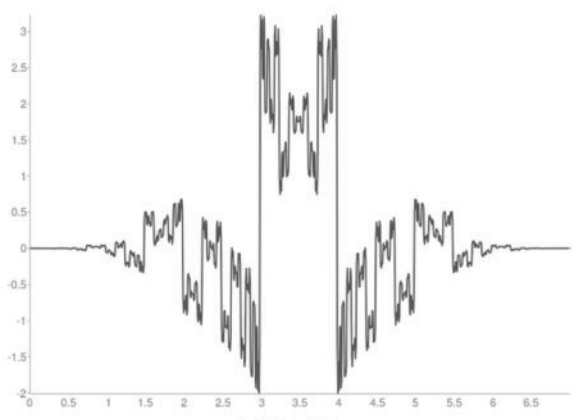
(c) bior3.3

Figure 3: Wavelet functions

(a) sym8



(b) db8



(c) bior3.3

Figure 4: Scaling functions

2.3 Feature Optimization

The hybrid wavelet features contain hundreds of wavelet coefficients. The excessively large feature vectors degrade the system's performance. Thus, feature optimization is required. The goal of feature optimization applied to the CAHRD system is to select the best features that maximize the prediction accuracy of the classified ECG signals. In this work, the hybrid features are optimized using Black Widow Optimization (BWO) [20]. Fig. 5 shows the BWO procedure to optimize hybrid wavelet features.

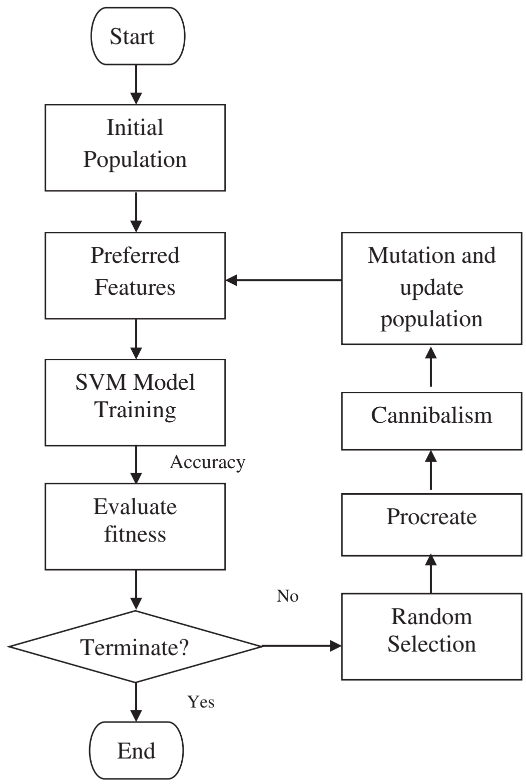


Figure 5: BWO procedure to optimize hybrid wavelet features

In BWO, the structure of the solution of selecting features is called as widow. It is defined as

$$widow = [f_1, f_2, f_3, \ldots f_N] \tag{7}$$

where f_i is the i^{th} selected features of N dimensional space and f_i is represented as either 0 (not selected) or 1 (selected). As the CAHRD system is a 5-class problem, the fitness function with control parameters α and β is

$$f(x) = \alpha \cdot EG - mean + \beta \left(- \frac{|S|}{N} \right) \tag{8}$$

where the number of features in the subset is $|S|$ and the G-mean's extension (EG) criterion is used. It is defined by

$$EG - mean = \left(\prod_{k=1}^{n} A_k \right)^{1/n} \tag{9}$$

where the accuracy of k^{th} class is A_K. If the fitness function in Eq. (8) is not terminated, then the parents are randomly selected. Then procreating is performed by mating in parallel. In cannibalism, the best individuals are identified and mutepop number of individuals is selected from the population. The termination conditions may be no change in the fitness value and a predefined number of iterations. The CAHRD system uses (0.8, 0.2) corresponding to (α, β) as it provides better performance.

2.4 Classifier Design

The CAHRD classifier system uses the training samples labeled by their actual rhythms. These labels are then used to guide the classifier during the learning process. Several methodologies have been developed for carrying out ECG classification based on the optimized features. Though there are many existing classifiers, KNN, BPNN, and PNN**,** SVM is the best choice for ECG classification due to its good generalization performance, robustness in high dimensions and computation efficiency [21].

Let us consider the acquired l observations (optimized wavelet features) $(x_i, y_i),\ i = 1, \ldots, l$ where $x_i \in \Re^n$ is a pattern and $y_i \in \{-1, +1\}$ is the corresponding label. The objective function of the SVM algorithm is [22],

$$\frac{1}{2}\,||w||^2 + C\left(\sum_i \xi_i\right)^k \tag{10}$$

where C is a factor controlling the cost of misclassification, w is the weight vector, and ξ_i is the positive slack variable in the constraints [22],

$$x_i \cdot w + b \geq +1 - \xi_i \quad for \quad y_i = +1 \tag{11}$$

$$x_i \cdot w + b \leq +1 + \xi_i \quad for \quad y_i = -1 \tag{12}$$

where $\xi_i \geq 0\ \forall i$. The objective function in Eq. (10) is a quadratic programming problem for different k values. In the training phase, the patterns only appear in the form of dot products $x_i \cdot x_j$. To map these patterns in a high dimensional space where they are linearly separable, special kernel functions are designed. The kernel functions are defined by [22],

$$K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j) \tag{13}$$

The proposed CAHRD system uses kernel SVMs to identify normalized ECG signal patterns using the optimized feature space. It uses linear (Eq. (14)), polynomial (Eq. (15)) and radial basis function (Eq. (16)) kernels defined in [22]

$$K(x_i, x_j) = x_i \cdot x_j \tag{14}$$

$$K(x_i, x_j) = (x_i \cdot x_j + 1)^d \tag{15}$$

$$K\left(x_i, x_j\right) = e^{-\frac{1}{2\sigma^2}||x_i - x_j||^2} \tag{16}$$

where d and σ are the user-controlled parameters. The performance assessment of the CAHRD system with a polynomial kernel in Eq. (15) uses a 3-degree polynomial. For the RBF kernel, a grid search method finds the ideal parameters from 10 distinct values of C: $[2^{-5}, 2^{-4}, \ldots, 2^3, 2^4]$ (Eq. (10)) and σ $[2^{-7}, 2^{-5}, \ldots, 2^1, 2^2]$ (Eq. (16)). The best results of the CAHRD system is discussed in the next section.

3 Results and Discussions

This section evaluates the major components of the CAHRD systems which have been applied to classify the ECG signals. Also, the evaluation of the CAHRD system using the concept of sensitivity and specificity is provided.

3.1 MIT-BIH Database

The proposed CAHRD system is evaluated using a benchmark database; MIT-BIH arrhythmia [14–16]. The digitized (11-bit resolution) ECG signals in MIT-BIH have been sampled at 360 Hz and a total of 48 half-hours of records are available. Fig. 6 shows the sample ECG signal in the LightWAVE Plot. The normal beats 'N' are represented by blue coloured dots. Table 1 shows the annotations of the MIT-BIH database and the available samples in the entire database.

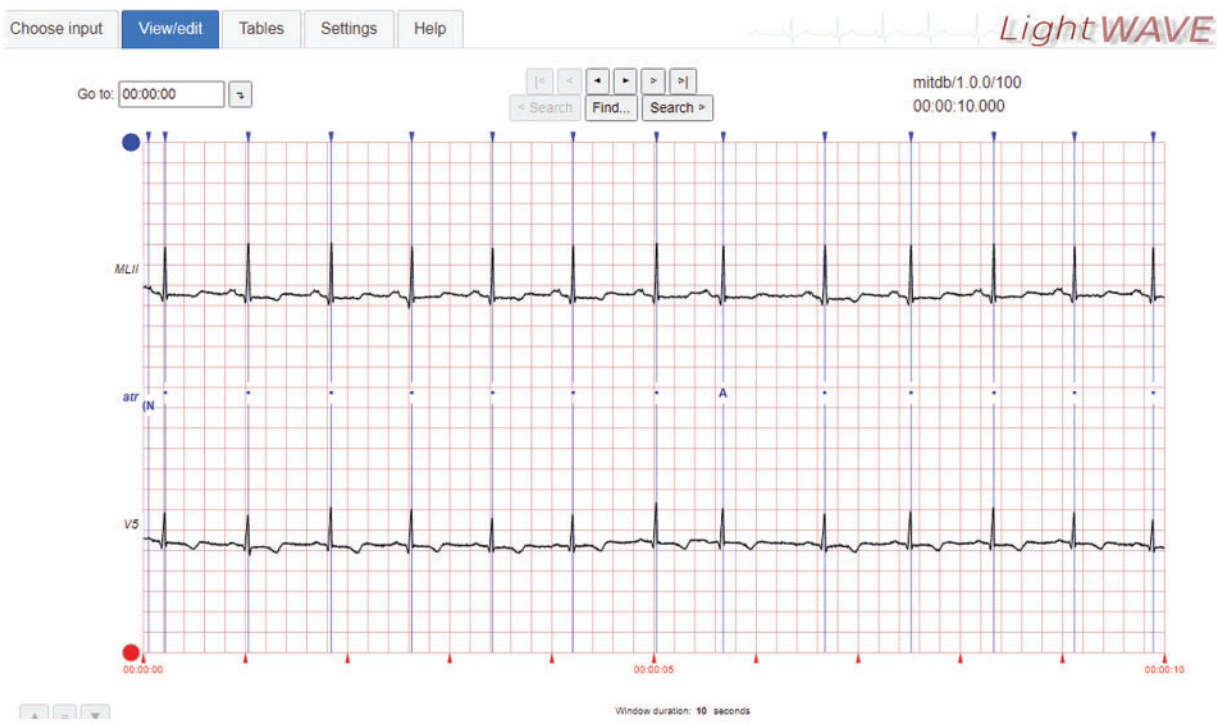


Figure 6: Sample ECG signal in the MIT-BIH database

Table 1: MIT-BIH database-beat annotations

Annotations	Type	Available samples
N	Normal	75052
A	Atrial (Premature)	2546
V	Ventricular contraction (Premature)	7130
R	Right bundle branch block	7259
L	Left bundle branch block	8075

It can be seen from Table 1 that there is a significant imbalance in the dataset. Though many approaches are available to overcome the class imbalance problem and to avoid computational complexity, stratification (stratified sampling) is employed in this study. In conventional k-fold cross-validation, the training samples are randomly partitioned. Hence, it has a uniform probability distribution which is inappropriate for the imbalanced database. To fix this problem, the same class distribution is maintained in each subset. Also, approximately ten times more samples are available for normal beats; only 10000 normal beats are randomly selected from the entire samples and all samples from other beats are used for performance evaluation.

3.2 Experimental Set-Up

The classifier's parameters are optimized in any pattern recognition system based on the training data. Therefore, an independent test set is required to make a reliable estimation of the classifier's applicability to new data. When no such test data is available, k-fold cross-validation (10-fold) is performed to measure the generalization performance of the CAHRD system. At first, the data is partitioned into k subsets randomly. Each subset is used once for testing and the results from each subset are averaged to get the overall result. Fig. 7 shows the cross-validation approach.

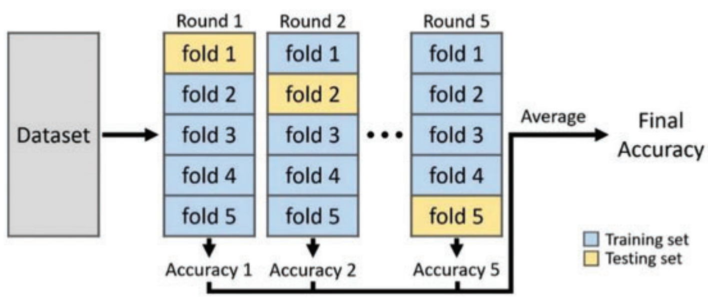


Figure 7: Procedure to measure CAHRD system's performance

3.3 Quantitative Measures

The two main quantitative measures for a screening test to identify people who have or do not have a specific disease are sensitivity and specificity. The former measure shows the system's ability to identify people who have the disease or the probability that a person has the disease when they have it. The later measure is an ability to correctly identify people who do not have a specific condition or the probability that a person does not have the disease when they are disease free. For binary classification, a table (Table 2) can be formulated based on the test outcomes and the ground truth data.

Table 2: Confusion matrix

Ground truth	Test outcomes	
	Abnormal	Normal
Abnormal heartbeat	True Positive (TP)	False Negative (FN)
Normal heartbeat	False Positive (FP)	True Negative (TN)

From the Table 2, Sensitivity and Specificity are defined as follows:

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{17}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{18}$$

The overall accuracy of CAHRD system is defined as

$$\text{Accuracy} = \frac{TP + TN}{FN + FP + TN + TP} \tag{19}$$

In this work, the multi-class classification problem with five conditions is studied. The above quantitative measures can also be computed for multi-class classification problems.

3.4 Discussions

The performance of the CAHRD system in classifying the samples using the optimized features is discussed. Table 3 shows the performance of the CAHRD system with 1st level hybrid wavelet features using kernel SVMs.

Table 3: Performance of the CAHRD system with 1st level hybrid wavelet features

Quantitative measure	Kernel SVM	Beat type					Average performance
		N	A	V	R	L	
Accuracy (%)	Linear	88.34	90.54	88.36	88.13	89.40	88.95
	Polynomial	90.48	92.26	90.50	90.28	91.54	91.01
	RBF	92.62	93.97	92.64	92.42	93.68	93.07
Sensitivity (%)	Linear	77.20	52.04	69.00	69.67	78.27	69.24
	Polynomial	81.20	59.90	74.61	75.18	83.22	74.82
	RBF	85.20	67.75	80.22	80.69	88.17	94.36
Specificity (%)	Linear	92.79	93.56	93.31	92.97	92.73	93.07
	Polynomial	94.19	94.79	94.56	94.23	94.03	80.41
	RBF	95.59	96.03	95.82	95.49	95.33	95.65

It can be seen from Table 3 that the RBF kernel based CAHRD system provides ~92% classification accuracy for all heartbeats. Though the CAHRD system by 1st level hybrid wavelet features has good classification accuracy and specificity, the system's sensitivity (67.75% to 85.20%) is very poor. For a good system, both quantitative measures should be at their maximum. Further analysis is performed on the same dataset by extracting hybrid features from the 2nd level of decomposition. Table 4 shows the performance of the CAHRD system with 2nd level hybrid wavelet features using kernel SVMs.

It can be seen from Table 4 that the CAHRD system shows encouraging results with ~99.9% classification accuracy for all heartbeat classes. The average increase in classification accuracy from 1st level hybrid features to 2nd level hybrid features is ~7% by the RBF classification whereas it is ~5% for linear and polynomial kernel based classification respectively. To further analyze how the proposed

CAHRD system performs at a higher level of decomposition, 3rd level features are analyzed. Table 5 shows the performance of the CAHRD system with 3rd level hybrid wavelet features using kernel SVMs.

It is observed from Tables 4 and 5 that the CAHRD's performance while using 3rd level hybrid wavelet features is less accurate than 2nd level hybrid features for all kernel SVMs. This performance degradation may be due to the redundant data being formed at a higher level of decomposition. Thus, the average performance of the CAHRD system is reduced from 99.91% (2nd level) to 95.92% (3rd level) when using the RBF kernel for classification. In order to show the effectiveness of the hybrid wavelet features, the performances of 2nd level features from individual wavelet filters ('db8', 'sym8' and 'bior3.3') using the RBF classifier are shown in Table 6.

Table 4: Performance of the CAHRD system with 2nd level hybrid wavelet features

Quantitative measure	Kernel SVM	Beat type					Average performance
		N	A	V	R	L	
Accuracy (%)	Linear	93.91	95.68	93.93	93.70	94.97	94.44
	Polynomial	96.34	97.68	96.78	96.56	97.40	96.95
	RBF	99.90	99.89	99.92	99.91	99.92	99.91
Sensitivity (%)	Linear	87.20	83.46	83.03	83.44	90.65	85.56
	Polynomial	91.20	91.32	91.44	91.71	95.60	92.25
	RBF	99.81	99.02	99.83	99.81	99.86	99.67
Specificity (%)	Linear	96.59	96.64	96.71	96.39	96.26	96.52
	Polynomial	98.39	98.18	98.15	97.83	97.93	98.10
	RBF	99.94	99.95	99.94	99.94	99.94	99.94

Table 5: Performance of the CAHRD system with 3rd level hybrid wavelet features

Quantitative measure	Kernel SVM	Beat type					Average performance
		N	A	V	R	L	
Accuracy (%)	Linear	91.25	93.63	91.27	91.05	92.31	91.90
	Polynomial	93.34	95.11	93.36	93.13	94.40	93.87
	RBF	95.48	96.83	95.50	95.28	96.54	95.92
Sensitivity (%)	Linear	82.20	74.82	76.02	76.55	84.46	78.81
	Polynomial	86.20	79.54	81.63	82.06	89.41	83.77
	RBF	90.20	87.39	87.24	87.57	94.37	89.35
Specificity (%)	Linear	94.87	95.10	95.17	94.84	94.66	94.93
	Polynomial	96.19	96.33	96.36	96.03	95.89	96.16
	RBF	97.59	97.57	97.61	97.29	97.19	97.45

It can be seen from Table 6 that the hybrid wavelet features increase the CAHRD system's performance more than their corresponding wavelet features such as 'db8', 'sym8' and 'bior3.3'.

Among the wavelet filters, 'bior3.3' provides better performance than 'db8', and 'sym8' with an average accuracy of 98.76% with 96.09% of sensitivity and 99.22% of specificity. It is concluded from Tables 3 to 6 that 2nd level hybrid wavelet features with RBK kernel SVM provide better results in terms of accuracy (99.91%), sensitivity (99.67%) and specificity (99.94%). The effect of changing the variables α and β in Eq. (8) is analyzed in this work to choose the best fit for arrhythmia classification. Fig. 8 shows the performance of 2nd level wavelet features with different α and β values where $\beta = 1 - \alpha$. The feature dimension of wavelet coefficients when hybridizing the decomposed signal of three wavelet filters is 600. The number of selected features is based on the α value. For example, if $\alpha = 0.5$ (50%), the BWO algorithm selects only 300 (600×0.5) features from the hybrid feature set. Fig. 9 shows the number of optimized feature dimension.

Table 6: Performance of individual wavelet features of 2nd level and hybrid wavelet features

Quantitative measure	Features	Beat type					Average performance
		N	A	V	R	L	
Accuracy (%)	db8	96.47	96.46	96.49	96.49	96.49	96.48
	sym8	97.61	97.60	97.63	97.63	97.63	97.62
	bior3.3	98.76	98.74	98.77	98.77	98.78	98.76
	Hybrid	99.90	99.89	99.92	99.91	99.92	99.91
Sensitivity (%)	db8	93.81	75.45	91.42	91.54	92.43	88.93
	sym8	95.81	83.31	94.22	94.22	94.91	92.49
	bior3.3	97.81	91.16	97.03	97.05	97.39	96.09
	Hybrid	99.81	99.02	99.83	99.81	99.86	99.67
Specificity (%)	db8	97.54	98.11	97.79	97.78	97.71	97.78
	sym8	98.34	98.72	98.50	98.50	98.45	98.50
	bior3.3	99.14	99.34	99.22	99.22	99.19	99.22
	Hybrid	99.94	99.95	99.94	99.94	99.94	99.94

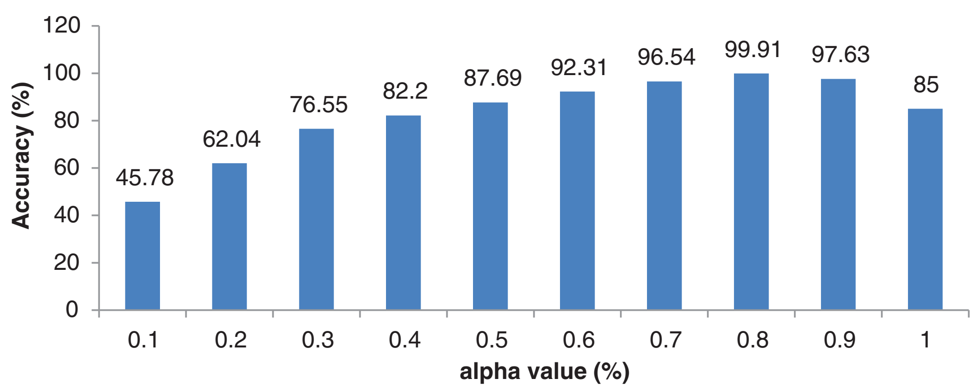


Figure 8: Performance of 2nd level wavelet features with different α and β values

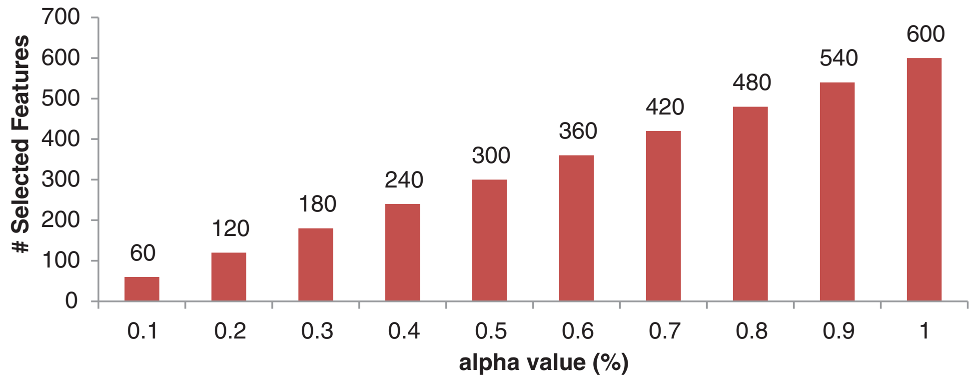


Figure 9: Number of optimized features for different α and β values

It can be observed from Fig. 8 that the best combination of (0.8, 0.2) corresponding to (α, β) in the fitness function provides the highest accuracy for arrhythmia classification. The overall results show that the proposed CAHRD system is a powerful tool for ECG analysis. Table 7 shows a comparative analysis of the proposed CAHRD system with the existing systems.

Table 7: Comparative analysis of the proposed CAHRD system with the existing systems

Method	Classifier	#beat types	Accuracy (%)	Sensitivity (%)	Specificity (%)
RR intervals and random projections [10]	Ensemble SVM	5	93.8	94.73	-
Morphological and ECG segment based features [8]	SVM-RBF	4	97.8	88.83	-
Convolution features [9]	CNN-LSTM	5	98.10	97.50	98.70
Human-machine collaborative knowledge representation [7]	Auto encoder	6	93.87	83.75	97.54
Incremental broad learning [11]	Neural Network	6	99	-	-
Combined parametric and visual pattern features [12]	KNN	15	97.70	-	-
Hybrid wavelet features + BWO (proposed)	**SVM-RBF**	**5**	**99.91**	**99.67**	**99.94**

4 Conclusions and Future Work

The proposed CAHRD system designed in this paper is a classification system, that aims to use ECG signals to determine whether a newly presenting patient has any abnormal heartbeats. After preprocessing the ECG signal, each ECG segment is described using a feature vector consisting of hybrid wavelet coefficients at a predefined decomposition level. The hybrid features are optimized using BWO techniques and kernel SVMs such as linear, polynomial and RBF are employed for the classification. The MIT-BIH provides an ideal dataset for arrhythmia classification due to its diversity and large size. This study utilizes the entire database for performance evaluation. The proposed CAHRD system reports average accuracy of 99% for discriminating between 5 different heartbeat rhythms using 2nd level hybrid wavelet features with RBF kernel based SVM. Automated ECG signal classification could provide an additional diagnostic support along with the traditional diagnostic systems for clinicians. The proposed CAHRD system uses BWO as an optimization technique and the main limitation of this work is that the Atrial (Premature) samples used in this study is very few compared to other types of abnormal heartbeats. The proposed system can be adopted in the future with different optimization techniques such as self organizing migrating algorithm and memetic algorithms for feature selection and a more balanced database can be used to achieve a near-perfect classification system.

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