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Correlation technique and least square support vector machine combine for frequency domain based ECG beat classification

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ABSTRACT

The present work proposes the development of an automated medical diagnostic tool that can classify ECG beats. This is considered an important problem as accurate, timely detection of cardiac arrhythmia can help to provide proper medical attention to cure/reduce the ailment. The proposed scheme utilizes a cross-correlation based approach where the cross-spectral density information in frequency domain is used to extract suitable features. A least square support vector machine (LS-SVM) classifier is developed utilizing the features so that the ECG beats are classified into three categories: normal beats, PVC beats and other beats. This three-class classification scheme is developed utilizing a small training dataset and tested with an enormous testing dataset to show the generalization capability of the scheme. The scheme, when employed for 40 files in the MIT/BIH arrhythmia database, could produce high classification accuracy in the range 95.51–96.12% and could outperform several competing algorithms.

1. Introduction

The electrocardiogram (ECG) is a low cost and non-invasive test which effectively presents valuable clinical information regarding the morphology, rate and regularity of the heart. It is of utmost importance to accurately detect ECG beats so that the timely diagnosis of worrying heart conditions can lead to immediate medical attention. Specially, the timely detection of premature ventricular contractions (PVCs) is of utmost importance as this may lead to cardiac arrhythmias that may turn out to be fatal. A premature ventricular contraction is a relatively common event where the heartbeat is initiated by the heart ventricles that are independent of the pace set by the sinoatrial node.

PVC can occur in a healthy person of any age but becomes more frequent in the elderly people and is more commonly found in men. The immediate detection and subsequent treatment of PVCs is essential for patients with cardiovascular disease because studies have shown that PVCs, when associated with heart attack, can be linked to mortality. Computer-aided automatic diagnosis of cardiac events assists doctors to ascertain the exigency and nature of the medical intervention required. Thus automatic detection and classification of ECG beats using biomedical signal processing techniques has evolved as an active area of research [7–16]. Such automated diagnostic tools can be advantageous utilized by people in medical fraternity as an efficient support system.

Several methods for automatic detection and classification of cardiac arrhythmias have been reported in the literature, including algorithms based on self-organizing maps [7], filter banks [8], hidden Markov models [9] and neural networks [10–12]. In [13], Senhadji et al. used discrete wavelet transform (DWT) aided linear discriminant classifier for ECG beat classification to achieve 98% classification accuracy. But their classifier used only 25 beats in training and 28 beats for testing. Shyu et al. could also achieve a high classification accuracy of 97.04% for PVC beat classification, utilizing wavelet transform based feature extraction in tandem with fuzzy neural network based classifier. However, their classification results were based on only seven files of the MIT/BIH arrhythmia database, out of which two files were used in the training dataset of the neural network [11]. In [12], Hosseini et al. achieved a classification accuracy of 88.3% using multilayer perceptron neural network (MLPNN) classifier using 10 files of the MIT/BIH arrhythmia database. Similar classifiers were also developed in [11–13] which were tested over small datasets.

In the literatures [10,15,16], classification results were reported on the basis of comparatively larger testing datasets. In [15] a linear discriminant based classification scheme was reported that could achieve a classification accuracy of 89% over 44 files of the MIT/BIH arrhythmia database. Hu et al. introduced a patient specific local classifier in addition to a global classifier in [16]. They implemented their algorithm with 20 files of the MIT/BIH arrhythmia database, using self-organizing maps and learning vector quantization. The

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classification accuracy of their local classifier was as high as 94%, but accuracy of their global classifier was as low as 62%. Inan et al. [10] used an MLPNN classifier and could achieve an overall accuracy of 95.16% over 40 files of the MIT/BIH arrhythmia database. Their method comprised features extracted from wavelet transform of heart beat morphology, coupled with R–R timing interval features and these augmented feature vectors were utilized for the training of their classifier. They argued that the performance of their classifier vastly depended on the inclusion of the timing interval feature because the performance of their classifier could only be 81.7% without incorporation of the timing interval feature. However it is a common belief among medical practitioners that the shape of the waveform is more important than R–R timing interval. Doctors commonly use heart beat morphology to diagnose most of the arrhythmias in patients.

In this work, a new ECG beat classification algorithm is proposed utilizing features extracted from waveform morphology only. Characteristic features from each signal are extracted by first computing the cross-correlogram of the signal and then transforming the cross-correlogram to the frequency domain and utilizing the cross-spectral density information. Suitable feature vectors thus created are then utilized to train a support vector machine (SVM) classifier [18,24], for ECG beat classification. This multiclass classifier is developed utilizing a popular variant of SVM, called least square SVM (LS-SVM). The system is developed utilizing a training dataset, as small sized as less than 1% of the size of the testing dataset, to demonstrate the generalization capability of the proposed scheme. The utility of the proposed scheme is demonstrated by implementing it for 40 files available from MIT/BIH arrhythmia database [25] and the proposed scheme could achieve overall classification accuracy as high as 95.51–96.12%. A comparison of this performance with competing algorithms, recently proposed in literatures, show the usefulness of the scheme.

The rest of the paper is organized as follows. Section 2 presents a brief description about the acquisition of ECG signals. The cross-correlation based feature extraction methodology is detailed in Section 3. The LS-SVM based multiclass classification scheme is presented in Section 4. The proposed scheme for ECG beat classification is detailed in Section 5. Section 6 presents the performance evaluation. Conclusions are presented in Section 7.

2. Acquisition of ECG signals

To develop a robust algorithm for ECG beat classification, we have utilized benchmark ECG signals, freely available from the MIT/BIH arrhythmia database [25]. The database contains 48 half-hour excerpts of two channel ambulatory ECG recording files, obtained from 47 different patients. Each file contains two leads, with V_1 in 40 files, modified lead-II in 45 files, and II, V_2, V_4 and V_5 distributed among 11 files [10]. The recordings were digitized with a sampling frequency of 360 Hz and acquired with 11 bit resolution over 10 mV range. The proposed algorithm used a total of 40 files from the database and analyzed modified lead-II signals from these files except in two file #102 and file #104. In case of these two files, lead V_5 recordings were utilized instead of modified lead-II recordings because modified lead-II recordings were not available.

Each record of MIT/BIH arrhythmia database is annotated by two or more cardiologists independently, both in timing information and beat classification. Like several previous works, this work used the annotation to locate beats in ECG signals for the classification of heart beats. This work does not focus on beat detection because several highly accurate beat detection algorithms are already available in the literature [21,22].

3. Cross-correlation based feature extraction

Cross-correlation is a mathematical operation that can be suitably utilized to find the extent of similarities between two signals. The cross-correlation technique has been successfully used in many applications like robotics and remote-sensing, sonar and radar systems for range and position detection, in the recovery of signals buried in noise, biomedical signal processing [1–4] and in several other domains [5,6]. In [1,2], cross-correlation technique was conveniently used for classification of gait and EEG signals respectively. One of the novelties of the present work lies in applying cross-correlation technique judiciously, as a feature extraction tool, for the problem of ECG beat classification.

The cross-correlation of two finite duration causal sequence $x[n]$ and $y[n]$, each of length N samples, is given by [26]

$$r_{xy}[m] = \sum_{n=0}^{N-|m|-1} x[n]y[n-m] \quad m = -(N-1), -(N-2), \ldots, 0, 1, 2, 3, \ldots, (N-1) \tag{1}$$

In this work recording of a normal heart beat is chosen as reference. Each ECG beat was extracted by selecting a window of −300 ms to 400 ms around the R-wave, as found in the database annotation. Each such one-dimensional signal vector comprises 252 samples and this vector is normalized to a mean of zero and standard deviation of unity. This preprocessing is carried out to reduce DC offset and magnitude variation among different files. Fig. 1 shows the various types of sample heart beats analyzed in the present study. All these preprocessed ECG heart beat signals are cross-correlated with the normal heart beat signal, chosen as the reference. This yields one cross-correlation sequence each corresponding to a heart beat. Some representative sets of such cross-correlation sequences are shown in Fig. 2. For this work a normal heart beat from file #100 has been chosen as reference. In Eq. (1) the reference signal is considered as $x[n]$ and the heart beat signal from any other file, for which the cross-correlation sequence is computed, is termed $y[n]$. To transform each cross-correlation sequence r_{xy} to the frequency domain we have computed Fourier transform of each r_{xy} to produce the cross-spectral density S_{xy} given as:

$$S_{xy}(f) = F(r_{xy}[m]) \tag{2}$$

From these cross-spectral density waveforms, for each heart beat, relevant features were extracted. These features should ideally responsible for characterizing each signal, but with a reduced dimension. From each such cross-spectral density information, the corresponding magnitude and phase cross-spectral density, i.e. $\left|S_{xy}(f)\right|$ and $\angle S_{xy}(f)$ vectors, are created. Figs. 3 and 4 show the plots of the sample $|S_{xy}(f)|$ and $\angle S_{xy}(f)$ curves for the cross-correlation sequences shown in Fig. 2, upto 20th frequency sample of discrete Fourier transform (DFT). Then the features extracted from $|S_{xy}(f)|$ and $\angle S_{xy}(f)$ can be given as:

$$fl\_mag(k) = |S_{xy}(f)|\Big|_{f=kf_0}, \quad k = 1, 2, 3, \ldots \tag{3}$$

$$fl\_phase(k) = \angle S_{xy}(f)\Big|_{f=kf_0}, \quad k = 1, 2, 3, \ldots \tag{4}$$

$$\boldsymbol{fl\_composite} = [fl\_mag(1), fl\_mag(2), \ldots, fl\_mag(k), \ldots, fl\_phase(1), fl\_phase(2), \ldots, fl\_phase(k), \ldots] \tag{5}$$

Here $fl\_mag(k)$ denotes the magnitude of cross-spectral density at kth frequency sample. Similarly $fl\_phase(k)$ denotes the phase of cross-spectral density at kth frequency sample. Then the composite feature vector $\boldsymbol{fl\_composite}$ is formed, considering all fl_mag and

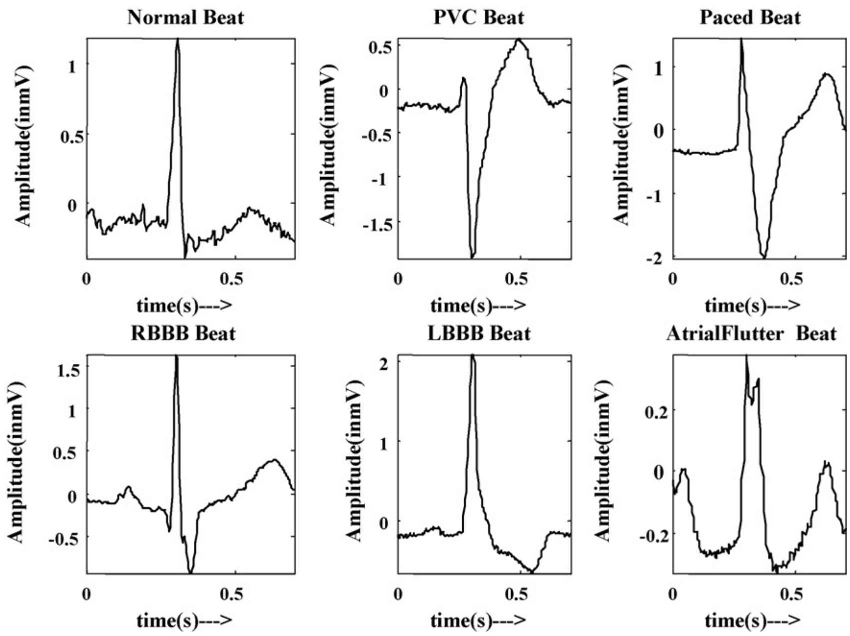

Fig. 1. Different types of heart beats.

fl_phase coefficients. Hence if we consider coefficients upto 10th frequency sample, the feature vector will be a 20 element vector.

4. Multiclass classification using least square support vector machine (LS-SVM)

The present work employs support vector machines (SVM) for the purpose of classification of ECG heart beats. The work employs a popular variant of SVM, called least square SVM (LS-SVM), employed for this purpose, with an aim to perform multiclass classification. A brief discussion on SVM for binary classification, LS-SVM methodology and LS-SVM based multiclass classification is follows.

4.1. Support vector machine

Support vector machine (SVM) is a powerful methodology for solving problems in function estimation, density estimation and non-linear classification. SVM has been introduced through the works of Vapnik [17], which has a firm grounding in statistical learning theory and essentially implements structural risk minimization [24]. In case of binary classification problems the main objective of SVM is to find optimal separating hyperplane between

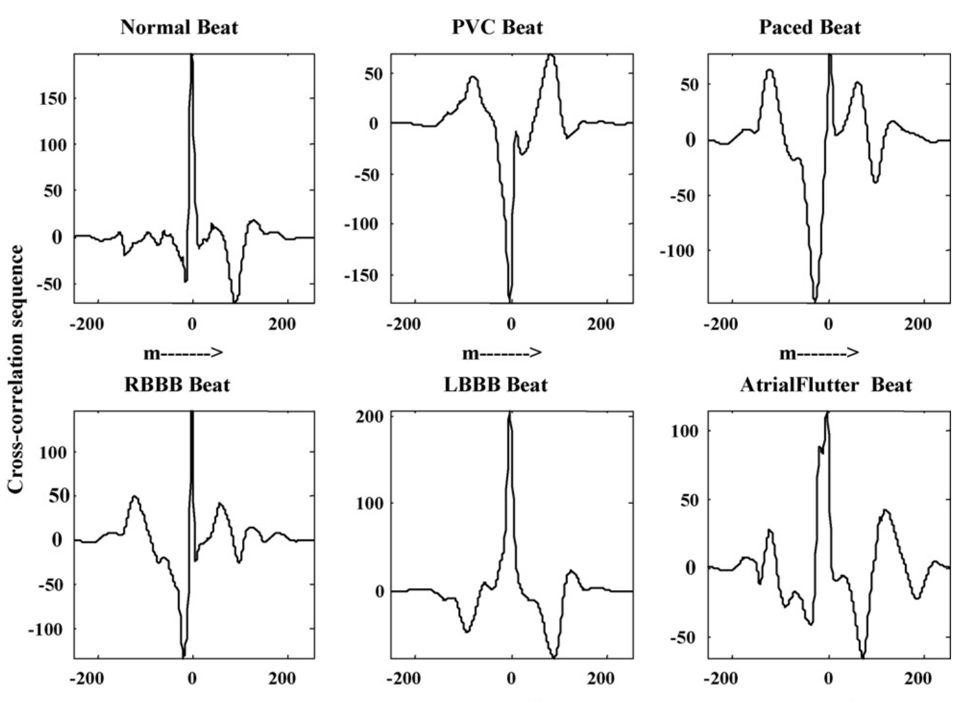

Fig. 2. Cross-correlation sequences of various heart beats, belonging to different classes, as shown in Fig. 1.

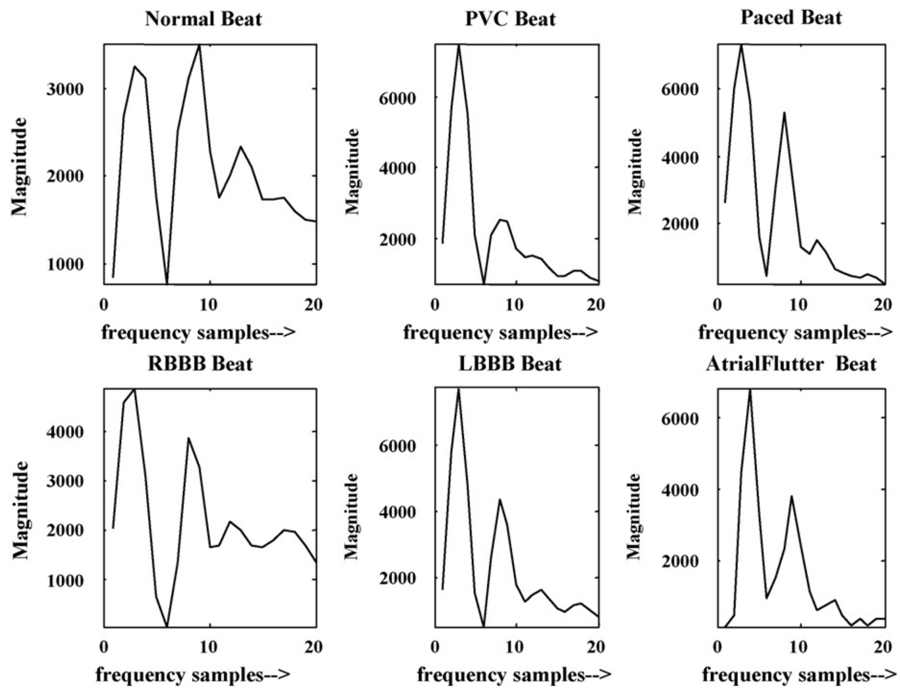

Fig. 3. Magnitude cross-spectral density of various sample heart beats belonging to different classes, as shown in Fig. 1.

the two classes in a manner such that the margin of separation between the two classes is maximized [18].

To develop an SVM based classifier for linearly separable patterns, a suitable training set is created that can be represented by $\{(\mathbf{x}_i, d_i)\}_{i=1}^{N}$, where $\mathbf{x}_i$ is the n-dimensional input feature vector and $d_i \in \{-1, +1\}$ is the target output, corresponding to two classes. To separate these classes, the SVM algorithm has to find the optimal separating hyperplane (with maximum separation or margin) so that SVM can produce good generalization ability. Fig. 5 shows a typical situation where for some data points $(\mathbf{x}_i, d_i)$, $\mathbf{w}.x + b = +1$ is satisfied and for other data points $(\mathbf{x}_i, d_i)$, $\mathbf{w}.x + b = -1$ is satisfied.

The equation of decision surface of a corresponding hyperplane can be written as $\mathbf{w}.x + b = 0$, where x is the input feature vector, $\mathbf{w}$ is the adjustable weight vector and b is the bias. For linearly separable patterns the optimal separating hyperplane can be determined by solving the optimization problem:

$$\begin{aligned} &\text{Minimize} \quad \varphi(\mathbf{w}) = \frac{1}{2}||\mathbf{w}||^2 \\ &\text{subject to} \quad d_i(\mathbf{w}.x + b) \geq 1, \quad i = 1, 2, \ldots, N \end{aligned} \tag{6}$$

The above constrained optimization problem is solved by using Lagrangian multiplier method, when we study linearly non-

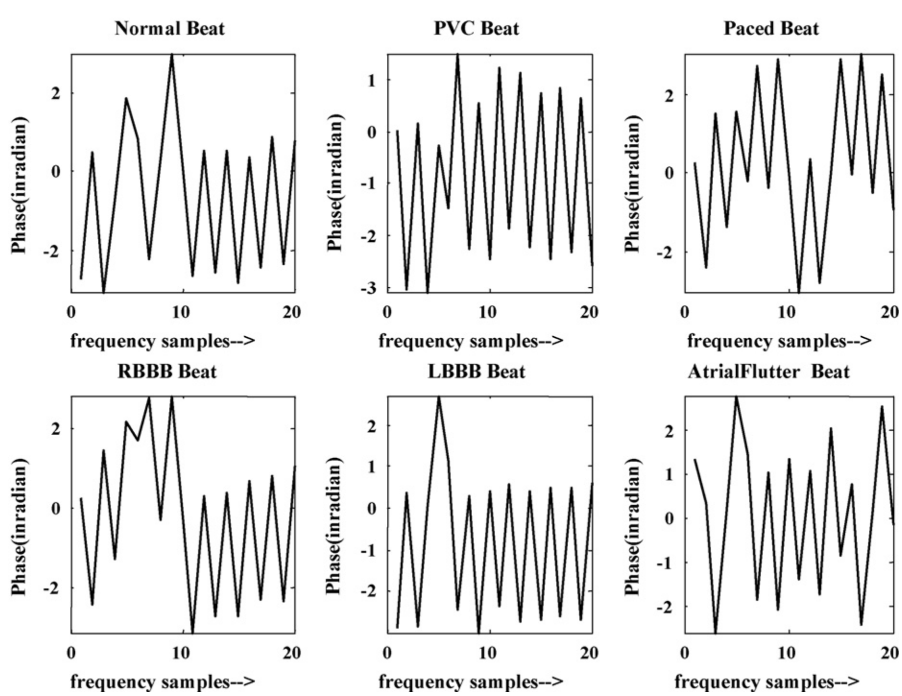

Fig. 4. Phase cross-spectral density of various sample heart beats, belonging to different classes, as shown in Fig. 1.

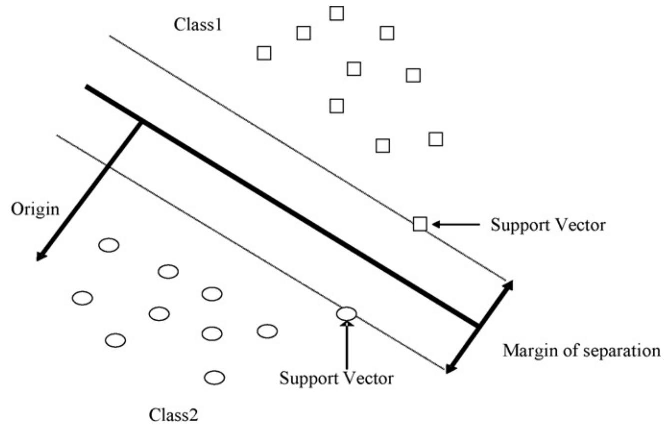

Fig. 5. The SVM for the linearly separable case. The bold middle line indicates optimal separating hyperplane.

separable patterns, in which the date points of different classes do overlap (Fig. 6). For classification of non-linearly separable data, slack variables $\xi_i \geq 0, i = 1, 2, \ldots, N$, are introduced. The optimization problem then gets modified to:

$$\begin{aligned} &\text{Minimize} \quad \varphi(\mathbf{w}, \Xi) = \frac{1}{2}||\mathbf{w}||^2 + C\left(\sum_{i=1}^{N}\xi_i\right) \\ &\text{subject to} \quad d_i(\mathbf{w}.x + b) \geq 1 - \xi_i \quad i = 1, 2, \ldots., N \end{aligned} \tag{7}$$

where C is the regularization parameter, assigns different relative weights to the two terms in the objective function.

In many practical situations, it will not be sufficiently satisfactory to consider linear decision functions in the pattern space. In those situations the classification accuracy can be improved by considering a non-linear decision boundary. The concept of linear SVMs can be extended to the domain of non-linear SVMs by introducing the notion of inner product kernel [24]. In this method the data points are transformed to a high dimensional Euclidean space H through a non-linear function ϕ such that $\phi : R^n \to H$. In this high dimensional feature space H, these data points can be separated by a linear decision boundary. Hence the concept of soft margin SVM classifier can be utilized in feature space, where the algorithm works, on $\phi(\mathbf{x})$ instead of $\mathbf{x}$. The training algorithm only depends on function of the form $\phi(\mathbf{x}).\phi(\mathbf{x}_i)$. Now if a 'kernel function' K is employed such that $K(\mathbf{x}, \mathbf{x}_i) = \phi(\mathbf{x}).\phi(\mathbf{x}_i)$, it is only required to use K in the training algorithm and no explicit knowledge of the actual form of ϕ is required [18]. Then the decision function is given by

$$f(\mathbf{x}) = sign\left(\sum_{i=1}^{N}\alpha_i d_i K(\mathbf{x}, \mathbf{x}_i) + b\right) \tag{8}$$

where α_i, $i = 1, 2, \ldots, N$ are called Lagrange multipliers. A popular Kernel function employs Gaussian radial basis kernel and is given by

$$K(\mathbf{x}, \mathbf{y}) = e^{-(||\mathbf{x}-\mathbf{y}||^2/2\sigma^2)} \tag{9}$$

where σ is kernel parameter or width. The values chosen for two kernel parameters (C, σ^2) significantly affect the classification accuracy of the SVM classifier.

4.2. Least square support vector machine (LS-SVM)

LS-SVMs were originally proposed in [19]. The most crucial difference between SVMs and LS-SVMs is that LS-SVMs use a set of linear equations for training while SVMs use a quadratic optimization formulation. Hence in contrast to the classification problem formulated for classical SVM approach given in Eq. (7), the optimization problem for LS-SVM can be formulated as:

$$\begin{aligned} &\text{Minimize} \quad \varphi(\mathbf{w}, b, e) = \frac{1}{2}||\mathbf{w}||^2 + \frac{\gamma}{2}\left(\sum_{i=1}^{N}{e_i}^2\right) \\ &\text{subject to} \quad d_i(\mathbf{w}.x + b) = 1 - e_i \quad i = 1, 2, \ldots, N \end{aligned} \tag{10}$$

Like SVM, LS-SVM can also be extended to the cases with non-linear boundaries employing kernel functions.

4.3. Multiclass classification methodology

The binary natured LS-SVM can be extended to multiclass classification problems [20], either by constructing and combining several binary classifiers or directly considering all data in one optimization formulation. The task of an M-class classifier is to predict the class label c_m, $m = 1, 2, \ldots, M$ for an input vector $x \in R^n$. One can solve M-class classification problems by reformulating it into a set of L binary classification problems. There are various methods to solve multiclass classification problems by combining binary LS-SVMs like one-versus-one, one-versus-all etc. In one-versus-one, method $(M(M-1))/2$ one-versus-one binary classifiers classify each pair of 2 classes. In another method each class, c_m, $m = 1, 2, \ldots, M$ is represented by unique binary code word $c_m \in \{-1, +1\}^L$ of L bits. Here L binary classifiers are trained to classify two opposing subsets with different output bits. In minimal output coding (MOC), LS-SVM based multiclass classifiers use L bits to encode up to 2^L classes. In one-versus-all coding, which uses $L = M$ bits, it substitutes mth bit of codeword c_m equal to +1 while all other bits of c_m equal to 0 or -1, depending on the type of coding.

The proposed classifier is configured as a three-class classification system (i.e. $c_m = 3$) where the classes correspond to normal heart beat (N), PVC beat (V) and other beat (O). In this work we proposed a scheme to classify these three types of beats. LS-SVM is activated using the feature obtained from cross-correlation sequence as discussed in Section 3. In this work, MOC method of LS-SVM based multiclass classifier is used for this three-class classification problem.

5. The proposed scheme for ECG beat classification

The present work intends to develop a classifier which can automatically classify heart beats into three different categories. Those three classes are normal heart beat (N), PVC heart beat (V) and other

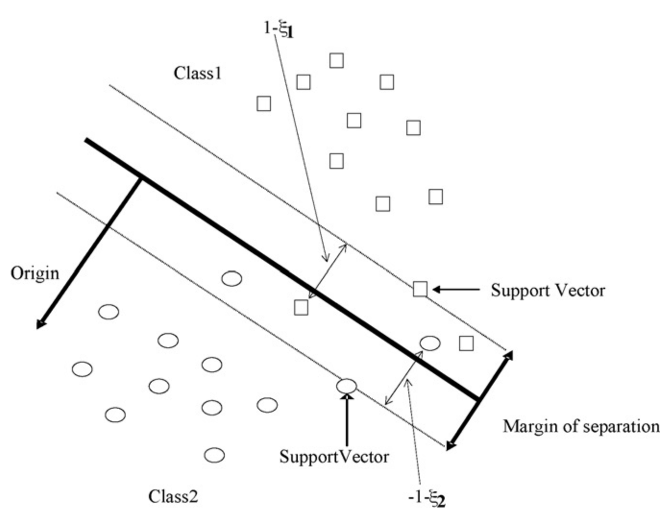

Fig. 6. The SVM for the linearly non-separable case. The bold middle line indicates optimal separating hyperplane.

types of heart beat (O). As discussed earlier, a window of −300 ms to 400 ms around R-wave, as found in the database annotation, was used in our work. After normalization, these ECG vectors are cross-correlated with the reference heart beat to obtain cross-correlation sequence for ECG beat under consideration. The cross-correlogram is then transformed to frequency domain using Fourier transform to obtain its magnitude and phase cross-spectral densities. From cross-spectral density curves we created several different sizes of feature vectors for our work. We considered 26, 28, 30, 32, 34, 36 and 38 feature set vectors, considering magnitude and phase quantities up to k = 13–19 frequency samples. These feature vectors were utilized to train separate LS-SVM based classifiers and each trained classifier was subsequently tested. For each training procedure, we selected heart beats from different files of the MIT/BIH arrhythmia database as representatives of various classes. To check the robustness of the LS-SVM based classifier developed, the system was tested over a large set of ECG data.

As discussed earlier, an LS-SVM based multiclass classifier is implemented for classification. This multiclass classification task was achieved by using a minimum output coding (MOC) scheme [20]. In this scheme, for each classifier developed, the number of neurons was set equal to number of features to be examined. This means, for feature vectors each of size k = 26, 28, 30, 32, 34, 36 and 38, the corresponding classifier was developed using 26, 28, 30, 32, 34, 36 and 38 neurons. This classification job was performed in MATLAB® version 7.0 platform, utilizing the LS-SVM package available in [23].

Each time the LS-SVM based classifier was trained with a total of 780 heart beats from 17 files of MIT/BIH arrhythmia database. These file were selected as representatives of the following heart beats: normal, PVC, left bundle branch block (LBBB), right bundle branch block (RBBB) and paced beats. The training dataset thus created contains 260 normal beats, 260 PVC beats, 150 paced beats and 110 LBBB and RBBB beats. The normal, PVC, paced beats, RBBB and LBBB beats were selected from file #100, 102, 104, 105, 106, 107, 118, 119, 200, 203, 205, 208, 212, 213, 214, 215 and 217 of MIT/BIH arrhythmia database. For these 17 files, normal beats were annotated as 'N' class, PVC beats as 'V' class and all other beats as 'O' class in the database. The total numbers of training exemplars considered were even less than 1% of the total beats used in the testing phase. This extreme skewness among the training and testing systems were employed to check the generalization capability of the proposed system.

The performance of the classifier was tested employing 93,246 beats from 40 files of the MIT/BIH database. As mentioned earlier, we used 780 sample beats from 17 files only for training, out of 40 files of MIT/BIH database. Hence many beats pertaining to these 17 files and all the beats pertaining to the remaining 23 files were completely unknown to the classifiers. Fig. 7 shows the proposed scheme in flow chart form.

Some popular performance metrics were considered to determine the performance of the classifier. They were: accuracy, sensitivity and positive predictivity. Here accuracy indicates performance of the classifier to perform three-class classification tasks, while sensitivity and positive predictivity indicate performance of the classifier to classify each class of heart beat specifically.

The overall accuracy of the classifier for each file in MIT/BIH database is measured using the formula:

$$A = 100\left(1 - \frac{N_e}{N_b}\right) \tag{11}$$

where A is the percentage classification accuracy, and N_e and N_b are the total number of classification errors and total number of beats in the file, respectively. The sensitivity (S_e) and positive predictivity

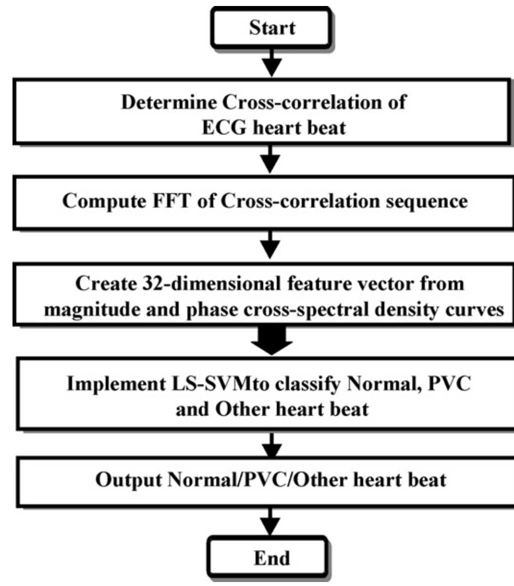

Fig. 7. Flowchart representation of proposed scheme.

(P_p) of beat classification in a file is computed by

$$S_e = \frac{TP}{TP + FN} \tag{12a}$$

$$P_p = \frac{TP}{TP + FP} \tag{12b}$$

where TP denotes true positives, FP denotes false positives and FN denotes false negatives. True positives are the number of beats which have been correctly assigned to a certain class whereas false positives are the number of beats which are incorrectly assigned to that same class. A false negative pertaining to a class are the number of beats which have been truly assigned to that class but was wrongly assigned to another class by the classification algorithm. The sensitivity S_e measures the percentage of true beats that were correctly classified by the algorithm. The positive predictivity P_p measures how exclusively it classifies a certain class.

Once the classification accuracy, sensitivity and positive predictivity for each file is individually determined, in the next step, the weighted average sensitivity and positive predictivity are calculated as a measure of the overall performance. This determination of weighted average sensitivity and positive predictivity can be considered as important issues because of the huge variation among files in absolute numbers of normal, PVC and other beats. Weighted average sensitivity for each class is calculated using the formula:

$$S_{e_{WA}}(c_m) = \frac{\sum_{q=1}^{F} S_{e_q}(c_m) N_{b_q}(c_m)}{\sum_{q=1}^{F} N_{b_q}} \tag{13}$$

where $S_{e_{WA}}$ is the weighted average sensitivity for the class c_m, F is the total number of files in the database, S_{e_q} and N_{b_q} are the sensitivity and the number of beats of file q belonging to class c_m. A similar expression is used to determine the weighted average positive predictivity for each class.

6. Performance evaluation

The previous discussions have already detailed the signal acquisition, feature extraction, creation of training and testing database

Table 1
Classification accuracy of LS-SVM for various feature sets.

Feature set	Accuracy (%)	Normal beats		PVC beats		Other beats	
		S_e	P_p	S_e	P_p	S_e	P_p
26	94.51	97.64	96.12	76.81	87.35	87.62	94.81
28	94.81	98.20	96.28	78.37	86.92	87.11	95.03
30	95.00	99.66	95.64	71.02	94.19	86.43	95.09
32	*95.82*	*99.17*	*96.66*	*83.39*	*91.12*	*87.45*	*96.52*
34	95.01	99.53	96.05	76.38	92.98	84.97	95.14
36	92.39	93.80	96.45	85.65	81.55	84.56	95.36
38	91.98	93.57	96.56	89.16	81.18	82.09	95.41

Best performance indicated in italics.

and the multiclass classification algorithms employed in the proposed scheme. The performance of LS-SVM to classify normal (N), PVC (V) and other heart beats (O) for seven different feature sets are shown in Table 1. A deeper study of these performances reveal that the classifier scheme showed overall best performance when 32 feature vector set was utilized. This system showed an overall accuracy of 95.82%. Calculation of the weighted average sensitivity using (13), showed a value of 99.17% for normal beats, 83.39% for PVC beats and 87.45% for other beats. Similarly the values of weighted average positive predictivity for normal, PVC and other beats are calculated to be 96.67%, 91.12% and 96.52% respectively. Table 2 shows classification accuracy with sensitivity and positive predictivity for each class in all 40 files of the MIT/BIH database. Table 3 shows the classification performance of the classifier, when training and testing sets are completely non-overlapping. The clas-

Table 2
Comprehensive results for training and testing files with 32 features.

File	Beats	Acc.	Normal beats			PVC beats			Other beats		
			Beats	S_e	P_p	Beats	S_e	P_p	Beats	S_e	P_p
100	2271	98.55	2237	100.00	98.55	1	100.0	100.00	33	0.00	–
101	1863	99.62	1858	99.89	99.73	0	–	–	5	0.00	0.00
102	2185	94.23	99	27.27	77.14	4	75.00	6.12	2082	97.45	96.57
103	2082	99.86	2080	99.95	99.90	0	–	–	2	0.00	–
104	2227	82.89	163	100.00	32.73	2	50.00	2.13	2062	81.57	100.00
105	2570	95.33	2524	97.03	98.20	41	2.44	1.32	5	0.00	0.00
106	2026	96.45	1506	99.80	95.61	520	86.73	99.34	0	–	–
107	2135	95.74	0	–	–	59	16.95	100.00	2076	97.98	100.00
109	2530	95.94	0	–	–	38	18.42	46.67	2492	97.11	100.00
112	2537	99.80	2535	99.88	99.92	0	–	–	2	0.00	0.00
113	1793	99.67	1787	100	99.67	0	–	–	6	0.00	0.00
114	1877	97.66	1818	98.52	99.30	43	97.97	84.00	16	0.00	0.00
115	1951	100.00	1951	100.00	100.00	0	–	–	0	–	–
116	2410	98.76	2300	98.91	99.78	109	96.33	82.03	1	0.00	0.00
118	2276	96.84	0	–	–	16	18.76	60.00	2260	97.39	100.00
119	1985	100.00	1541	100.00	100.00	444	100.00	100.00	0	–	–
121	1861	99.57	1859	99.62	99.95	1	100.00	12.50	1	0.00	0.00
122	2474	100.00	2474	100.00	100.00	0	–	–	0	–	–
123	1516	99.87	1513	100.00	100.00	3	33.33	100.00	0	–	–
200	2599	97.08	1742	99.54	96.39	825	95.64	98.87	32	0.00	0.00
201	1961	92.71	1623	99.57	94.45	198	99.50	82.08	140	3.57	50.00
202	2134	95.88	2059	98.45	97.45	19	94.74	85.71	56	1.79	3.03
203	2978	93.02	2527	95.41	96.32	444	80.86	75.74	7	0.00	0.00
205	2654	99.02	2569	99.53	99.53	71	100	83.53	14	0.00	0.00
208	2953	87.13	1585	99.87	82.84	992	98.39	94.94	376	3.72	100.00
210	2648	96.30	2421	98.93	97.32	194	79.38	90.06	33	3.03	6.25
212	2746	98.51	922	100.00	95.74	0	–	–	1824	97.75	100.00
213	3249	87.50	2639	99.47	88.27	220	94.55	81.57	390	2.56	50.00
214	2260	91.46	0	–	–	256	59.77	85.00	2004	95.51	99.95
215	3361	95.72	3193	99.97	95.74	164	15.24	92.59	4	0.00	0.00
217	2206	84.95	244	100.00	48.22	162	71.61	62.37	1800	84.11	100.00
219	2152	98.28	2080	99.38	98.85	64	75.00	87.27	8	0.00	0.00
220	2046	97.65	1952	99.90	97.70	0	–	–	94	51.06	96.00
221	2425	99.88	2029	100.00	99.85	396	99.24	100.00	0	–	–
223	2603	87.21	2027	99.75	86.52	473	50.11	97.13	103	10.68	50.00
228	2051	94.15	1686	95.14	97.75	362	90.33	79.76	3	0.00	0.00
230	2254	100.00	2253	100.00	100.00	1	100.00	100.00	0	–	–
231	1569	94.46	314	100.00	78.50	2	50.00	100.00	1253	93.14	99.91
233	3077	93.05	2229	99.06	92.15	830	78.92	96.32	18	0.00	0.00
234	2751	98.18	2698	99.92	98.22	3	100.00	100.00	50	2.00	33.33
Total	93,246	–	67,037	–	–	6957	–	–	19,252	–	–
Avg	2331.20	95.82	1675.9	–	–	173.93	–	–	481.30	–	–
Wt. Avg	–	–	–	99.17	96.66	–	83.39	91.12	–	87.45	96.52

Table 3
Classification performance breakup for non-overlapping training and test sets with 32 features.

Dataset	Beats	Acc.	Normal beats			PVC beats			Other beats		
			Beats	S_e	P_p	Beats	S_e	P_p	Beats	S_e	P_p
Training set	780	97.44	260	100.00	92.86	260	92.31	100.00	260	100.00	100.00
Testing set	92,466	95.81	66, 777	99.16	96.67	6697	83.02	90.78	18, 992	87.27	96.48

Table 4
Classification accuracy of LS-SVM.

Algorithms	Feature set						
	26	28	30	32	34	36	38
BPNN	75.78	76.9	82.23	73.34	73.38	76.27	72.16
ERNN	72.09	81.87	81.58	82.76	80.15	76.9	72.58
LS-SVM	*94.51*	*94.81*	*95.00*	*95.82*	*95.01*	*92.39*	*91.98*

Best performance indicated in italics.

sifier produced a classification accuracy of 97.44% for 780 beats training dataset and 95.81% for the remaining 92,466 unseen testing beats. The performance variation of the classifier when it was tested with non-overlapping testing set and entire dataset (95.82%) is marginal. From Tables 1 and 2 it can be seen that the proposed cross-correlation based LS-SVM classifier can comfortably attain at least 91% classification accuracy in performing, three-class classification task.

The classification performance of LS-SVM is next compared with back propagation neural network (BPNN) and Elman's recurrent neural network (ERNN) based classifiers with all feature sets used being identical in each of these classifiers. BPNN produced maximum classification accuracy of 82.23% using 30 features vector, whereas ERNN produces maximum classification accuracy of 82.76% using 32 features vector. Both BPNN and ERNN incorporate a MLP three layer architecture where the second layer contains hidden layer neurons. ERNN contains context units in second layer in addition with hidden layer neurons. Number of hidden layer neurons used for both BPNN and ERNN classifiers is equal to number of features considered in each case. Table 4 shows a comparison of the performances of BPNN, ERNN and LS-SVM based multiclass classifiers for seven different feature sets as discussed. It can be easily seen that LS-SVM based system is much superior compared to other competing algorithms in terms of overall classification accuracy.

To have a realistic understanding of the strength of proposed scheme, the results can be compared with the results of some other classification algorithms reported so far. When compared to the scheme proposed in [11], for the seven records they considered they could achieve an overall accuracy of 97.04%. For the same set of files our algorithm could achieve an accuracy of 98.85%. In [10], the classification accuracy reported with 40 files of MIT/BIH database was 95.16%. This scheme considered 43 features which included one R–R time interval feature and 42 dyadic wavelet decomposition samples. In comparison our LS-SVM based classifier would produce classification accuracy 95.82% by using 32 features only and our scheme studied heartbeat morphology only. The classification accuracy reported in [10] was as low as 81.7% when they did not consider R–R interval feature.

An important point to be considered is the sensitivity of the algorithm as a function of the choice of the reference beat for determining the cross-correlation sequences. As mentioned earlier, the results reported so far are based on cross-correlation carried out using a normal beat from file #100. Now we demonstrate the robustness of our proposed algorithm where same beat classification job is performed using five sample reference beats, chosen as five different normal beats from five different files. Table 5 shows the overall classification performance with different choices of reference beats. It can be seen that the variation in performances is from 95.51% to 96.12% which is quite small, and in each case the performance is found to be better than other competing algorithms, discussed before. This experiment aptly demonstrates the satisfactory robustness of the proposed algorithm.

Table 5
Classification performance variation with variation in choice of reference beat.

Sl. No.	Reference beat no. and file information	Beat classification accuracy (%)
1.	Beat no. 19 (file #100)	95.82
2.	Beat no. 424 (file #105)	96.12
3.	Beat no. 6 (file #119)	95.56
4.	Beat no. 197 (file #205)	95.51
5.	Beat no. 2410 (file #215)	95.66

7. Conclusion

In this work an attempt has been made to develop a robust heart beat recognition algorithm that can automatically classify normal/PVC/other heart beats. This work proposes cross-correlation as a formidable feature extraction tool, which when coupled with the LS-SVM classifiers, can be efficiently employed as an automated ECG beat classifier. This multiclass classification tool has been efficiently demonstrated to segregate input ECG beats pertaining to the categories normal beats, PVC beats, and other beats which includes RBBB, LBBB, artial flatter beats and paced beats. The performance of the proposed scheme has been evaluated by considering several benchmark signals available in MIT/BIH arrhythmia database and the overall performance was found to be as encouraging as very close to 96%. This scheme showed how effectively frequency domain information from cross-correlation sequences can be utilized to extract relevant features. The classifiers was so designed that the training dataset was very small (<1%) compared to the testing dataset, so that the generalization capability can be effectively demonstrated. A comparative study with several competing algorithms, recently developed, has been carried out to justify the usefulness of the proposed scheme.

It should be noted that the feature extraction process could have been carried out directly from cross-correlation sequences (i.e. in sequence or time domain) instead of using cross-spectrum (in frequency domain). Theoretically speaking, both time-domain and frequency-domain information can be individually useful for developing such classification tools. However, for this particular application, it was found that when such systems were developed using time-domain information for feature extraction, the classification performances were significantly poor compared to systems proposed in this work, using frequency-domain information for feature extraction. However, it should be remarked that no general conclusion can be drawn and there may be application domains where time-domain information may give better classification performances compared to frequency-domain information based systems. Another important point to be considered is that, as shown in Table 1, the best performance is achieved when 32 feature vector set is considered. However it is true that with incorporation of new measurements in the test set, this chosen size of feature vector set may not remain optimal anymore and the performance may degrade. However a closer scrutiny of Table 1 reveals that with choice of size of each feature vector in the range of 28–34, the overall accuracy that can be achieved approximately is 95% or more, which should be considered satisfactory in most cases. Here it should also be kept in mind that other competing algorithms too reported their best possible performances for a given test set and incorporation of new measurements in their test sets are also expected to similarly degrade their performances.

Conflict of interest

The authors have no conflict of interest related to this paper.

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