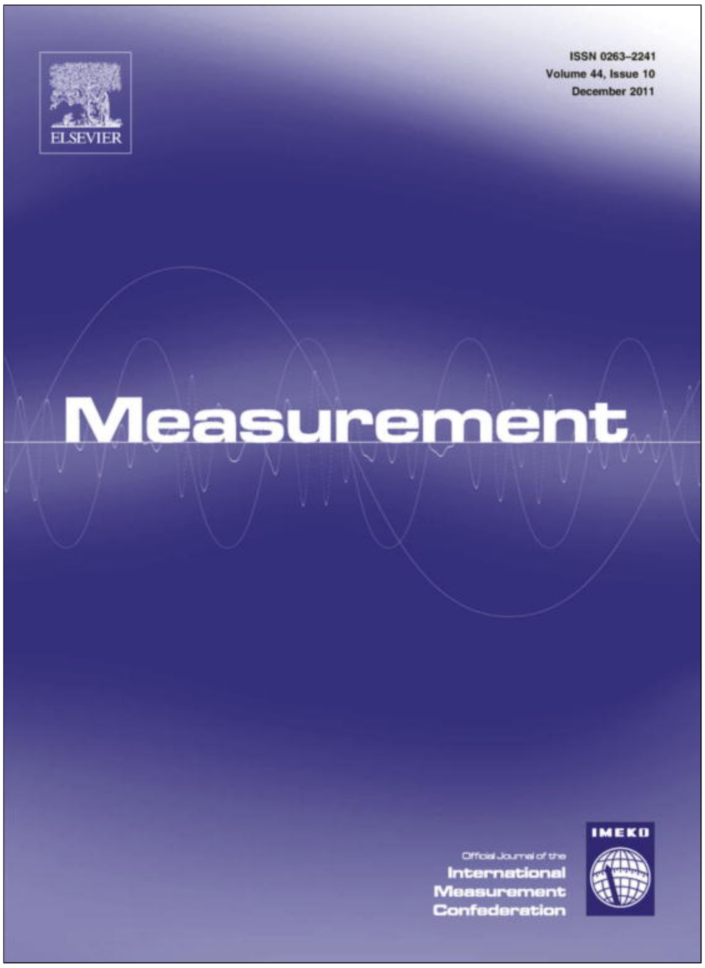
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Identification of ECG beats from cross-spectrum information aided learning vector quantization

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ABSTRACT

This work describes the development of a computerized medical diagnostic tool for heart beat categorization. The main objective is to achieve an accurate, timely detection of cardiac arrhythmia for providing appropriate medical attention to a patient. The proposed scheme employs a feature extractor coupled with an Artificial Neural Network (ANN) classifier. The feature extractor is based on cross-correlation approach, utilizing the cross-spectral density information in frequency domain. The ANN classifier uses a Learning Vector Quantization (LVQ) scheme which classifies the ECG beats into three categories: normal beats, Premature Ventricular Contraction (PVC) beats and other beats. To demonstrate the generalization capability of the scheme, this classifier is developed utilizing a small training dataset and then tested with a large testing dataset. Our proposed scheme was employed for 40 benchmark ECG files of the MIT/BIH database. The system could produce classification accuracy as high as 95.24% and could outperform several competing algorithms.

1. Introduction

Millions of people around the world are suffering from some form of cardiovascular disease. Many of them have witnessed myocardial infarction or heart attack. Myocardial infarction is one of the most common causes of human death in recent times. American Heart Association (AHA) recently reported that cardiovascular diseases were the underlying causes of 1 in every 2.8 deaths in 2008 [1]. World Health Organization (WHO) estimated that by 2030, almost 23.6 million people will die from cardiovascular diseases, mainly from heart disease and stroke [2]. Hence early detection and prevention of cardiovascular diseases is extremely crucial. The most common and inexpensive way to detect the problems in cardiac conditions is Electrocardiogram (ECG) analysis [3]. The ECG is a non-invasive test, which effectively presents valuable clinical information regarding the rate, morphology and regularity of the heart. Specially, Premature Ventricular Contractions (PVCs), which are the most common form of cardiac arrhythmias, can be detected using ECG analysis [4]. PVC is a common event occurring in a person of any age but more frequent in elderly people where the heart beat is initiated by the heart ventricles that are independent of the pace set by the sinoatrial node. The immediate detection and subsequent treatment of PVCs is essential for patients with cardiovascular disease because many studies have shown that PVCs, when associated with heart attack, can be linked to mortality [5,6]. Computer-aided automatic detection and classification of cardiac events assist doctors to ascertain the exigency and nature of medical intervention required. In the last decade, development of bio signal processing aided automatic diagnosis of ECG beats has become more and more important as an active area of research for researchers worldwide [7–16]. Many of them are currently engaged in developing such efficient medical support systems with accuracy, reliability, and robustness as high as possible.

The methods reported so far for automatic detection and classification of cardiac arrhythmias include self organizing maps [7], hidden Markov models [8], filter banks [9]

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and ANN based algorithms [10–12]. In research carried out by Senhadji et al. [13], discrete wavelet transform was hybridized with linear discriminant classifier for performing ECG beat classification. They achieved an accuracy as high as 98% but they used only 25 beats in the training phase and 28 beats for the testing phase. Shyu et al. [11] achieved a high classification accuracy of 97.04% for PVC beat classification. Their algorithm used wavelet transform based feature extraction followed by a neuro fuzzy classification system. However, this system also suffered from the drawback of utilizing small-sized testing datasets, as they used only seven files from the MIT/BIH arrhythmia database. In research carried out by Hosseini et al. [10], a Multilayer Perceptron Neural Network (MLPNN) classifier could achieve a poor classification accuracy of 88.3% even while using only 10 files of the MIT/BIH arrhythmia database.

On the other hand, classification results reported in the literatures [12,14,15] were obtained on the basis of comparatively larger testing datasets. Hu et al. [14] achieved a classification accuracy of 62% over 20 files of MIT/BIH arrhythmia database, using self-organizing maps and learning vector quantization. They introduced a patient specific local classifier in addition to a global classifier, which yielded much better results (94%). Chazal and Reilly [15] achieved a classification accuracy of 89% over 44 files of MIT/BIH database. They used linear discriminant based classification, which involved fusing heart beat morphology with timing interval features for the training of their classifier. Inan et al. arrived at an accuracy of 95.16% over 40 files of the MIT/BIH arrhythmia database using an MLPNN based classifier [12]. Their classifier was trained on features extracted from wavelet transform of heart beat morphology, coupled with R–R timing interval features. They argued that the improvement in the performance of their classifier with a large set of test data vastly depended on the inclusion of the timing interval feature, because, without R–R timing interval feature, the classifier could only produce a classification accuracy of 81.7%. However, in general, medical practitioners think that the ECG waveform morphology is a better way to detect underlying cardiac disorders in comparison to the R–R timing interval. Cardiologists commonly study ECG beat shapes to diagnose most of the cardiac arrhythmias in patients [4–6].

In this work, a novel algorithm for ECG beat classification is proposed, which combines cross-correlation based feature extraction and LVQ neural network based classification algorithms to achieve the desired objective. The classification algorithm only utilizes the features extracted from ECG beat morphology. To study the robustness of the proposed classification algorithm, the classifier was tested with a large set of data. The suggested classifier not only achieved a high classification accuracy and robust classification of ECG beats but could also outperform several competing algorithms, recently published in literatures.

The rest of the paper is organized as follows. Section 2 presents a brief description about the benchmark ECG signals. Section 3 describes the feature extraction strategy proposed in this work, using cross-correlation methodology. The LVQ based multiclass classification scheme is detailed in Section 4. The proposed scheme for ECG beat classification is described in Section 5. Section 6 presents the performance evaluation. Conclusions are presented in Section 7.

Table 1
Three categories of interest into which the ECG beats of the study are classified.

Beat descriptor	Beat label	Test label
Normal beat	N	1
Premature Ventricular Contraction (PVC) beat	V	2
Any other beat that does not fall into N and V categories (Right Bundle Branch Block (RBBB) beat, Left Bundle Branch Block (LBBB) beat, paced beat, etc.)	O	3

2. The benchmark ECG signals under consideration

In this study, the records of ECG signals from the MIT/BIH arrhythmia database [16] have been utilized, for the development and evaluation of the proposed classifier. The database comprised with 48 records of ECG files. Each file contains two leads, with modified lead-II signal available in 45 files, V_1 signal in 40 files and II, V_2, V_4 and V_5 signal distributed among 11 files [12]. The signals considered were prepared by band-pass filtering the raw recordings at 0.1–100 Hz and sampled at 360 Hz. Two or more cardiologists annotated each record of the database independently. The availability of the annotated MIT/BIH database has enabled the evaluation of performance of the proposed ECG beat classification algorithm. The present scheme does not focus on beat detection because highly accurate beat detection algorithms are already available in the literatures [17,18]. Instead, it focuses on the problem of beat classification.

In this study we are interested in classifying three different categories of ECG beats, as indicated in Table 1. A total of 40 records have been used (see Tables 2 and 4) from the database for this purpose, focusing on modified lead-II signals, except in two files viz. #102 and #104, in which lead V_5 recordings were utilized. These data files are representatives of normal beats, PVC beats and other beats which includes Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB) and paced beats. The significance of accurate detection of PVC beats has been discussed in the previous section and hence can be considered as natural choice to analyze this category of ECG beats along with normal beats. On the other hand, the third category of ECG beats i.e. other beats has been added to allow the proposed algorithms to differentiate the PVC beats from the LBBB and RBBB beats and the normal beats from the paced beats, because LBBB and RBBB beats have very similar morphological features to PVC beats and paced beats are similar to normal beats [3,6].

3. Feature extraction by cross-correlation approach

Cross-correlation is a mathematical operation that is very similar to convolution. Cross-correlation is used to find the extent of similarities between two signals. The

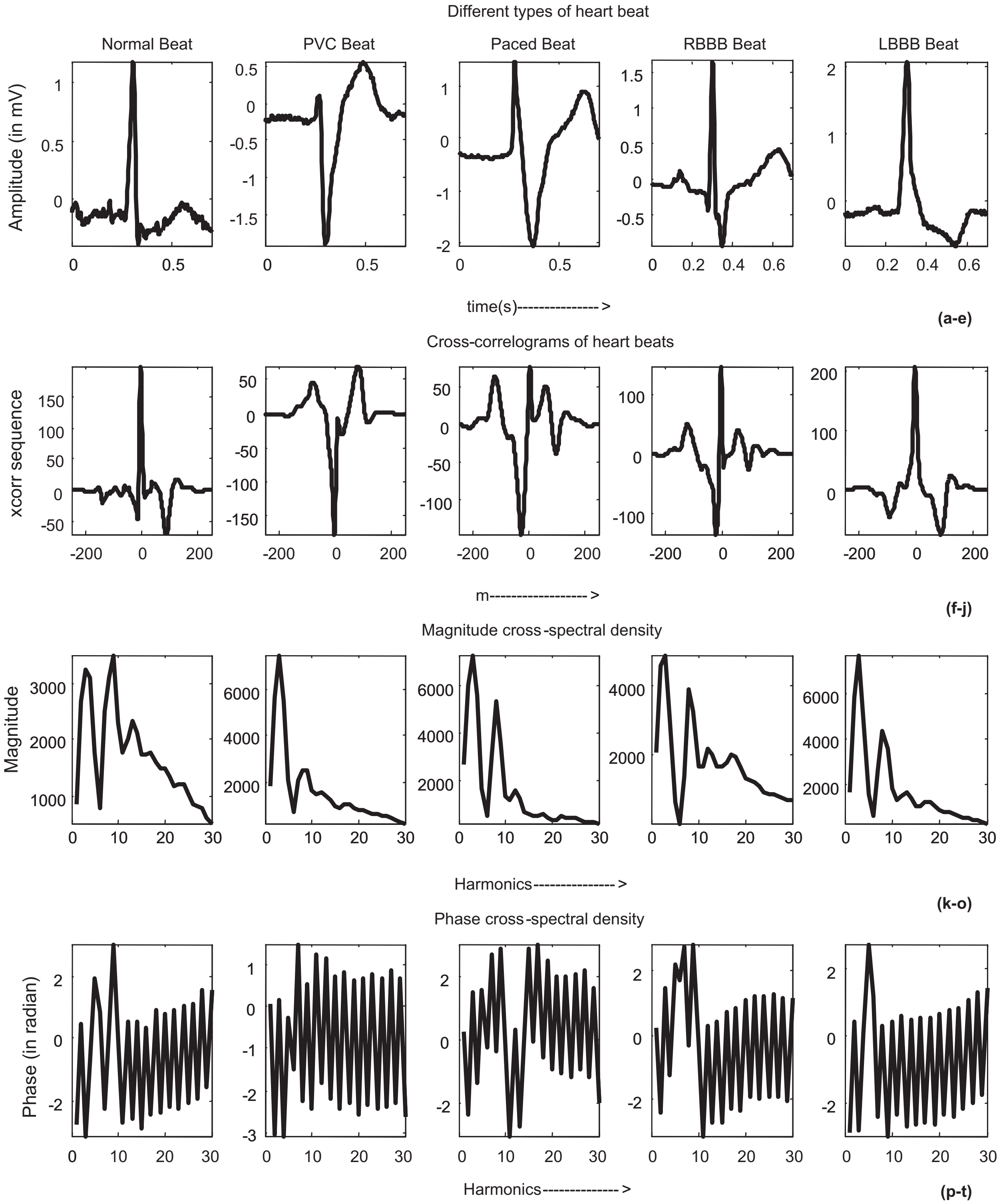

Fig. 1. Different types of sample heat beats, their cross-correlograms, and magnitude and phase cross-spectral density.

cross-correlation technique has been conveniently used in many applications like biomedical signal processing [19–21], image processing [22], robotics and remote-sensing, sonar and radar systems and in several other domains [23,24]. In [19,20] cross-correlation technique has been successfully used for pattern recognition of gait and EEG signals respectively. One of the important achievements of the present work is the successful use of cross-correlation technique in frequency domain for the analysis of ECG beats. The cross-correlation of two finite duration causal sequences $x[l]$ and $y[l]$, each of length L samples, is given by [24,25]:

$$r_{xy}[m] = \sum_{l=0}^{L-|m|-1} x[l]y[l-m] \tag{1}$$

where $m = -(L-1), -(L-2), \ldots, 0, 1, \ldots, (L-2), (L-1)$. The index m represents the time shift or lag parameter and the subscript xy represent the sequences being correlated. Eq. (1) represents the formula of cross-correlation in time domain or sequence domain. Here the reference signal is considered as $x[l]$ and any other signal, which is cross-correlated with $x[l]$, is represented as $y[l]$. As discussed, we analyzed cross-correlation in frequency domain, which was obtained from the Fourier transform of the cross-correlation sequence given in Eq. (1). This is known as cross-spectral density S_{xy} and given as [24,25]:

$$S_{xy}(f) = \sum_{m=-\infty}^{\infty} r_{xy}[m]e^{-j2\pi fm} \tag{2}$$

In the present work, a normal heart beat from file #100 has been selected as the reference. Each heart beat was extracted by choosing 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. In order to reduce DC offset and magnitude variation among different files of MIT/BIH arrhythmia database, each 252-sample vector is normalized to a mean of zero and standard deviation of unity. Fig. 1a–e show 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, chosen as the reference. This yields one cross-correlogram corresponding to each heart beat. Some representative sets of such cross-correlograms are shown in Fig. 1f–j. Using Eq. (2), for each cross-correlation sequence, we have computed cross-spectral density waveforms. These features should ideally be 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. $|S_{xy}(f)|$ and $\angle S_{xy}(f)$ vectors, are created. Fig. 1k–o and p–t shows the plots of the sample $|S_{xy}(f)|$ and $\angle S_{xy}(f)$ curves respectively, for the cross-correlogram sequences up to the 30th harmonic. Then the features extracted from $|S_{xy}(f)|$ and $\angle S_{xy}(f)$ are given as:

$$fl\_mag(n) = |S_{xy}(f)|\big|_{f=nf_0}, \; n = 1, 2, 3, \ldots, N \tag{3}$$

$$fl\_phase(n) = \angle S_{xy}(f)\big|_{f=nf_0}, \; n = 1, 2, 3, \ldots, N \tag{4}$$

$$fl\_composite = \begin{bmatrix} fl\_mag(1), fl\_mag(2), \ldots, fl\_mag(n), \ldots, fl\_mag(N), \\ fl\_phase(1), fl\_phase(2), \ldots, fl\_phase(n), \ldots, fl\_phase(N) \end{bmatrix} \tag{5}$$

Here $fl\_mag(n)$ denotes the magnitude of cross-spectral density at frequency $f = nf_0$, the nth harmonic, where f_0 is the fundamental frequency. Similarly $fl\_phase(n)$ denotes the phase of cross-spectral density at frequency $f = nf_0$, the nth harmonic. Then the composite feature vector *fl_composite* is formed, considering all *fl_mag* and *fl_phase* coefficients extracted. N is the maximum value of the harmonic number up to which features are considered, for a given problem. Hence, if we consider $N = 15$, it implies that the coefficients are considered up to the 15th harmonic. Then there will be 15 coefficients each for phase and magnitude information and hence the feature vector created will be a 30-element vector i.e. a feature vector will contain $2N$ number of entries or features.

4. Learning Vector Quantization (LVQ) based classifier

The presented work employs Learning Vector Quantization (LVQ) algorithms for the purpose of classification of ECG beats. LVQ belongs to the category of supervised clustering approaches and was proposed by Kohonen [26]. Basically an LVQ neural network is a transformed version of self-organizing map based unsupervised neural network, where each output unit represents a particular class. Usually LVQ networks comprise a competitive layer, followed by a linear layer. The competitive layer is used to learn to classify input vectors in a manner very similar to that adopted in self organizing algorithms and the linear layer is used to transform the competitive layer's classes into desired output classes [27]. The weight vector for an output unit is often referred to as a codebook vector for the class that the unit represents. If different feature vectors grouped within the same class label are actually drawn from different classes, then classification error occurs. To minimize classification error, the LVQ algorithm adjusts the boundary (or boundaries) between the clusters of different classes. Different LVQ algorithms have so far been developed to handle different natures of classification problems. In our proposed approach, the optimized learning rate LVQ1 and LVQ2.1 algorithms have been used for training and fine-tuning purposes respectively [28,29].

In LVQ1, for a given M-dimensional input vector p, an M-dimensional code word w_k is found such that

$$k = \arg\min_i \{\|p - w_i\|\} \tag{6}$$

The *code word* is then updated as follows:

$$w_k(t+1) = w_k(t) + \alpha(t)s(t)[p - w_k(t)] \tag{7}$$

where $s(t) = +1$ if p and w_k are in same class and $s(t) = -1$, otherwise; $\alpha(t)$ is the time-varying learning rate. The other code words in the codebook remain unchanged. The procedure adopted to update the code word for the LVQ2.1 algorithm is a little different from that of the LVQ1 algorithm. In LVQ2.1 algorithm, two weight vectors that are closest to the input vector may be updated, provided that one belongs to the correct class and the other one belongs to a wrong class and the other condition to be satisfied is that the input falls in a "window" near the midplane of the two vectors. The window is defined as [29]:

$$\min\left(\frac{d_i}{d_j}, \frac{d_j}{d_i}\right) > (1-\varepsilon) \quad \text{and} \max\left(\frac{d_i}{d_j}, \frac{d_j}{d_i}\right) < (1+\varepsilon) \tag{8}$$

where d_i and d_j are the Euclidean distances of p from w_i and w_j respectively i.e. $d_i = \sqrt{\sum_{m=1}^{M}(p_m - w_{im})^2}$ and $d_j = \sqrt{\sum_{m=1}^{M}(p_m - w_{jm})^2}$. Here each M-dimensional p and w_k vectors can be denoted as: $p = \{p_1, p_2, \ldots, p_m, \ldots, p_M\}$ and $w_k = \{w_{k1}, w_{k2}, \ldots, w_{km}, \ldots, w_{kM}\}$. The value of ε is recommended to lie between 0.2 and 0.3 [27]. If the input is 'near' the midplane, the two adjoint weight vectors are adjusted, under the assumption that the input vector p and w_j belong to the same class, and p and w_i do not belong to the same class. The code word will be updated as follows:

$$w_i(t+1) = w_i(t) - \alpha(t)[p - w_i(t)] \tag{9a}$$

$$w_j(t+1) = w_j(t) + \alpha(t)[p - w_j(t)] \tag{9b}$$

This moves the weight vector w_j more towards the input vector p and the weight vector w_i away from the input vector p. Thus, given two weight vectors closest to the input, such that one belongs to the wrong class and the other belongs to the correct class, and so long as the input falls in a midplane window, the two weight vectors will be adjusted. Usually the classification results obtained with LVQ2.1 algorithm are more robust than with LVQ1 algorithm. The usual practice is to employ the LVQ2.1 algorithm after the LVQ1 algorithm has been implemented.

In the presented work, the proposed LVQ based classifier is configured as a three-class classification system where the classes correspond to normal heart beats (N), PVC beats (V) and the other beats (O). The reason behind using both LVQ1 and LVQ2.1 training algorithms to train LVQ neural network in classifying three categories of heart beats is to effectively separate the normal beats from the paced beats and the PVC beats from the LBBB and RBBB beats. Our experimentations demonstrated that LVQ1 algorithm alone was not able to create sharp and accurate boundaries between the classes, if the different types of heart beats have almost similar morphological characteristics but belong to different classes.

5. The proposed scheme for ECG beat classification

The presented work intends to develop a robust classification algorithm that can automatically classify ECG beats. As mentioned earlier, for this work, a window of −300 ms to 400 ms around R-wave was selected, as found in the database annotation. After preprocessing, each of the one-dimensional 252 sample ECG vectors is cross-correlated with the reference heart beat to obtain cross-correlogram 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 magnitude and phase cross-spectral density curves we created five different sizes of feature vectors. We considered 20, 30, 40, 50 and 60 feature set vectors considering magnitude and phase quantities up to N = 10, 15, 20, 25 and 30 harmonics. These feature vectors were utilized to train separate LVQ based classifiers and each trained classifier was subsequently tested. For training, we selected heart beats from different files of the MIT/BIH arrhythmia database as representatives of various classes. The robustness of the classifier was tested over a large set of ECG data files.

The classifier was trained with a total of 1975 heart beats from 18 files of MIT/BIH arrhythmia database. Those heart beats were selected from files #102, 104, 105, 106, 107, 114, 118, 119, 200, 201, 203, 208,210, 212, 214, 215, 228 and 231 of MIT/BIH arrhythmia database. The training dataset contains 810 normal beats, 455 PVC beats and 710 other beats. The total numbers of heart beats used for training were very small in comparison to the total beats of the database. This extreme skewness among the training and testing systems was employed to check the generalization capability of the proposed system, when implemented in testing phase.

In this scheme, for each LVQ classifier developed, the number of hidden layer neurons was set equal to the number of features to be examined. This means, for feature vectors, each of size $2N$ = 20, 30, 40, 50 and 60, the corresponding classifier was developed using 20, 30, 40, 50 and 60 neurons, respectively. After training, the classifier was tested using 93,246 beats from 40 files of the MIT/BIH database, out of which, training dataset used only 18 files, and the remaining 22 files were completely new to the classifiers. In addition, less than 5% (i.e.1975) of the total beats in 18 training files were used for training the LVQ network. The flow chart of the proposed scheme is shown in Fig. 2. All programs were developed using MATLAB® version 7.0 platform, utilizing the neural network toolbox [27].

To determine the performance of the classifier, three popular performance metrics are considered. They are: accuracy, sensitivity and positive predictivity [12,14]. Accuracy indicates the performance of the classifier to perform three-class classification tasks, while how specific the classifier is in classifying each class of heart beat is measured using sensitivity and positive predictivity metrics. The overall accuracy of the classifier for each file in MIT/BIH database is measured using the formula

$$A = 100\left(1 - \frac{N_e}{N_b}\right) \tag{10}$$

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

$$S_e = 100\left(\frac{TP}{TP+FN}\right) \tag{11a}$$

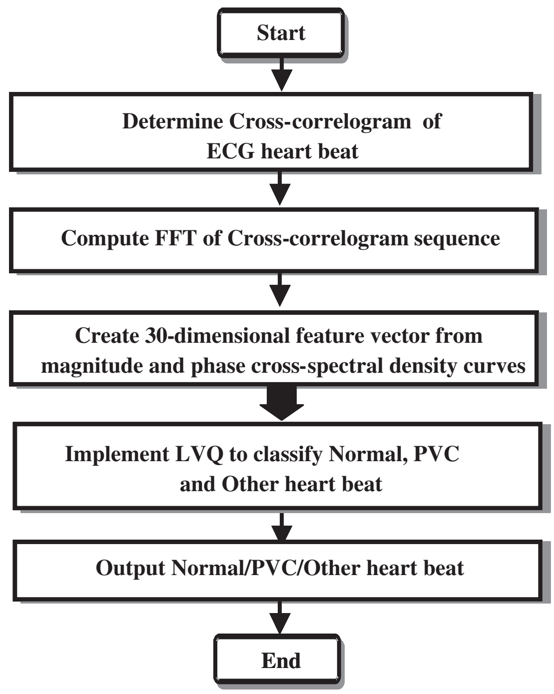

Fig. 2. Flowchart representation of the proposed scheme.

$$P_p = 100\left(\frac{TP}{TP + FP}\right) \tag{11b}$$

where TP represents true positives, FN represents false negatives and FP represents false positives. True positives are the number of heart beats, which have been correctly assigned to a certain class, whereas, false positives pertaining to a class are the number of heart beats, which actually belong to other classes but were incorrectly assigned to this specific class. A false negative pertaining to a class is the number of beats which actually belong to that class but was miss-classified and was assigned to other classes. The sensitivity S_e measures how successfully a classifier classifies true beats whereas positive predictivity P_p measures how exclusively it classifies a certain class.

After the classification accuracy, sensitivity and positive predictivity for each file in MIT/BIH database are individually determined, the next important step is to calculate the weighted average sensitivity and positive predictivity as a measure of the overall performance of the classifier. 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

$$S_{e_{WA}}(c) = \frac{\sum_{q=1}^{F} S_{e_q}(c) N_{b_q}(c)}{\sum_{q=1}^{F} N_{b_q}} \tag{12}$$

where $S_{e_{WA}}$ denotes weighted average sensitivity for the class c, 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 respectively, of file q belonging to class c. A similar equation was also used to determine the weighted average positive predictivity for each class.

6. Performance evaluation

We tested our LVQ based classifier over a large set of data files, using each of five feature sets discussed earlier. The accuracy, weighted sensitivity and positive predictivity of LVQ to classify normal (N), PVC (V) and other beats (O) for these feature sets are shown in Tables 2 and 3. A deeper study of Tables 2 and 3 reveals that the classifier produced best performance when the 30-feature vector set was utilized. The average overall accuracy obtained with 30-feature vector was 93.39% for the 18 files of the training set and 96.76% for the other 22 files. The overall average accuracy in beat classification over all files was 95.24%. Using Eq. (12), we found that, with 30-feature vector, the weighted average sensitivity was 97.49% for normal beats, 85.02% for PVC beats and 89.70% for other beats. Similarly the values of weighted average positive predictivity for normal, PVC and other beats were 97.25%, 88.77% and 94.91% respectively. Table 3 shows that these results, using 30-feature vectors, produced best results for S_e in two out of three classes, best results for P_p in two out of three classes and the second best result for P_p in the remaining class. This justifies our rationale behind choice of 30-feature vectors, for the classifier designs carried out. Table 4 shows a comprehensive tabulation of classification accuracy with sensitivity and positive predictivity, for each class in all 40 files of the MIT/BIH database, obtained with 30 feature set vector.

The classification performance of LVQ is next compared with Back Propagation Neural Network (BPNN) and Elman's Recurrent Neural Network (ERNN) based classifiers [19], with each classification algorithm developed using identical

Table 2
Classification accuracy of 40 files obtained with different feature sets using LVQ.

FILE	20 features	30 features	40 features	50 features	60 features
100	97.97	98.55	94.50	97.36	97.97
101	99.09	99.25	98.82	98.87	98.77
102	83.20	96.89	96.06	95.84	95.61
103	99.57	99.90	99.62	99.62	99.62
104	84.15	86.84	86.71	89.54	86.84
105	90.31	90.04	89.57	87.82	88.05
106	85.00	89.29	88.60	89.39	89.39
107	94.43	97.10	93.26	91.66	84.78
109	61.98	98.78	98.66	98.34	94.07
112	98.82	99.72	98.38	96.65	98.58
113	10.93	99.72	92.75	38.93	96.82
114	71.71	89.45	73.36	60.15	60.20
115	98.62	100.0	99.13	99.33	99.74
116	98.55	99.46	98.51	97.68	98.67
118	94.46	98.24	98.11	98.64	98.16
119	99.85	99.95	98.94	99.60	99.75
121	93.77	96.29	89.84	88.66	78.99
122	99.68	99.96	95.39	99.80	99.84
123	99.54	99.67	99.60	99.74	99.54
200	93.84	94.54	93.19	90.46	93.50
201	93.06	93.17	92.66	93.17	92.91
202	87.16	95.74	89.74	89.60	89.27
203	64.20	80.99	78.21	66.82	59.57
205	98.27	98.53	98.57	98.38	98.61
208	86.01	88.25	87.06	90.86	90.48
210	83.50	93.73	71.90	79.38	76.17
212	45.16	97.74	95.48	93.15	96.83
213	87.87	86.89	46.17	77.69	45.86
214	88.14	96.59	95.58	96.90	96.64
215	93.07	96.40	95.63	94.67	96.28
217	76.47	81.78	45.92	82.55	40.44
219	84.29	96.00	96.84	95.86	95.73
220	95.36	96.24	95.50	95.41	95.41
221	99.84	99.79	99.30	99.51	99.75
223	87.40	93.24	90.40	90.93	88.74
228	88.05	91.91	86.93	86.35	89.03
230	97.87	98.98	97.52	98.23	98.36
231	95.35	99.81	99.36	99.87	98.92
233	87.85	94.70	94.83	94.87	94.77
234	95.31	95.57	88.95	66.38	91.60
Average accuracy (%)	87.24	95.24	90.74	90.22	89.86

Table 3
Sensitivity and positive predictivity evaluation for various feature sets.

Feature set	Average accuracy (%)	Normal beats		PVC beats		Other beats	
		S_e	P_p	S_e	P_p	S_e	P_p
20	87.24	92.27	95.77	75.39	88.46	73.51	93.98
30	**95.24**	**97.49**	**97.25**	**85.02**	**88.77**	**89.70**	**94.91**
40	90.74	92.16	96.85	85.31	85.48	84.81	94.60
50	90.22	91.08	97.02	82.94	86.39	89.16	94.64
60	89.89	91.18	97.05	86.72	84.08	83.58	95.03

Table 4
Comprehensive results for training and testing files with 30-features.

File	Beats	Accuracy	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	100.0	98.55	1	100.0	100.0	33	0.00	0.00
101	1863	99.25	1858	99.52	99.78	0	–	–	5	0.00	0.00
102	2185	96.89	99	91.92	85.05	4	50.00	3.77	2082	97.21	99.95
103	2082	99.90	2080	100.0	99.90	0	–	–	2	0.00	0.00
104	2227	86.84	163	53.37	34.39	2	100.0	1.85	2062	89.48	98.88
105	2570	90.04	2524	91.44	99.18	41	9.76	2.48	5	40.00	2.44
106	2026	89.29	1506	96.28	91.25	520	69.04	90.89	0	–	–
107	2135	97.10	0	–	–	59	84.75	50.51	2076	97.45	99.66
109	2530	98.78	0	–	–	38	60.53	71.88	2492	99.36	99.76
112	2537	99.72	2535	99.80	99.92	0	–	–	2	0.00	0.00
113	1793	99.72	1787	100.0	99.72	0	–	–	6	16.67	100.0
114	1877	89.45	1818	90.15	99.09	43	86.05	57.81	16	18.75	1.89
115	1951	100.0	1951	100.0	100.0	0	–	–	0	–	–
116	2410	99.46	2300	99.78	99.87	109	93.58	97.14	1	0.00	0.00
118	2276	98.24	0	–	–	16	31.25	83.33	2260	98.72	99.87
119	1985	99.95	1541	100.0	100.0	444	99.78	100.0	0	–	–
121	1861	96.29	1859	96.40	99.89	1	0.00	0.00	1	0.00	0.00
122	2474	99.96	2474	99.96	100.0	0	–	–	0	–	–
123	1516	99.67	1513	99.80	100.0	3	33.33	100.0	0	–	–
200	2599	94.54	1742	98.97	94.73	825	88.73	99.46	32	3.13	2.33
201	1961	93.17	1623	99.63	93.90	198	95.46	91.30	140	15.00	65.63
202	2134	95.74	2059	98.01	97.58	19	89.47	68.00	56	14.29	19.51
203	2978	80.99	2527	81.36	96.80	444	79.96	58.48	7	14.29	0.40
205	2654	98.53	2569	99.77	99.07	71	73.24	94.55	14	0.00	0.00
208	2953	88.25	1585	98.42	90.02	992	93.45	89.83	376	31.65	63.30
210	2648	93.73	2421	96.65	97.62	194	72.68	77.47	33	3.03	1.45
212	2746	97.74	922	99.24	94.72	0	–	–	1824	96.96	99.66
213	3249	86.89	2639	99.85	87.34	220	84.55	83.78	390	0.51	20.00
214	2260	96.59	0	–	–	256	82.42	90.56	2004	98.40	98.95
215	3361	96.40	3193	99.88	97.26	164	31.10	98.08	4	0.00	0.00
217	2206	81.78	244	68.44	63.02	162	93.21	34.09	1800	82.56	99.20
219	2152	96.00	2080	96.83	99.60	64	78.13	81.97	8	25.00	2.90
220	2046	96.24	1952	99.59	96.57	0	–	–	94	26.60	75.76
221	2425	99.79	2029	99.90	99.90	396	99.24	99.75	0	–	–
223	2603	93.24	2027	99.31	93.37	473	87.53	97.41	103	0.00	0.00
228	2051	91.91	1686	94.37	99.13	362	81.22	90.18	3	0.00	0.00
230	2254	98.98	2253	98.98	100.0	1	100.0	7.69	0	–	–
231	1569	99.81	314	100.0	99.37	2	50.00	100.0	1253	99.84	99.92
233	3077	94.70	2229	98.39	95.35	830	86.51	96.38	18	16.67	9.38
234	2751	95.57	2698	97.22	98.31	3	100.0	37.50	50	6.00	4.00
Total	93,246	–	67,037	–	–	6957	–	–	19,252	–	–
Average	2331.20	95.24	1675.9	–	–	173.93	–	–	481.30	–	–
Wt. avg.	–	–	–	97.49	97.25	–	85.02	88.77	–	89.70	94.91

feature sets in each case. BPNN and ERNN both incorporate an MLP three layer architecture where the second layer contains hidden layer neurons. In second layer, ERNN contains context units in addition to hidden layer neurons. Number of hidden layer neurons for both BPNN and ERNN classifiers is equal to the number of features considered in each case. The performances of BPNN, ERNN and LVQ based multiclass classifiers, for five different feature sets, as discussed, are shown in Table 5. BPNN produced maximum classification accuracy of 84.16% using 30 features vector, whereas ERNN produces maximum classification accuracy of 88.43% using 20 features vector. Out of five cases, in four cases LVQ produced superior results. The best result obtained is with LVQ when 30-feature vectors are employed and it could produce an average accuracy of 95.24%. Hence, it can be easily seen that LVQ based system is much superior compared to other competing algorithms in terms of overall classification accuracy.

To have another realistic understanding of the strength of the proposed scheme, the results can be compared with

Table 5
Performance of LVQ in comparison with BPNN and ERNN.

Algorithms	20 features	30 features	40 features	50 features	60 features
BPNN	83.31	84.16	82.48	82.25	82.42
ERNN	**88.43**	85.39	80.39	80.23	78.76
LVQ	87.24	**95.24**	**90.74**	**90.22**	**89.86**

the results of some other competing classification algorithms reported so far, for similar problems. The classification accuracy reported by Inan et al. [12] was 95.16%. This scheme used 43 features that included 42 dyadic wavelet decomposition samples and one R–R time interval feature. The classification accuracy reported in [12] without R–R interval feature was only 81.7%. In comparison, our proposed LVQ based classifier could produce a classification accuracy of 95.24%, using 30 features and this scheme considered heart beat morphology only. When compared to the scheme proposed by Shyu et al. [11], for the seven records considered, they could achieve an overall accuracy of 97.04%. For the same set of files, our proposed algorithm could achieve an accuracy of 98.08%. Hence, it can be inferred that the proposed algorithm was able to achieve better accuracy, even with smaller-sized feature vectors that can reduce the computational burden and storage requirement.

7. Conclusions

In this presented work an effort has been made to develop a robust heart beat detection algorithm that can classify normal/PVC/other heart beats automatically. This work proposes a hybrid methodology of using cross-correlation as an efficient feature extraction tool, which, when coupled with the LVQ classifiers, can efficiently be employed as an automated ECG beat classification mechanism. The classifier can efficiently segregate input ECG beats into normal beats, PVC beats, and other beats which includes RBBB, LBBB and paced beats. The performance of the proposed scheme has been tested using benchmark signals available in MIT/BIH arrhythmia database, where a small sized training file and large-sized testing file was used to demonstrate the generalization capability of the system, when presented with unknown inputs. An overall classification accuracy of 95.24% was achieved over the 40 files of the database. This scheme has shown how effectively frequency domain information of cross-correlograms can be utilized to extract relevant features. A comparative study with other ANN based classifiers and with several competing algorithms, recently developed for the same purpose, has been carried out to justify the usefulness of the proposed scheme. It has been ably demonstrated that the proposed scheme could outperform all previous schemes and could mostly achieve encouraging results with a lighter computational burden.

The proposed algorithm was tested for 40 data files from the MIT/BIH arrhythmia database and these 40 files were chosen identical to those chosen in the work of Inan et al. [12]. The rationale behind this choice was to make an appropriate comparison between two competing algorithms on the basis of identical choice of benchmark data.

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