Patient-specific ECG beat classification technique

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Electrocardiogram (ECG) beat classification plays an important role in the timely diagnosis of the critical heart condition. An automated diagnostic system is proposed to classify five types of ECG classes, namely normal (N), ventricular ectopic beat (V), supra ventricular ectopic beat (S), fusion (F) and unknown (Q) as recommended by the Association for the Advancement of Medical Instrumentation (AAMI). The proposed method integrates the Stockwell transform (ST), a bacteria foraging optimisation (BFO) algorithm and a least mean square (LMS)-based multiclass support vector machine (SVM) classifier. The ST is utilised to extract the important morphological features which are concatenated with four timing features. The resultant combined feature vector is optimised by removing the redundant and irrelevant features using the BFO algorithm. The optimised feature vector is applied to the LMS-based multiclass SVM classifier for automated diagnosis. In the proposed technique, the LMS algorithm is used to modify the Lagrange multiplier, which in turn modifies the weight vector to minimise the classification error. The updated weights are used during the testing phase to classify ECG beats. The classification performances are evaluated using the MIT-BIH arrhythmia database. Average accuracy and sensitivity performances of the proposed system for V detection are 98.6% and 91.7%, respectively, and for S detections, 98.2% and 74.7%, respectively over the entire database. To generalise the capability, the classification performance is also evaluated using the St. Petersburg Institute of Cardiological Technics (INCART) database. The proposed technique performs better than other reported heartbeat techniques, with results suggesting better generalisation capability.

1. Introduction: Electrocardiogram (ECG) is a non-invasive tool that is used to diagnose the electrical activity of heart. It is very difficult for doctors to analyse long ECG records in a very short duration, and also human eye is poorly suited to detect the morphological changes of ECG signal continuously. A real-time automated ECG signal analysis system is generally used by clinicians in their own clinical settings for detecting cardiac abnormalities, which regularly appears as an indication of a heart disease that may be life-threatening and need instant therapy [1]. Therefore, a powerful computer-aided diagnosis (CAD) system is required for early detection of cardiac arrhythmias. Nowadays, the automatic ECG signal analysis faces a difficult problem due to a large variation in morphological and temporal characteristics of the ECG waveforms of different patients and the same patients [2]. At different times, the ECG waveforms may differ for the same patient to such an extent that they are unlike each other and at the same time alike for different types of beats. Owing to this, the beat classifiers perform well on the training data but provide poor performance on the ECG waveforms of different patients [2].

In the last decade, a number of researchers have reported automated classification and detection of heartbeat patterns based on the features extracted from ECG signals, such as frequency-based features [3], Hermite polynomials [4] and wavelet transform coefficient features [5]. Most of them use either time- or frequency-domain representation of the ECG signals as features. Depending on the features, the classification is allowed to recognise between classes. In most cases, the performances of ECG classification techniques based on earlier researchers are not consistent when classifying the ECG waveform of a new patient. This makes them unreliable to use clinically and causes serious degradation in their classification performance when used for a larger database [6]. Furthermore, the Association for the Advancement of Medical Instrumentation (AAMI) offers the standards and recommended practices for reporting the performance results of the ECG heartbeat classification technique [7]. This recommended practice gives a protocol for a reproducible test with realistic clinical requirements, and shows a record-by-record presentation of results that reflect an algorithm's ability to detect events of clinical significance [7]. However, despite many ECG signal classification methods being explained in the earlier literature, only a few [1, 6, 8, 9] have followed the AAMI standards. The proposed method follows the AAMI standards, and the experimental results are compared with these techniques [1, 6, 8, 9].

In this Letter, a novel approach is proposed for a patient-adapted ECG heartbeat classification technique that consists of a pre-processing stage, feature extraction, feature selection and a classifier. Here, the features are extracted in the time-frequency domain using the S-transform (ST) [10]. The ST has the following advantages compared to the wavelet transform (WT): (i) frequency invariant amplitude response, (ii) progressive resolution and (iii) absolutely referenced phase information. In addition, ST represents the signal in the time-frequency domain, rather than the time-scale axis used in WT [10]. Therefore, interpretation of the frequency information in the ST is more straightforward than that in the WT. This will be beneficial in extracting the important features from the ECG signal. A bacteria foraging optimisation (BFO) algorithm is used to remove the redundant and irrelevant features from the extracted feature vectors of ECG signals. The selected best features are applied to the input of the classifier for ECG beat classification.

In the present work, a least mean square (LMS)-based [11] multiclass support vector machine (SVM) is proposed to improve the performance of the ECG beat classification. SVM is based on the structural risk minimisation principle and uses the empirical risk minimisation method to provide better generalisation ability than the traditional classification technique [12]. The goal of this method is to project the input data into higher dimensional space where the different classes become linearly separable to reconstruct an optimal separating hyperplane. Many kernel functions such as polynomials, splines, radial basis functions (RBF) and sigmoids can be used in the SVM classifier. The performance of the SVM classifier depends mostly on these kernel functions and adjustable weight vectors. However, no such method exists that allows one to decide the best kernel function in a data-dependent way [13]. In one of our earlier works [14], LMS is used in one-class SVM to detect normal or abnormal heart sound. The RBF kernel is taken empirically in this work and a one-against-all (OAA) strategy of multiclass SVM

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is considered here because of its simplicity and better performance. The proposed technique relies on the basic idea that, in order to improve the performance of the SVM classifier, the pattern separability or the margin between the clusters needs to be increased. To implement this idea, the LMS algorithm is adopted to modify the Lagrange multiplier, which, in turn, modifies the weight vector to minimise the classification error, and the width of the separation region between the clusters will be increased. If the system is an adaptive linear combiner, and the input vector and the desired response are available, the LMS algorithm is generally the best choice because of its simplicity, ease of computation, and that it does not require off-line gradient estimations or repetitions of data [11, 15]. The LMS algorithm also provides stable and robust performance against different signal conditions [11]. Here, the classification error is represented by the minimum distance of data points from the margin of the separation region for those data points that fall inside the region of separation or make misclassification. Therefore, as the number of iterations of the LMS algorithm increases, weight vector performs a random walk [11, 14] about the solution of optimal hyperplane having a maximal margin [16] that minimises the classification error. The experimental results show that the proposed method yields better classification performance compared to earlier reported techniques [1, 6, 8, 9].

This Letter is organised as follows: Section 2 represents the ECG database used in this work. The proposed framework is explained in Section 3. The experimental results and comparisons with earlier reported works are described in detail in Section 4. Finally, conclusions are given in Section 5.

2. ECG data: The MIT-BIH arrhythmia database [17] contains 48 ECG recordings, each containing a 30 min segment selected from 24 h recordings of the 48 individuals and sampled at 360 Hz. Four recordings of the MIT-BIH ECG database mostly contains paced beats. According to the AAMI recommended practice, these paced recordings are excluded in the experimental evaluation process because they do not retain sufficient signal quality for reliable processing [1, 7]. The classification performances are evaluated using 44 recordings from the MIT-BIH arrhythmia database [17]. The AAMI recommendations are used to combine the beats into five classes of interest [6, 7]: normal beat, left bundle branch block, right bundle branch block, atrial escape and nodal junction escape beats belong to class N category, class V contains premature ventricular contraction and ventricular escape beats, class S consists of atrial premature (AP), aberrated premature (aAP), nodal junction premature (NP) and supra-ventricular premature (SP) beats, class F contains only fusion of ventricular and normal (fVN) beats and class Q which is represented as an unknown beat and contains paced beat (P), fusion of paced and normal (fPN) beats and unclassified beats. On the other hand, the INCART database contains 75 recordings, each containing 30 min segments selected from 24 h recordings of 32 Holter records and sampled at 257 Hz [18]. In this work, the INCART database is used to validate the generalisation capability of the proposed technique.

3. Proposed framework: The detail block diagram of the ECG signal classification is shown in Fig. 1. It mainly consists of the following stages: pre-processing, QRS complex detection, feature extraction, feature selection and classification.

3.1. Pre-processing and QRS complex detection: The pre-processing stage involves the following two sub-stages: (i) The amplitude of ECG signals is normalised to a mean zero and the amplitude variance for each ECG signal is eliminated. (ii) Each ECG signal is passed through a band pass filter at 0.1–100 Hz to remove the noises [17]. The QRS complexes are determined by the Pan-Tompkins algorithm [19] from the pre-processed ECG signal.

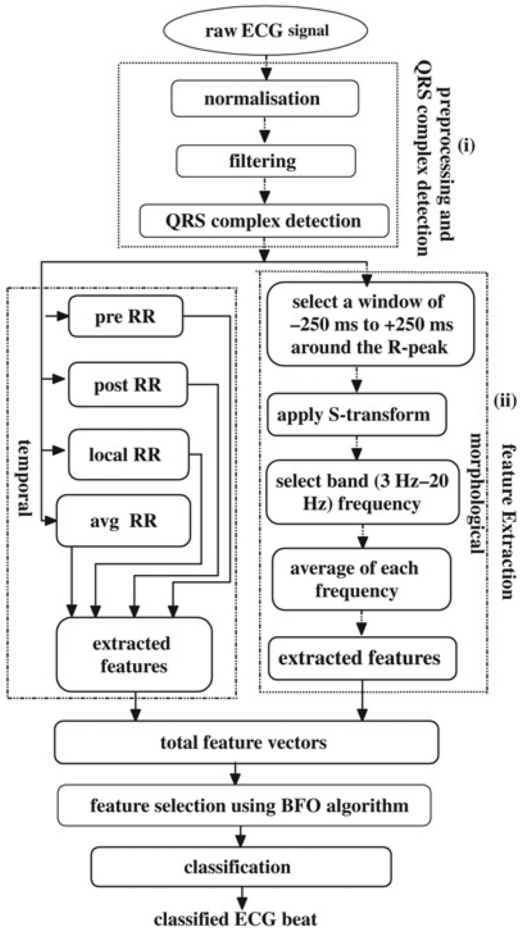

Figure 1 *Block diagram of the proposed methodology*

3.2. Feature extraction: Two types of features are extracted from one ECG heartbeat: (i) temporal features and (ii) morphological features. However morphological information is not sufficient to classify the ECG heartbeats due to a significant variation in ECG morphology among different patients. Therefore, ECG morphological information is coupled with timing information, which is more constant among patients, in order to achieve high classification performance for a larger dataset [5]. A block diagram of the feature extraction method is depicted in Fig. 1(ii).

3.2.1 Temporal feature: RR-intervals are calculated as the interval between successive heartbeats. The four ways to extract the temporal features are as follows: (i) pre-RR interval: RR-interval between a given heartbeat and the previous heartbeat; (ii) post RR-intervals: the RR-interval between a given heartbeat and the following heartbeat; (iii) average RR-interval: the mean of RR-intervals for a recording that is considered as the same value for all heartbeats in a recording; and (iv) local average RR-interval: averaging the RR-intervals of ten RR-intervals surrounding a heartbeat [6]. Thus, the four-dimensional temporal features are obtained from each ECG heartbeat.

3.2.2 Morphological feature: The proposed morphological feature extraction technique is briefly described in Algorithm 1 (see Fig. 2). In time-frequency domain-based ST, the ECG signal is represented by (1).

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] e^{-2\pi^2 m^2/n^2} e^{i2\pi mj/N} \qquad (1)$$

where $H[n/NT]$ is the Fourier transform of the time-domain ECG

Algorithm 1

1: Select a window of -250ms to +250ms around the R-peak which is found from the QRS detection algorithm, i.e. 180 samples are selected around the R-peak.
2: Apply ST on selected ECG signal to represent in time-frequency domain.
3: Select the information within 3-20 Hz band frequency from time-frequency domain represented ECG signal, because QRS complex energy and least amount of high and low frequency noises are laid in this band [19].
4: Obtain the morphological feature from each sample by averaging its frequency from the time-frequency domain represented ECG signal.

Figure 2 *Morphological feature extraction*

signal and j, m, $n = 0, 1, \ldots, (N-1)$ [10, 20]. In the proposed method, a 184-sample combined feature set is obtained from each ECG heartbeat by appending the four temporal features with 180 sample morphological features.

3.3. Feature selection: The length of the combined features are reduced here using the BFO algorithm which removes the redundant and irrelevant features. The BFO technique is used in this work because it can deal with complex search spaces in situations where only minimum knowledge is available, and it converges quickly in order to reach the global minimum solution [21]. The feature set of each record is optimised individually by the BFO algorithm [22]. The resultant optimised feature subset is applied to the input of the classifier for classifying the ECG arrhythmias.

3.3.1 Fitness function: A fitness function of the BFO assesses the quality of a solution in the evaluation step. In every generation, the fitness value of each bacteria is evaluated by a fitness function. This evolution is driven by the fitness function J [22]. Let $p_1, p_2, \ldots, p_L$ and $N_1, N_2, \ldots, N_L$ denote the classes and number of samples within each class, respectively. Let M_i be the mean of ith class in the feature space, where $i = 1, 2, \ldots, L$. Then M_i can be calculated as $M_i = (1/N_i)\sum_{j=1}^{N_i} P_j^i$, $i = 1, 2, \ldots, L$, where P_j^i, $j = 1, 2, \ldots, N_i$, represents the samples from class p_i and contains only the selected features, and the total mean is $M_0 = (1/r)\sum_{i=1}^{L} N_i M_i$, where r is the total number of samples for all classes. The fitness function is computed as $J = \sqrt{\sum_{i=1}^{L} (M_i - M_0)^T (M_i - M_0)}$. The proposed classification technique is patient-specific, thus it allows variable feature length. For example, the reduced feature length of the ECG tape no 201 is 92, whereas for tape no 207 and 220 it is 89 and 96, respectively.

3.4. Classifier model: SVM is an excellent tool for classification problems with a good generalisation performance. It was originally a binary classification method designed by Vapnik [23]. ECG beat classification involves simultaneous discrimination of multiple classes; therefore, a number of multiclass SVM strategies can be adopted. The OAA strategy of multiclass SVM is a popular one, it is very simple, extremely powerful and also produces results that are often at least as accurate as other methods [24]. Therefore, the OAA strategy is followed in this work. An LMS-based multiclass SVM classifier is also proposed in this Letter to classify the heartbeats of an ECG signal. The procedure for making the proposed classifier is given as follows:

Step 1: Let us first consider, for simplicity, a supervised binary classification problem. Assume a training set consists of N data points $(x_i, y_i)_{i=1}^{N}$, where $x_i \in \Re^m$ is the ith input pattern and $y_i \in \Re$ is the ith output pattern. The input patterns are mapped by ϕ: $x_i \to \phi(x_i)$ from the input space to a feature space. To construct an optimal separating hyperplane with maximum margin and to minimise the classification errors, ξ_i, one solves the following quadratic programming (QP) problem

$$\min_{w,\xi} \left[\frac{1}{2} ||w||^2 + C \sum_{i=1}^{N} \xi_i \right] \quad (2)$$
$$\text{subject to } y_i(w\phi(x_i) + b) \geq 1 - \xi_i, \quad i = 1, 2, \ldots, N$$

where w represents the weight vector, C is the regularisation parameter that creates a tradeoff between the complexity of the machine and the number of non-separable points [11]. A kernel function is represented as $k(x_i, x) = \phi(x_i)^T \phi(x)$, the Lagrange function of (2) is simplified to

$$\max_{\alpha} \left[\sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_j y_i y_j k(x_i, x_j) \right] \quad (3)$$

$$w = \sum_{i=1}^{N} y_i \alpha_i \phi(x_i) \quad (4)$$

$$\sum_{i=1}^{N} \alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq C, \quad \forall i \quad (5)$$

where the α_is are Lagrange multipliers related to each training point. A kernel is used to construct the optimal hyperplane in the feature space without considering the feature space itself in explicit form [11]. The SVM constructs a decision function for a classifier in the following form

$$f(x) = w^T \phi(x) + b \quad (6)$$

where b is a real constant. Substituting the value w from (4) in (6).

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i \phi(x_i)^T \phi(x) + b \quad (7)$$

We know the kernel function $k(x_i, x) = \phi(x_i)^T \phi(x)$, so (7) is rewritten as

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i k(x_i, x) + b \quad (8)$$

Table 1 Summary table of beat-by-beat classification results for 24 recordings of the MIT-BIH arrhythmia database

	Class	N	V	S	F	Q		Class	N	V	S	F	Q
Proposed-1 method	N	40 936	303	538	50	15	Proposed-2 method	N	41 056	222	525	27	12
	V	273	4327	122	71	14		V	248	4393	82	68	17
	S	631	84	1612	3	9		S	512	86	1729	2	9
	F	127	67	22	393	3		F	107	80	13	410	2
	Q	3	3	0	0	2		Q	3	3	0	0	2

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Table 2 Classification performance (in %) of Ince *et al.* [1] and the proposed methods for 24 recordings of the MIT-BIH arrhythmia database

Method	N				V				S				F				Q			
	Acc	Sen	Spe	Ppr	Acc	Sen	Spe	Ppr	Acc	Sen	Spe	Ppr	Acc	Sen	Spe	Ppr	Acc	Sen	Spe	Ppr
Ince *et al.* [1]	95.0	97.0	84.1	97.0	97.6	83.4	98.1	87.4	96.1	62.1	98.5	56.7	99.2	61.4	99.7	73.4	99.9	0.0	99.9	0.0
Proposed-1	96.1	97.8	86.7	97.5	98.1	90.0	99.0	90.5	97.2	68.9	98.6	70.3	99.3	64.3	99.7	76.0	99.9	25.0	99.9	4.6
Proposed-2	96.7	98.1	88.8	97.9	98.5	91.4	99.1	91.8	97.5	74.0	98.7	73.6	99.4	67.0	99.8	80.9	99.9	25.0	99.9	4.8

We may define the decision function in the following form

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{N} y_i \alpha_i k(x_i, x_j) + b\right) \tag{9}$$

Step 2: It is seen from (9) that the decision function depends on desired outputs y_i, Lagrange multiplier α_i, kernel function $k(x_i, x)$ and bias b, where y_i and b are constant. Generally, a fixed kernel function is used at the training phase, which is taken empirically. Now, the decision function changes with changing the Lagrange multiplier. On the other hand, from (4), it can be shown that the weight vector w depends on three variable parameters y_i, α_i and $\phi(x_i)$, respectively. Now, the weight vector w changes with the changing of α_i, which in turn modifies the decision function. In this work, α_i is modified using the LMS algorithm to find out the optimal hyperplane with the maximum separating margin between classes such that the classification error is minimised at the training phase and the width of the separation region between the clusters will be increased. Those data points that fall inside the region of separation or show misclassified data at the training phase are taken to determine the classification error. The mean square error (MSE) is calculated as $\text{MSE} = (1/N_e)\sum_{j=1}^{N_e} E(j)^2$, where $E(j)$ is misclassification error and N_e is the number of data points that make misclassification. It is seen from the experiments that almost all data points are outside of the boundary of the separation region after weight vector modification. It is also noted that the region of separation between the clusters is enlarged for the proposed technique than when using standard SVM technique. Therefore, classification is easier for the proposed technique than the standard SVM technique.

Step 3: The classification of ECG beats involves simultaneous discrimination of multiple classes. Therefore, the OAA approach of multiclass SVM is applied for a K-class classification problem, where K is an independent binary classifier, each trained with distinguished training samples for one class with regard to the remaining class. In the multiclass SVM classifier, the Lagrange multiplier of each K independent binary classifier is modified which in turn modifies the weight vector using Step 2.

Step 4: The updated weights are stored based on modified Lagrange multipliers of each independent binary classifier and are used for testing purposes only.

4. Experimental results: In this work, 44 recordings of the MIT-BIH arrhythmia database are considered for classification of five heartbeat types following the AAMI standards and recommendations. A common training dataset [1], which contains a total of 245 representative beats, including 75 from each type-N, S and V beats, all (13) type F and all (7) type Q beats, is developed in this work. These beats are randomly selected from the first 20 recordings (picked from the range 100–124). The proposed LMS-based SVM classifier is trained with 245 common training beats and the first 5 min of the patient-specific ECG record. The remaining 25 min beats of each record, in which 24 (in the range of 200–234) out of 44 recordings are completely new to the classifier and are used as test patterns for performance evaluation. In this Letter, classification performances are evaluated using two approaches. The first approach is indicated as Proposed-1 method, whereas the second approach is represented as Proposed-2 method. The Proposed-1 method uses the original combined features, which include a morphological and temporal feature set, whereas the Proposed-2 method is based on a BFO reduced combined feature set. These feature sets from the two techniques are separately classified using the proposed LMS-based SVM classifier.

Table 1 summarises beat-by-beat classification results of ECG heartbeat patterns for 24 test recordings using Proposed-1 and Proposed-2 techniques. It is seen from Table 1 that 631 beats of S class are misclassified as N class beats in the Proposed-1 method, whereas for the Proposed-2 method, 512 beats S class are misclassified as N class beats. Similarly, for F class, 50 beatss of N class are misclassified as F class beats and 127 F class beats are misclassified as N class beats in the Proposed-1 technique. In the Proposed-2 method, 27 beats of N class are misclassified as beats of F class, whereas 107 F class beats are misclassified as N class beats. Table 2 represents the comparative performances of the proposed methods with the Ince *et al.* [1] method for five ECG heartbeat classes from 24 test recordings from the MIT-BIH arrhythmia database. Classification performance is evaluated using four common metrics, Accuracy (Acc), Sensitivity (Sen), Specificity (Spe) and Positive predictivity (Ppr) [1]. The proposed methods are also compared with the existing four methods [1, 6, 8, 9] that follow AAMI standards and recommendations in Table 3 in terms of V and S detection [1, 6] considered individually. The V detection in Table 3 is performed based on 11 recordings that are common to all existing methods. The performance results of S detection are based on 14 recordings that are used in [1, 6, 9] but not used in [8], since the work [8] is limited to V detection. The V and S classification performances are shown in Table 3 using 44 recordings from the MIT-BIH arrhythmia database. For the evaluation of the range of 100–124 recordings, the proposed classifier is trained with 245 common training beats and the first 5 min of the patient-specific beats. These recordings are tested on the rest of the beats of these ECG recordings in a patient-specific way. It can be noticed from Table 3 that the performance of the proposed method is better than earlier reported techniques for V and S detection. Tables 2 and 3 represent that the Proposed-1 method shows superior performance for most of the beats, whereas the Proposed-2 method yields better performance than earlier reported techniques. It is seen from Table 3 that the specificity of the Proposed-1 technique is comparably less than the other techniques in case of S detection due to a higher number of normal beats being misclassified as supra-ventricular beats. The atrial escape beat in class N is difficult to distinguish from the atrial premature beat in class S owing to its similar morphological characteristics. In the Proposed-2 method, sensitivity, accuracy, specificity and positive predictivity of V detection are 95.7%, 99.0%, 99.6% and 96.3%, respectively, whereas the Proposed-1 method achieves sensitivity, accuracy, specificity and positive predictivity as 93.9%, 98.5%, 99.5% and 96.1%, respectively for selected 11 ECG records. For S detection, the Proposed-2 technique shows the sensitivity, accuracy, specificity and positive predictivity as 84.9%, 98.2%, 98.9% and 82.6%, respectively, whereas the Proposed-1 technique provides 82.3%, 97.5%, 98.4% and 75.4%, respectively, for 14 ECG records. From the performance statistics, it is seen that the sensitivity of S detection is not as good as V detection due to a deficiency in

Table 3 Performance comparison (in %) of V and S detections

Methods	Recordings	V				S			
		Acc	Sen	Spe	Ppr	Acc	Sen	Spe	Ppr
Hu *et al.* [8]	200, 202, 210, 213, 214, 219, 221, 228, 231, 233, 234 for V detection and 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234 for S detection	94.8	78.9	96.8	75.8	N/A	N/A	N/A	N/A
Chazal *et al.* [6]		96.4	77.5	98.9	90.6	92.4	76.4	93.2	38.7
Jiang *et al.* [9]		98.8	94.3	99.4	95.8	97.5	74.9	98.8	78.8
Ince *et al.* [1]		97.9	90.3	98.8	92.2	96.1	81.8	98.5	63.4
Proposed-1		98.5	93.9	99.5	96.1	97.5	82.3	98.4	75.4
Proposed-2		99.0	95.7	99.6	96.3	98.2	84.9	98.9	82.6
Ince *et al.* [1]	44 recordings of the MIT-BIH arrhythmia database	98.3	84.6	98.7	87.4	97.4	63.5	99.0	53.7
Proposed-1		98.5	90.8	99.1	88.2	97.0	70.0	98.7	62.1
Proposed-2		98.6	91.7	99.1	89.3	98.2	74.7	99.0	66.9

Table 4 Performance comparison between the proposed method and [18, 25] using INCART database

Method	Database	V		N		S		F	
		Sen	Ppr	Sen	Ppr	Sen	Ppr	Sen	Ppr
Peng *et al.* [18]	All recordings from INCART	93.4	66.5	–	–	–	–	–	–
Llamedo [25]		82.0	88.0	92.0	99.0	85.0	11.0	–	–
proposed		94.3	89.1	93.3	99.7	87.0	19.3	51.8	15.3

class S patterns during the training phase and also because the intra-variation of patterns makes it complex to detect [9]. It is difficult to classify between N class and S class because the QRS complex associated with an atrial premature beat in the S class has normal QRS duration and the same morphology as that of the sinus beat. Therefore, more S beats are misclassified as normal beats. Fusion beats are difficult to distinguish from normal beats because fusion beats are the union of ventricular and normal beats and their morphology and timing information also closely resembles those of normal beats. However, the detection accuracy of normal beats and fusion beats are comparably more than the earlier reported techniques [1].

After the training process, the performance of the proposed method is evaluated using INCART database. The proposed technique is validated on an independent INCART database [17, 18]. The validation results are shown in Table 4, which are compared with the other existing methods. The results verify the validity of the technique achieving significant performance improvement over the existing methods.

The automatic ECG beat detection provides some errors in beat detection, such as missed heartbeats, errors in heartbeat fiducial point identification and erroneously detected heartbeats. A number of beat-detection techniques have been reported. Its error rate is much lower than the error rate of our ECG beat classification method. Thus, it is strongly recommended that automating the heartbeat detection process would not degrade the ECG beat classification performance.

5. Conclusion: In this Letter, an automatic classification technique is proposed to classify the ECG beats for each patient individually. Feature extraction, feature selection and classification are important steps for the detection of ECG heartbeats. In the proposed technique, the ST is employed to extract the significant morphological features which are appended with four temporal features to form a combined feature set. The BFO algorithm is used in this work to optimise the feature vectors by removing redundant and irrelevant features and the reduced feature set is used as an input of the LMS-based multiclass SVM classifier. The Lagrange multiplier is modified based on the LMS algorithm, which in turn modifies the weight vector to minimise the classification error at the training phase, and these updated weights are used in the testing phase to classify ECG beats. The experiments are conducted on the benchmark of the MIT-BIH arrhythmia database based on the AAMI standards and recommendations. The results in Table 4 suggest that the selected features have good generalisation capability when evaluating the performance in heartbeats not considered during the training phase, like the ones from the INCART database. For 24 common testing records, the V detection shows an accuracy of 98.4%, sensitivity of 91.4%, specificity of 99.1% and positive predictivity of 91.8%, whereas the S detection finds the accuracy as 97.5%, sensitivity as 74.0%, specificity as 98.7% and positive predictivity as 73.6% using the Proposed-2 method. An overall average sensitivity of 74.7% and specificity of 99.8% are achieved for S detection using the Proposed-2 technique, whereas an average sensitivity of 91.7% and specificity of 99.1% are achieved for V detection over all 44 patient-recordings of the MIT-BIH arrhythmia database. These results show that a significant improvement is achieved for the proposed ECG heartbeat classification methods when compared to other existing methods.

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