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SVM Based ECG Beat Classification Method for Unsupervised ECG Diagnosis Systems

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ABSTRACT

This paper presents a support vector machine (SVM) based electrocardiogram (ECG) beat classification method for clear identification of nature of illness under unsupervised ECG diagnosis environments. The proposed method takes reference of data on the linear separable line. The linear line is termed as decision line where the positive information and negative information will be separated by the hyper plane and required data will be acquired. So that SVM gives best classification output in terms of accuracy. Based on the previous signal quality assessment (SQA) method the accuracy and robustness are evaluated using different normal and abnormal ECG signals taken from the standard MIT-BIH arrhythmia database. The SQA method undergoes three stages: the ECG signal quality assessment, ECG signal reconstruction and R-peak detection, ECG beat classification. In ECG signal by preserving QRS waveform we can decrease background noises.

KEYWORDS: *ECG beat classification, ECG arrhythmia recognition, ECG signal quality assessment, support vector machine.*

INTRODUCTION

Electrocardiogram (ECG) is one of the most common signals used in medical practice because of its noninvasive nature and the information it contains. Its analysis can be used to assess the patho physiological condition of the heart. Several systems for ECG recording and analysis have been developed for more than a century. Modern systems use computer technology to provide automated diagnosis. Several methods have been proposed for arrhythmia detection and classification. Those methods are based on the processing of the signal to remove noise and artifacts, extraction of certain features related to diseases, and analysis of the features to obtain the final decision. These systems are evaluated using standard databases. The ECG beat classification method generally consists of three main stages: (i) preprocessing, (ii) feature extraction and (iii) classification.

A. *Related Works and Motivation:*

Error free and reliable classification of electrocardiogram (ECG) beats is most important in automatic ECG diagnosis applications. Studies demonstrated that the accurate determination of R-peaks, ECG beat extraction, and ECG morphological feature extraction is still a tough task in the presence of different kinds of artifacts and noises including baseline wander (BW), abrupt change (ABC), flat line (FL), power line interference (PLI), muscle artifacts (MA) and instrument noise (IN). The existence of the noises leads to more false

alarms due to the measurement of noisy feature parameters. Denoising technique(s) are used to reduce the effect of the aforementioned noise sources but these alter the morphological shapes of the local waves of both noise-free and noisy ECG signals which can lead to wrong diagnosis. Thus, an automatic quality assessment of ECG signals can capable of reducing false alarm rates and misclassification rates. Numerous attempts have been made for assessing and grading the quality of the ECG signals.

B. *ECG Signal Quality Assessment Algorithms:*

Existing ECG-SQA methods were based on the linear signal subspace analysis with empirical mode decomposition and statistical approaches, QRS complex and RR interval-based features and modified complete ensemble empirical mode decomposition and temporal features. Most aforementioned methods include two major steps: feature extraction and signal quality grading. For computing the signal quality indexes (SQIs), different time-domain and spectral features, RR-interval and QRS complex-based features are extracted from the processed ECG signal which classifies the recorded ECG signals into two quality groups such as acceptable and unacceptable; good and bad based on the measured SQI values.

C. *Contribution of this Paper:*

This paper presents a new quality-aware ECG beat classification method for unsupervised ECG monitoring applications. It consists of three major stages: (*i*) the ECG signal quality assessment (ECG-SQA) ("*acceptable*" or "*unacceptable*") based on our previous modified complete ensemble empirical mode decomposition (CEEMD) and temporal features, (*ii*) the ECG signal reconstruction and R-peak detection and (*iii*) the ECG beat classification. At first the ECG-SQA is implemented based on the modified CEEMD algorithm and temporal features. In the second stage, the acceptable ECG signals are further sort out for classifying the ECG beats present in the ECG signal. In the third stage, the heartbeat classification is performed using the normalized cross-correlation (NCC) based waveform similarity metric score which is computed between a test heartbeat template and the reference templates that are stored in the heartbeat database.

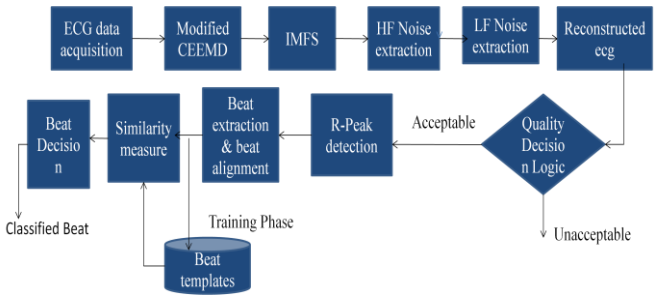


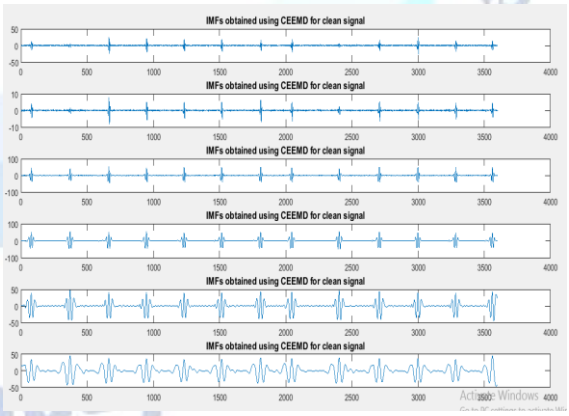
Fig.1: Block diagram of the quality-aware heartbeat classifier

PROPOSED QUALITY-AWARE ECG BEAT CLASSIFIER

A simple block diagram shown in fig.1 consists of five steps: modified CEEMD based ECG decomposition, the CEEMD based ECG signal quality assessment, the combined R-peak detection and ECG enhancement, R-peak alignment and the ECG beat extraction and the beat similarity matching.

A. *Modified CEEMD Based ECG Decomposition:*

At first we have to check the signal quality and then apply the empirical mode decomposition (EMD) it is a general nonlinear, non-stationary signal processing method. According to the principle of EMD, it decomposes a signal into a sum of oscillatory functions called intrinsic mode functions (IMF).



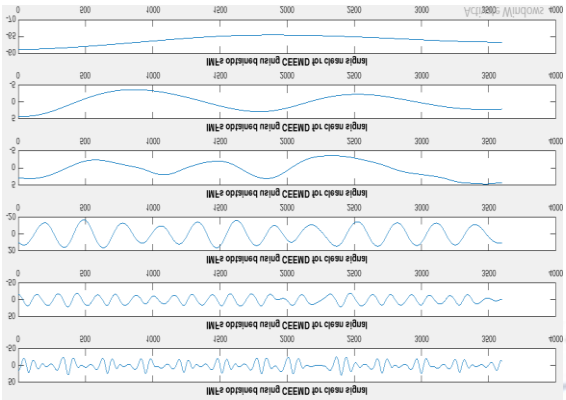


Fig.2: The IMFs obtained using the modified CEEMD algorithm for the clean ECG signal including baseline wanders and muscle artifacts

The CEEMD is used for decomposition of the ECG signals instead of the EMD and ensemble EMD algorithms because of two reasons: (i) the mode mixing problem of the basic EMD, where different oscillations exist in the same IMF or similar oscillations exist in different IMFs; and (ii) the ensemble EMD (EEMD) producing varying number of IMFs. In CEEMD method, a particular noise is added at each stage of the decomposition and a unique residue is computed to obtain each mode. It was shown that the CEEMD algorithm provides exact signal reconstruction and division of the modes have been improved with low mathematical cost which requires less than half the sifting iterations as compared to that of the EEMD algorithm. The proposed stopping criteria is based on number of zero crossings (NZC) and maximum absolute amplitude (MAA) to obtain the baseline wanders and to know its severity in the residue signal. This stopping criterion can reduce the computational load by stopping the further decomposition which may not be required for analysing the ECG components

B. ECG Signal Quality Assessment:

For signal quality assessment, the decomposed IMFs are grouped into the HF sub-signals including the MA, PLI, IN and HF components of QRS complexes, the LF signal including baseline wanders. The baseline wander is captured by the residue obtained using modified CEEMD algorithm The ECG signal corrupted with both BW and abrupt change. It is noted that the abrupt change disturbance causes the sudden amplitude variations in the residue a global thresholding of 0.2 mV and local MAA thresholding of 0.1 mV are used to detect the presence of the abrupt amplitude variation. Meanwhile, the BW can be effectively removed before the heartbeat waveform extraction. However, abrupt amplitude variation can distort the morphological shapes of the signal while suppressing the abrupt components. Thus, the ECG signal segments corrupted with abrupt change are considered as Unacceptable. The HF noises such as MA, PLI, IN are adequately captured in initial three IMFs. To analyze the severity of the HF noises, the signal is constructed by adding the first three IMFs as follows:

$$h[n] = \sum_{i=1}^{3} IMF_i\,[n] \qquad (1)$$

Where, $h[n]$ is the constructed HF signal

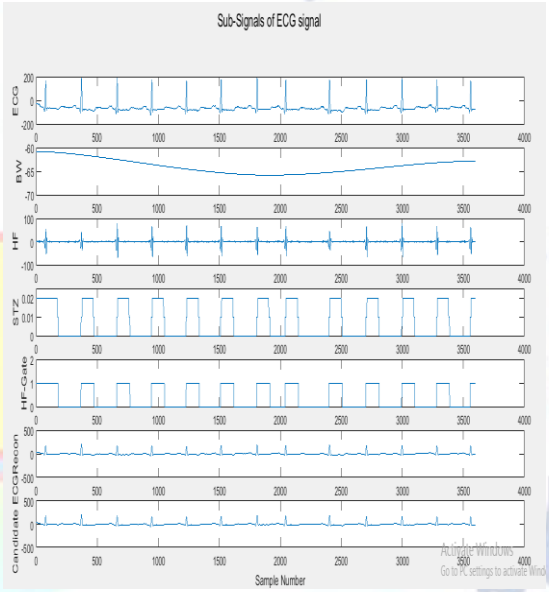


Fig.3: SQA approach in detecting the signal quality with performance improvement in beat classification for clean ECG signal with BW and MA and ECG signal with localized PLI

the reconstructed HF signals adequately capture the MA, PLI and the HF information of QRS complexes. Removal of HF noises can alter the shape of the heartbeat waveform that can lead to false classification of heartbeats. For detecting the presence of HF noises, smoothed feature envelopes of short term zero crossing (STZ) are extracted and for noise-free ECG signal.

$$y[n] = \sum_{k=4}^{I} IMF_i[n] \qquad (2)$$

reconstructed ECG is obtained by summing all the IMFs except the first three IMFs, where $y[n]$ is the reconstructed ECG signal and I is the total number of IMFs. Since the first three IMFs and residue are excluded, the reconstructed signal is free from the baseline wanders and some of HF noises.

Meanwhile, the STZ feature envelopes show the spurious peaks with wider duration for the ECG signals corrupted with HF noises. Thus, the gate signal can be computed as

$$g[n] = \begin{cases} 1, STZ[n] > 0 \\ 0, \text{ Otherwise} \end{cases} \quad (3)$$

In this study, the maximum absolute amplitude (MAA), short-term zero crossing (STZ) and gate width duration features are used for the classifying the signal into acceptable and unacceptable quality. The acceptable quality signals are further processed for classification of heartbeats.

C. Combined R-Peak Detection and ECG Signal Enhancement:

The preservation of the QRS complex portions is most important for accurate classification of different shapes. In this study, we present the ECG denoising approach with simultaneous QRS complex preservation and background noise suppression. It is observed that the HF components of the QRS complexes are not preserved by this reconstruction process. The QRS complex shape variation can lead to misclassification of the heartbeats. Therefore, this study focuses on the preservation of the QRS complex portion by processing the localized residual components that are present in the first three IMFs. Here, the candidate ECG signal is constructed by adding reconstructed ECG signals $y[n]$ and the extracted HF portions of QRS complex (from the HF signal $h(n)$) within the duration of 100 ms centered at the detected R-peak instants.

$$q_{HF}[n] = \begin{cases} h[n], \ for \ ni - \frac{P}{2} \leq n \leq ni + \frac{P}{2} \\ 0, \text{ Otherwise} \end{cases} \quad (4)$$

Where P corresponds to the block size of "100 ms". The candidate ECG signal is constructed as

$$z[n] = y[n] + q_{HF}[n] \quad (5)$$

The reconstruction results of this process are shown in fig. 4. Results show that the proposed denoising approach can capable of preserving the HF portions of the QRS complexes. Finally, the heartbeats are extracted from the reconstructed ECG signal using the detected R-peaks.

D. R-Peak Alignment and ECG Beat Extraction:

The importance of the R-peak alignment process is the extracted ECG beats from the two types of ECG signals and the ensemble of the extracted ECG beats with and without using the R-peak alignment process.

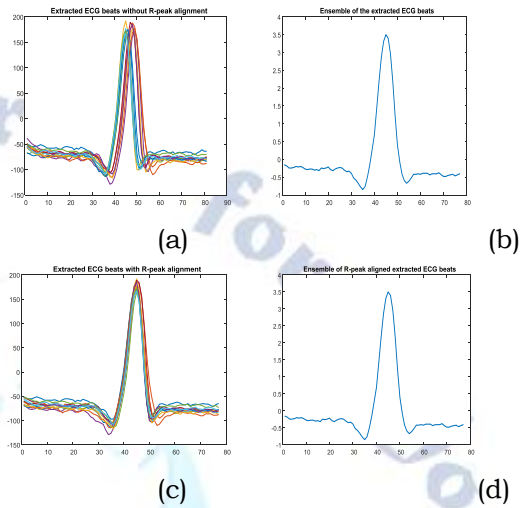


Fig.4: The significance of the R-peak alignment for ECG beat template creation.
(a)Extracted ECG beats without R-peak alignment;(b) Ensemble of the extracted ECG beats as shown in (a); (c) Extracted ECG beats with R-peak alignment; and (d) Ensemble of the R-peak aligned extracted ECG beats as shown in (c) of ECG signal.

E. ECG Beat Classification:

In this study, we evaluate the proposed quality-aware ECG beat classification method for recognizing the normal beat (N), ventricular ectopic beat (V), supraventricular ectopic beat (S), and paced beat (P) using the normalized cross correlation measure between the reference heartbeat templates and the test heartbeat template. The heartbeat similarity is measured as

$$S = \frac{\sum_{m=1}^{M}[b_m(k)-\mu_0]\sum_{p=1}^{P}[T_p(k)-\mu_1]}{\sqrt{\sum_{m=1}^{M}[b_m(k)-\mu_0]^2}\sqrt{\sum_{p=1}^{P}[T_p(k)-\mu_1]^2}} \quad (6)$$

Where S represents the similarity measure, b_m is m^{th} ECG beat, P is the number of classes of heartbeat types, M is the number of heartbeats and μ_0 , μ_1 are mean of the mth heartbeat b_m and template T_p, respectively. Based on the RR-interval and S values, the test heartbeats are classified into different heartbeat classes. It can be seen that the heartbeats are correctly classified by using the reconstructed ECG signal. It is noted that

heartbeats are not correctly classified in presence of severe MA and abrupt amplitude variation. Results demonstrate that the signal quality assessment plays an important role in constructing the reliable heartbeat templates by preserving the actual shapes of the heartbeats. Otherwise the original shapes of the heartbeat templates can be altered due to the averaging of the noise-free heartbeats with noisy heartbeats which may be included in the unsupervised reference heartbeat database creation during the training phase. Otherwise, the noisy features may be stored in the case of ECG waveform feature based heartbeat classification methods. Further, the SQA based heartbeat classification method can capable of reducing the false alarm rates and misclassification of the noisy heartbeats which are unavoidable in many practical ECG recording scenarios.

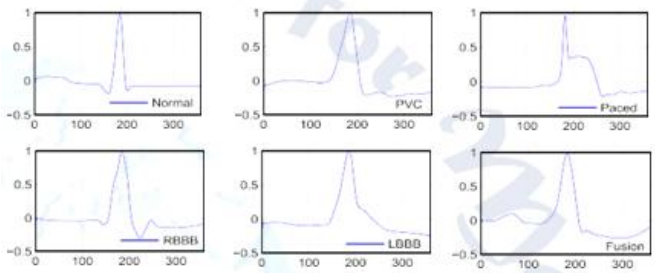


Fig.7: Examples of reference templates for different ECG beats.

RESULTS AND DISCUSSION

The performances are evaluated on several normal and abnormal ECG signals taken from 48 recordings of the MIT-BIH arrhythmia database The ECG signals were digitized with a sampling rate of 360 Hz and 11-bit resolution over 10 mV range. In this study, the noisy ECG signals are obtained by adding the electrode motion and muscle artifacts which are provided in the ECG noise generator database. The benchmark measures such as sensitivity (Se), specificity (Sp), positive predictivity (Pp), and overall accuracy (OA) for evaluating the performance of the ECG-SQA approaches that are computed from the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) which are obtained for each of test ECG recordings. The classification accuracy (CA), F1-score, and Kappa measures are used for evaluating the performance of the heartbeat classification methods with and without signal quality assessment approach. In this study, the SQA classifies the recorded ECG signals into "*acceptable*" and "*unacceptable*". The acceptable ECG signal segment is further processed in the heartbeat classification stage. Otherwise the noisy ECG signal is not processed if it is detected as the unacceptable quality. The main objective of this study to demonstrate that the false alarms can be reduced by using the SQA algorithm at the preprocessing stage. Table I shows that the false alarm reduction performance for each of the methods. Results show that the proposed method can achieve FAR ranging from 24% to 93% under noisy ECG recordings.

TABLE I
PERFORMANCE OF THE ECG BEAT CLASSIFICATION METHODS

		Without SQA			With SQA			FAR(%)
Methods	Beat	Kappa	F1	CA(%)	Kappa	F1	CA(%)	
CEEMD+NCC	N	0.78	0.85	74.53	0.98	0.97	95.07	93.38
	S	0.74	020	10.99	0.93	0.72	55.74	83.08
	V	0.47	0.32	19.11	0.66	0.70	53.94	57.31
	P	0.72	0.78	64.60	0.88	0.93	87.51	76.23
Hermite[5]	N	0.99	0.97	93.88	0.99	0.97	94.55	24.58
	S	0.87	0.87	76.62	0.91	0.91	83.74	53.68
	V	0.99	0.95	90.71	0.99	0.95	89.94	41.94
	P	0.43	0.60	42.96	0.52	0.68	51.92	51.63
Geometric[6]	N	0.97	0.98	95.74	0.98	0.98	96.98	62.73
	S	0.91	0.58	40.78	0.93	0.69	53.25	49.35
	V	0.81	0.89	79.41	0.82	0.90	81.52	39.27
	P	0.96	0.96	92.00	0.97	0.97	94.73	63.79
Wavelet[7]	N	0.91	0.94	88.05	0.91	0.94	89.01	42.80
	S	0.78	0.58	41.03	0.85	0.67	50.49	55.79
	V	0.60	0.45	29.43	0.63	0.51	34.45	38.37
	P	0.60	0.59	41.36	0.71	0.65	47.69	58.22

CONCLSION

A new quality-aware ECG beat classification method which can be capable of reducing the false alarms and ensuring the consistency of class specific accuracies for the four classes of heartbeats under noisy ECG recordings. Evaluation results on the standard MIT-BIH arrhythmia database demonstrate that the preservation of QRS complexes is most essential for improving the beat classification when the denoising process is applied for suppression of background noises. Results further demonstrate that a quality-aware ECG analysis system is most essential to ensure the accuracy and reliability of diagnosis of different types of arrhythmias under noisy ECG recording environments.

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