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Atrio-Ventricular Beat Classification Of Ecg Based On Semisupervised Method

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Abstract: ***Accurate detection of cardiovascular diseases requires automatic ECG signal monitoring. Semisupervised method which is a combination of automatic monitoring and analysis by an expert cardiologist is considered for the prevention of error in detection. Ventricular arrhythmias were detected to classify ventricular beats earlier. An extension to this method is obtained by classifying the atrial beats. Atrial arrhythmias like Atrial Fibrillation and other abnormalities like First degree block, Atrial Tachycardia, Ventricular Tachycardia is obtained. A Switching Kalman Filter(SKF) is used and a third mode known as X-factor which consists of unknown characteristics is also considered for quality detection. MIT-BIH arrhythmia database is used. The F1 score of 98.11% and Jα of 98.08% were obtained.***

Keywords: ***Semisupervised method; Switching Kalman Filter(SKF) ; quality detection; heartbeat classification.***

I. INTRODUCTION

Cardiovascular arrhythmias are one the major causes of mortality across the world. Accurate monitoring and diagnosis is very important as some of the arrhythmias when undetected can lead to severe threats in life. ECG monitoring in routine is the best method for detection of arrhythmias. Semi-supervised method is used which is a combination of automatic analysis and expert assistance is used for accurate detection of arrhythmia. The method makes use of automatic classification along with expert assistance from cardiologist/trained technician. Premature ventricular contraction (PVC) is an arrhythmia related to ventricles. Such arrhythmias can be detected by classifying the ventricular beats. The ECG signals are classified into atrial(normal), ventricular beats of the heart for diagnosis. Unknown signal is classified as X-factor to provide accurate detection.

A Switching Kalman Filter [4] is used for the automatic selection of the most desired mode of beat type, while simultaneously filtering the signal using appropriate previous knowledge. A beat classifier is used which automatically clustered heartbeats and requested expert labelling of the output clusters by a trained cardiologist. Beats from a recording of a single cluster would belong to the same class[1].

II. MATERIALS AND METHODS USED

Data

The database used is MIT-BIH arrhythmia database. This database contains 30 minutes duration of 48 recordings containing two leads. This database consists of two sets: DS1 which is used for training and DS2 for testing [9].

Method

1) Preprocessing: Each of the ECG signal was downsampled to 125 Hertz [8] when necessary and for computing efficiency. Two open source QRS detectors (*wqrs* and *eplimited*) was made to perform on each channel individually. The noise level in the segment was determined using signal quality index's(SQI's) [5]. Seven SQI's are calculated, including kurtosis(kSQI), skewness(sSQI), relative power in QRS complex(pSQI), relative power in baseline(basSQI), fraction of beats detected by *wqrs* to eplimited(bSQI), ratio of number of beats detected by eplimited and wqrs(peak detectors)[8], ratio between principal component analysis and eplimited algorithm.

The Fusion of several objective signal features by means of a support vector machine(SVM) [7] has been used by the algorithm. The values obtained is fed into support vector machine for classification. The output of SVM varies from zero to one corresponding to a scale of poor or (bad) to excellent signal quality. Initialization of the Gaussian parameters for each mode utilized the SQI. Poor quality heartbeats less than the threshold, t_{SQI} ie, SQI< t_{SQI} were discarded during the computation of the average template of a heartbeat mode. The ECG signal was pre-processed with a simple baseline wander suppression filter, consisting of a second order Butterworth high-pass filter with a 0.5 Hz cutoff frequency. The preprocessing stage is executed for testing phase.

2) *Gaussian Parameter Initialization*: Initialization of Gaussian parameters is the first step in modelling. The procedure of initialization of parameters was run simultaneously and independent of all leads used. Peak detector is used to identify and segment beats which is used to form the average template beat. ECG signal segmentation is done around the R-peak. The segmentation was performed by mapping the R-R intervals [2] to a cyclic phase. In ECG, a phase between 0 and 2π (-π to π) exists between two consecutive R-peaks. A phase shift of -π/3 was provided to the R-peak. It was done to completely include the T-wave in one cyclic phase even if large RR variability occurs. Each cycle was then segment from -π to π radians. M. Llamedo and J.P. Mart´ınez [2]describes the R-R interval features determination from R-R sequence. Heartbeat with an SQI having a threshold, t_{SQI} was then compared to the mean heart cycle using cross correlation. If the value obtained was above the threshold t_c, then the heartbeat was classified as dominant class, else weak class. A new class was formed when the heart-cycle was not belonging to the existing class. Cross correlations are performed subsequently among both beat types.

The beat was put in a third class, when the cross correlation was not above t_c for either of the two new groups. The process is repeated for all the heartbeats. Then the ECG beats are assembled into different clusters. Relevant modes are obtained from the clusters are used for the estimation of Gaussian parameters. The number of cycles in each cluster is counted for determining the relevant modes. Clusters with cycles greater than the threshold, t_r cycles are only considered. Nonlinear fitting of seven Gaussian functions over the set of all the cycles contained in one class is performed for the estimation of Gaussian parameters for each relevant class. Some initial values for each parameter is required for the nonlinear fitting procedure. The quality of fit depends on these Gaussian parameters, precisely on the initial position of the center of each Gaussian. The Gaussian parameters were estimated for each class. To perform the classification of beats, each class were distinguished as normal(atrial) and ventricular. The interpretation of each type of cluster depends on cardiologist or expert technician. Each average cycle consisting of sum of Gaussian functions [3] was compared to the typical cycle of other classes. If two classes have a normalized cross correlation greater than threshold,t_{c1} then these clusters are merged.

3) *Switching Kalman Filter*: A Switching Kalman Filter (SKF) is used for correct mode selection of heartbeat while simultaneously filtering the ECG signal. Multiple morphologies are obtained which includes normal(atrial), ventricular and unknown beats. The switching Kalman Filter is run as the number of modes, n and Gaussian parameters for each mode is estimated. Residual likelihood ,$lk(i)$ [4] is estimated by performing mode classification. Mode with highest likelihood is selected. Switching Kalman Filter predicts the values of peak positions and corrects the predicted values. A Gaussian window[4] is used to slide over the ECG signal is given by

$$l^c(\mathrm{i}) = \int_{k2}^{k1} exp\,((\varphi_k - \pi/3)^2/\,\sigma_\Theta) \cdot l_k(\mathrm{i})\, dk \tag{1}$$

where $l^c(i)$ represents a likelihood cycle for ith mode, φ representing artificial phase signal, sample k_1 represents the $\varphi_{k1} =$ -π and k_2 defined as $\varphi_{k2} =$ π ,σ_Θ represents a parameter which defines the width of an exponential window. The quality of Kalman filter depends on a set of parameters and the process covariance matrix Q and the observation noise covariance matrix R. The state noise is defined by Sayadi *et al*. [3] as $\{\alpha_{i,k}, \xi_{i,k}, b_{i,k}, \omega, \eta_P, \eta_C, \eta_T\}$ and its covariance matrix [4], which is a diagonal matrix itself is represented as

$$Q=\mathrm{diag}(q_G I_7,\ 0.5q_G I_{14},\ q_p\omega^2_{sd},(q_0\, e_{sd})^2,(q_0 e_{sd}/2)^2\ I_2) \tag{2}$$

Equation (2) is represented by I_n as an identity matrix of the order n × n, ω_{sd} is the heart rate standard deviation over the recording, e_{sd} is the heart rate cycle standard deviation computed during Gaussian parameter initialization. The three parameters that are to be tuned are q_G, q_0, q_p .Observation noise [4] is described as $\{v_{1,k}, v_2, k\}$, and its covariance matrix [4] is given by

$$\mathrm{R} = \mathrm{diag}\ (r_P\,(\omega/f_s)^2/12,\ r_e e^2_{sd}) \tag{3}$$

where ω is the heart rate mean over the total length of the signal, The sampling frequency is represented by f_s .The two parameters r_p and r_e that are adjusted for setting the uncertainity on the observation of the phase and ECG signals. The X-factor is defined by the state vector $\{v_{1,k}, v_{2,k}\}$ and its covariance matrix [4] is represented by

$$Q_X = \mathrm{diag}\ (q_x e^2_{sd}\ .q^2{}_x e^2_{sd}) \tag{4}$$

where q_x is the parameter for which setting is needed. The observation covariance matrix [4] is represented as

$$R_X = [r_e e^2_{sd}] \quad (5)$$

Equation(5) is similar to the observation covariance matrix of ECG model.

The heartbeats classification was assessed to evaluate the quality of parameters. We consider atrial and ventricular arrhythmia as true positives (TP), actually arrhythmia condition but detected as normal is taken as false negatives (FP) and not arrhythmia condition but detected as arrhythmia is considered as false positives (FP). We consider the beats with X-factor belonging to normal class as pseudo false positive (PFP) and beats with X-factorbelonging to ventricular class as pseudo false negatives (PFN). The harmonic mean of sensitivity (*Se*) and positive predictive value (+*P*) is given by F_1 score [4] is calculated and it is represented as

$$F_1 = 2TP/(2TP+FN+FP) \quad (6)$$

The conditions FN and FP are equally weighted. A score J_α [4] is calculated and it is given by

$$J_\alpha=2(\alpha+1)TP/(2(\alpha+1)TP+\alpha(FN+FP)+(PFN+PFP)) \quad (7)$$

The value of α is set as 10 and this value controls the relative weighting of pseudo incorrect classifications due to X-factor.

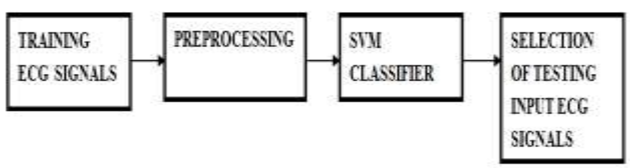

Fig.1. Training phase

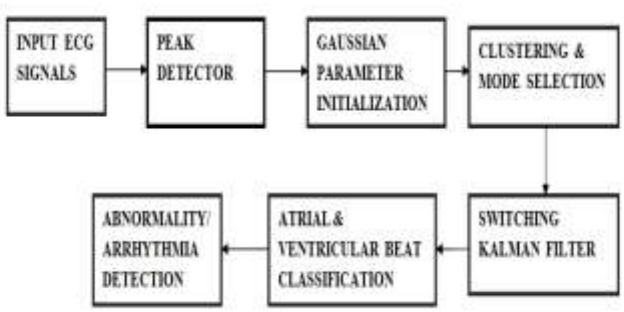

Fig.2. Testing phase

The P-QRS-T waves are analysed for the detection of various abnormalities and arrhythmia detection including Atrial Fibrillation, First degree block and Premature Ventricular Contraction. In Ventricular and Atrial Tachycardia in which heart rate is considered along with QRS wave analysis.

III. RESULTS

A $J\alpha$ score of 98.08% and an F_1 score of 98.11% was obtained. The sensitivity calculated was obtained 100% since there was no occurrence of false negatives(FN) in the cases considered. Cluster 1 represents normal(atrial) mode, Cluster 2 represents ventricular mode and Cluster 3 represents X-factor mode. The various abnormalities and arrhythmias are represented by the following figures.

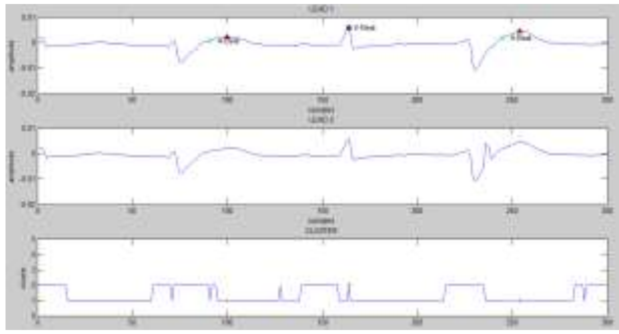

Fig.3. Ventricular Tachycardia

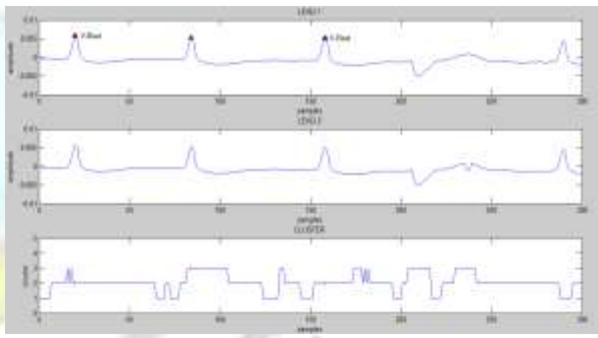

Fig.4. Premature Ventricular Contraction

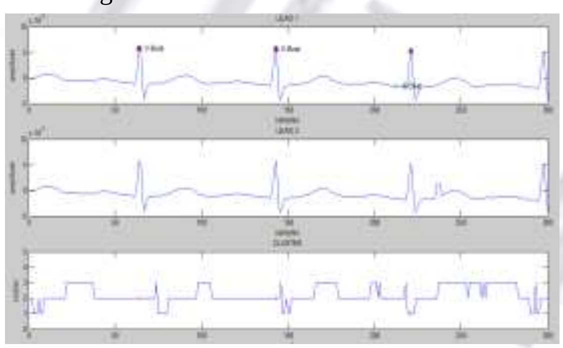

Fig.5. First degree block

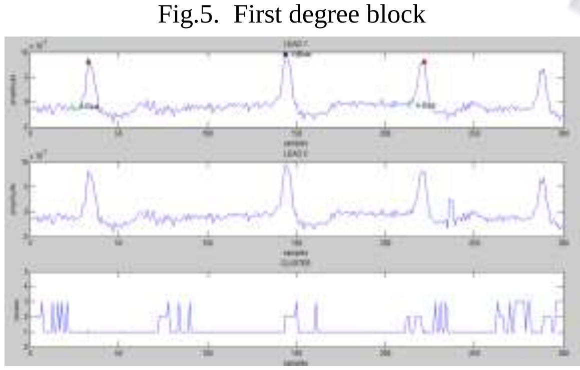

Fig.6. Atrial Fibrillation

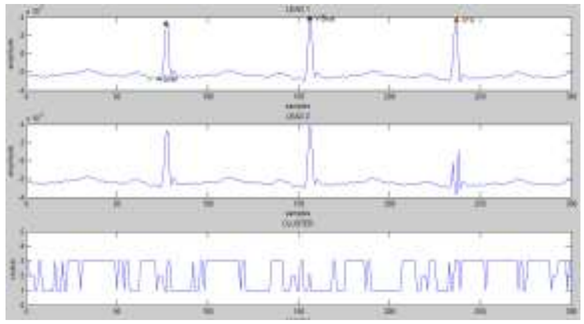

Fig.7. Atrial Tachycardia

SCORES OBTAINED ON DS2(MIT-BIH) DATABASE

Methods	Atrial and Ventricular beats		
	Se	***+P***	***F_1***
de Chazal *et al.* [6]*	85.1	81.9	83.5
Llamedo and Martinez [9]*	94.6	88.1	91.2
automatic Llamedo and Martinez [1]*	90.1	86.0	88.0
assisted Llamedo and Martinez [1]	93.8	96.7	95.2
SKF with no X-factor	92.7	96.2	94.5
SKF with X-factor	100	96.6	98.1

*The methods are completely automatic.

IV. CONCLUSION

The ECG signals were analyzed by the P-QRS-T waves using peak detector. The classification of ECG into ventricular beats was used for the detection of arrhythmia in ventricles like Premature Ventricular Contraction(PVC). As an extension, classification of atrial beats is performed for atrial arrhythmia detection. Various arrhythmias and abnormalities like Atrial Fibrillation, First degree block, Premature Ventricular Contraction etc were determined from the P-QRS-T waves and Ventricular and Atrial Tachycardia from the heart rate and analysis of QRS waves.

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