DETECTION OF P-WAVE IN ECG COMPLEXES USING COMBINED ENTROPY CRITERION USING LS-SVM BASED ALGORITHM

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Abstract: ***An ECG signal is composed of successive repetition of P, QRS and T waves The ECG is the most useful and feasible diagnostic tool for initial evaluation, early risk stratification and triage for cardiac ailments. The identification of P-Wave in ECG complexes using LS-SVM as classifier has been presented in the paper. Combined Entropy of the ECG is an important discriminating feature. Using LS-SVM as a classifier, the P-wave has been detected with an accuracy of 92.42 % with percentage of false positive detections and false negative detections is 1.5% and 7.58% respectively.***

Index Terms: ECG, P-complex, entropy and combined entropy, detection rate

I. INTRODUCTION

An ECG signal is composed of successive repetition of P, QRS and T waves. In the beginning, a crust is generated from the linear signal to form the P wave. The declining linear wave soon gets a downward deflection labeled as Q wave. A sudden upright deflection can be observed just beyond the Q wave to form a high cone that is, the R wave. On its decline a slight downward defection is the S wave. A noticeable hinge after the S wave is known as T wave that marks the end of a segment of the ECG signal. Electrocardiogram (ECG) is the representation of the electrical activities of the heart.

. T-wave changes are one of the most common abnormalities noted on an ECG. Changes in the T-wave may be a normal variant in some healthy individuals or related to age, body configuration or position, medications, anemia, pericarditis and a host of other conditions. T-wave abnormalities may also be caused by virtually any type of cardiovascular disorder such as coronary artery disease, valve impairments and hypertensive cardiovascular disease. A serious underlying cardiac impairment is much more likely if the T-waves are deeply inverted rather than simply flattened. T-wave abnormalities are classified by their degree of abnormality. T-wave changes are either considered to be minor or major changes. Ratings will depend upon this classification and the presence or absence of other risk factors.

LS-SVMs based classification methods have established their impact in the field of pattern recognition research. LS-SVM can be applied for ECG signal analysis and arrhythmia classification, where in QRS-detection is accomplished by using some other technique. Criteria namely entropy of the ECG signal has been used in the present work as a feature. The LS-SVM is then used as a classifier for the accurate and reliable detection of the QRS-complexes.

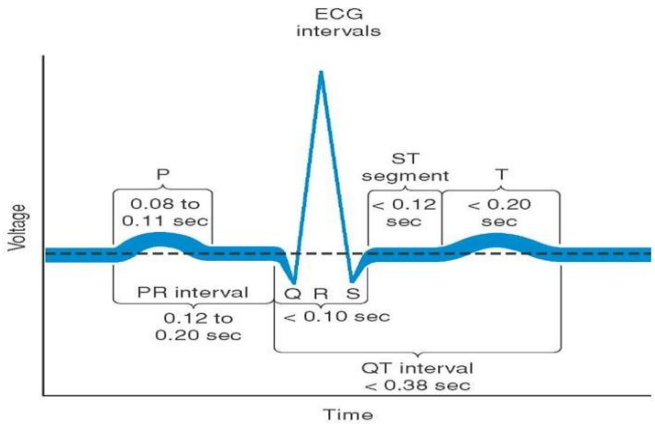

Fig.1 ECG signal

II. LEAST-SQUARE SUPPORT VECTOR MACHINE

Least Square Support Vector Machine (LS-SVM) is re-formulations of the standard SVM's. LS-SVM classifier proposed by Suykens and Vandewalle is a class of kernel based learning methods. By LS-SVM one can find the solution by solving a set of linear equations instead of a convex quadratic programming (QP) for classical SVM's.

Here a modification to the Vapnik SVM classifier formulation which leads to solving a set of linear equations, which is for many practitioners in different areas; is easier to use than QP solvers. The following SVM modification was originally proposed by Suykens[6,9,21,22] :

$$\left[\begin{array}{l} \boxed{P}: \min_{w,b,e} J_p(w,e) = \frac{1}{2}w^T w + \gamma\frac{1}{2}\sum_{k=1}^{N} e_k^2 \\ such\ that \quad y_k[w^T\varphi(x_k)+b] = 1 - e_k, k = 1, \dots\dots, N \end{array}\right] \quad (1)$$

for a classifier in the primal space that takes the form

$$y(x) = sign[w^T\varphi(x_k) + b] \quad (2)$$

where $\varphi(\cdot) : \mathbb{R}^n \to \mathbb{R}^{n_h}$ is the mapping to the high dimensional feature space as in the standard SVM case. The Vapnik formulation is modified here at two points. First, instead of inequality constraints one takes equality constraints where the value 1 at the right hand side is rather considered as a target value than a threshold value. Upon this target value an error variable e_k is allowed such that misclassifications can be tolerated in the case of overlapping distributions. These error variables play a similar role as the slack variables ξ_k in SVM formulations. Second, a squared loss function is taken for this error variable. These modifications will greatly simplify the problem. In the case of a linear classifier one could easily solve the primal

problem, but in general *w* might become infinite dimensional. Therefore let us derive the dual problem for this LS-SVM nonlinear classifier formulation. The Lagrangian for the problem is where $\varphi(\cdot) : \mathbb{R}^n \to \mathbb{R}^{n_h}$ is the mapping to the high dimensional feature space as in the standard SVM case. The Vapnik formulation is modified here at two points. First, instead of inequality constraints one takes equality constraints where the value 1 at the right hand side is rather considered as a target value than a threshold value. Upon this target value an error variable e_k is allowed such that misclassifications can be tolerated in the case of overlapping distributions. These error variables play a similar role as the slack variables ξ_k in SVM formulations. Second, a squared loss function is taken for this error variable. These modifications will greatly simplify the problem. In the case of a linear classifier one could easily solve the primal problem, but in general *w* might become infinite dimensional. Therefore let us derive the dual problem for this LS-SVM nonlinear classifier formulation. The Lagrangian for the problem is

$$\mathcal{L}(w,b,e;\alpha) = J_P(w,e) - \sum_{k=1}^{N} \alpha_k \{ y_k [w^T \varphi(x_k) + b] - 1 + e_k \} \quad (3)$$

where the α_k values are the Lagrange multipliers, which can be positive or negative now due to the equality constraints.

The conditions for optimality yields

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial w} = 0 \;&\to\; w = \sum_{k=1}^{N} \alpha_k y_k \varphi(x_k) \\ \frac{\partial \mathcal{L}}{\partial b} = 0 \;&\to\; \sum_{k=1}^{N} \alpha_k y_k = 0 \\ \frac{\partial \mathcal{L}}{\partial e_k} = 0 \;&\to\; \alpha_k = \gamma e^k \qquad k = 1, \dots, N \\ \frac{\partial \mathcal{L}}{\partial \alpha_k} = 0 \;&\to\; y_k [w^T \varphi(x_k) + b] - 1 + e_k = 0, \;\; k = 1, \dots, N \end{aligned} \quad (4)$$

Defining $Z^T = [\varphi(x_1)^T y_1; \dots \dots; \varphi(x_N)^T y_N]$, $y = [y_1; \dots; y_N]$, $1_v = [1; \dots; 1]$, $e = [e_1; \dots; e_N]$, $\alpha = [\alpha_1; \dots; \alpha_N]$ and eliminating *w,e,* one of the following linear Karuh-kuhn-Tucker (KKT) system.

$$\left[\boxed{D} : \text{solve in } \alpha, b: \quad \left[\begin{array}{c|c} 0 & y^T \\ \hline y & \Omega + I/\gamma \end{array} \right] \left[\begin{array}{c} b \\ \hline \alpha \end{array} \right] = \left[\begin{array}{c} 0 \\ \hline 1_v \end{array} \right] \right] \quad (5)$$

where $\Omega = Z^T Z$ and the kernel trick can be applied within the Ω-matrix

$$\Omega_{kl} = y_k y_l \varphi(x_k)^T \varphi(x_1) = y_k y_l K(x_k, x_l) \;,\; k,l = 1; \dots; N \quad (6)$$

The classifier in the dual space takes the form

$$y(x) = sign[\textstyle\sum_{k=1}^{N} \alpha_k y_k K(x_k, x_l) + b] \quad (7)$$

The least squares support vector machine (LSSVM) is a least squares version of SVM, which considers equality constraints instead of inequalities for classical SVM. As a result, the solution of LS-SVM follows directly from solving a system of linear equations, instead of quadratic programming. Implementation of LS- SVM for QRS-detection in single-lead ECG signal is done by using LS-SVMlab toolbox. It contains MATLAB implementations of LS-SVM algorithm, which can be used for classification, regression, time-series prediction and unsupervised learning[6,9,22].

III. ENTROPY AS A FEATURE

The probability, $P_i(x)$ of absolute slope at each QRS and non- QRS region of sampling instant belonging to each of the two classes is calculated using equation 8 [13].

$$P_i(\mathrm{x}) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left[-\frac{1}{2} \left(\frac{\mathrm{x} - m_i}{\sigma_i} \right)^2 \right], \quad i = 1, 2;\ \mathrm{x} = 1, 2, \dots, s \quad (8)$$

where σ_i and m_i are the standard deviation and mean of i^{th} class and *s* represents total number of samples in the ECG signal. Entropy is a statistical measure of uncertainty. A feature, which reduces the uncertainty of a given situation are considered more informative than those, which have opposite effect. Thus a meaningful feature selection criterion is to choose the features that minimize the entropy of the pattern class under consideration .

The entropy $h_i(x)$ at each sampling instant belonging to QRS and non-QRS-class is calculated using equation 9.

$$h_i(x) = -P_i(x) \log_e P_i(x), \quad i = 1, 2;\ x = 1,2, \dots, s \quad (9)$$

These entropies are then normalized using equation (10)

$$h_{in}(x) = (h_i(x) - H_{imin}) / (H_{imax} - H_{imin}) \quad i = 1,2;\ x = 1,2, \dots\dots, s \quad (10)$$

where $h_{in}(x)$ is normalized entropy

H_{imin}, H_{imax} are the minimum and maximum values of entropy $h_i(x)$

Fig. 2 shows the results of the preprocessing stage of lead aVF of record MO1_114 of the CSE ECG data-set 3. As depicted in Fig. 2 (b), the preprocessor removes power line interference and baseline wander present in the raw ECG signal. The absolute slope of the ECG signal is much more in the QRS-region than in the non-QRS-region as displayed in Fig. 2 (c). Fig. 2 (d) shows $h_1(x)$, entropy curve for QRS-region. It can be seen from this curve that it has lower values in the QRS-region and higher values in the non-QRS-region. The low value of entropy in the QRS-region indicates lower uncertainty or in other words higher certainty of that region belonging to QRS-region. Similarly, higher values of entropy in the non-QRS-region indicate higher uncertainty or in other words lower certainty of that region belonging to QRS-

region. Thus the entropy $h_1(x)$ curve provides critical information about the degree of certainty of a region belonging to QRS-region.

Fig. 2 (e) shows $h_2(x)$, entropy curve for non-QRS-region. It can be seen from this curve that it has lower values in the non-QRS-region and higher values in the QRS-region. The low value of entropy in the non-QRS-region indicates lower uncertainty or in other words higher certainty of that region belonging to non-QRS-region. Similarly, higher values of entropy in the QRS-region indicate higher uncertainty or in other words lower certainty of that region belonging to non-QRS-region. Thus the entropy $h_2(x)$ curve provides critical information about the degree of certainty of a region belonging to non-QRS-region.

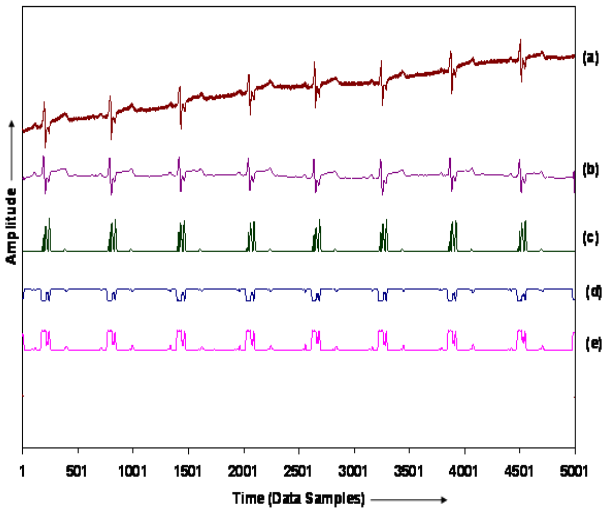

Fig. 2 Preprocessing of ECG signal (a) Raw ECG of lead aVF of record MO1_014 of CSE ECG data-set 3, (b) Filtered ECG, (c) Absolute slope curve, (d) Entropy QRS, (e) Entropy non-QRS

IV. CSE ECG DATABASE

During last three decades, rapid growth has occurred in computer-aided ECG analysis and interpretation. To allow an exchange of measurements and criteria between different ECG analysis programs, CSE database has been developed aimed at standardization of computer-derived ECG measurements. Dataset-3 of the CSE multi-lead measurement library [25] consists of 125 original 12-leads simultaneously recorded ECGs i.e. 1500 single lead ECGs. Every record picked from CSE ECG database is of 10 sec duration sampled at 500 samples per second thus giving 5000 samples. Median results of the referee's coincided best with the medians derived from all the programs studied in the CSE library and therefore combined program median can be used as a robust reference along with the referee's manual annotations[24,25,26].

V. P-WAVE DETECTION ALGORITHM

This section describes the algorithm developed for the detection of P-waves in simultaneously recorded 12-lead ECG signal. Though the algorithm is based on 12-lead ECG data, Fig. 3 displays the results obtained at each step of the algorithm with the help of single-lead ECG curve for the sake of clarity. The steps involved in the detection of P-waves are as follows:

1. 12-lead Raw ECG signal is acquired Fig 3 (a) displays a raw ECG signal.
2. Digital filtering techniques are used to remove baseline wander and power line interference. Fig 3 (b) displays a filtered ECG signal.
3. Fig 3 (c) displays locations of detected QRS-complexes in the 12-lead ECG signal.
4. The detected QRS-complexes are then removed from the from the ECG signal for the detection of T-waves. Fig 3 (d) shows QRS-less ECG signal.
5. Fig 3 (e) displays detected T-waves in the 12-lead ECG signal.
6. The detected T-waves are then removed from the from the QRSless ECG signal for the detection of P-waves. Fig 3 (f) shows QRS and T-wave less ECG signal.
7. The absolute slope is again used as an important discriminating feature because slope of the ECG signal is greater in the P-wave region as compared to region other than P-waves as displayed in Fig. 3 (g).The value of slope at every sampling instant of QRS and T-wave - less ECG signal is calculated to enhance the signal in the region of P-waves. If sometimes the offsets of the T-waves are not correctly detected by the LS-SVM algorithm, the values of the absolute slope increases abruptly suppressing the P-waves. This problem is eradicated by removing the edges of the detected T-waves by few samples equals to the mean error of T-offsets calculated. The T-edge removed signal is displayed in Fig. 3 (h).

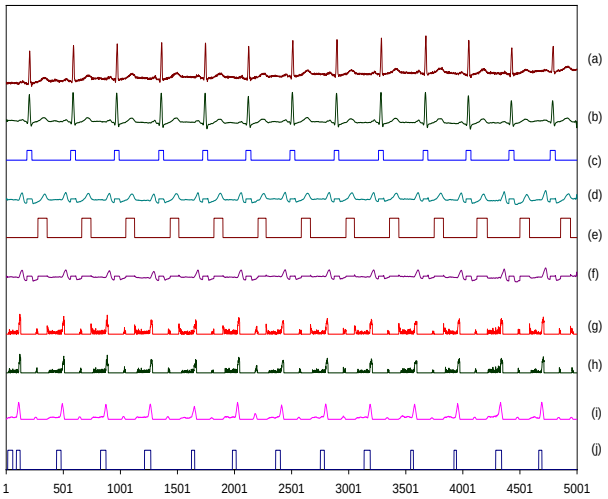

Fig 3 Algorithm steps for the detection of P-waves in simultaneously recorded 12-lead ECG signal in record MO1_019

8. These slope values are then normalized after applying moving averaging criterion. Thus, a normalized slope curve with enhanced P-waves for each lead of a record is obtained Fig. 3 (i). This signal is named as P-wave enhanced signal in the present work. For 12-lead

simultaneously recorded ECG, twelve curves are obtained for each record.

9. The LS-SVM is again trained and tested for the detection of P-waves. The training set containing 9747 sampling instances covering certain portions of different ECG records with a wide variety of P-wave morphologies.
10. The locations of the P-wave as detected by the LS-SVM are shown by the curve Fig. 3 (j).

VI. IMPLEMENTATION AND RESULTS OF P-WAVE

Implementation of LS-SVM for the detection of P-waves in ECG signal is also done by using LS-SVMlab software [6,9]. The validation of the proposed algorithm for P wave detection is done using 125, simultaneously recorded, 12-lead ECG records of data-set 3 of CSE multi-lead measurement library [24,25]. Every record picked from CSE ECG data-set 3 is of 10 second duration sampled at 500 Hz thus giving 5000 samples. Detection is said to be true positive (TP) if the algorithm correctly detect the P waves, it is said to be false positive (FP) if non-P-wave is detected and it is said to be false negative (FN) if the algorithm fails to detect the P wave. The algorithm, when tested gives detection rate (DR) of 92.42% for P -waves. The percentage of false positive detections and false negative detections is 1.5% and 7.58% respectively.

- **Case I:** Fig. 4 shows detection of P-wave in record MO1_044, with the help of lead I. P-waves are normal in this case but T-waves are of quite large amplitude in nature. The proposed LS-SVM based algorithm accurately detects these normal P-waves as displayed in Fig. 4 (e) respectively. The algorithm successfully detects the P -waves present even after the last detected QRS-complex.

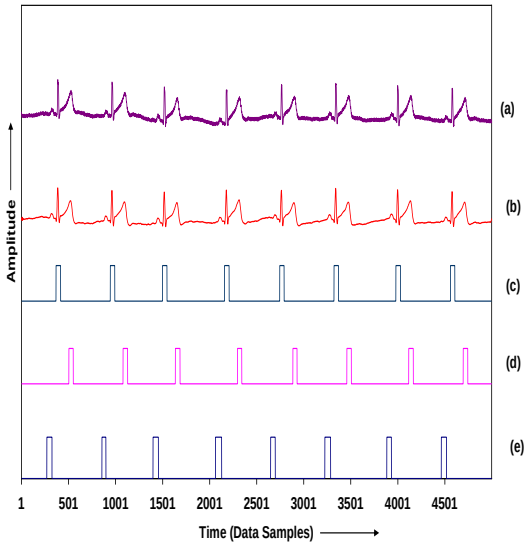

Fig 4 Detection of P -wave in record MO1_044
(a) Raw ECG (b) Filtered ECG (c) QRS detection (d) T wave detection (e) P wave detection by LS-SVM

- **Case II:** Fig. 5 shows P and T-wave detection in record MO1_019 with the help of lead II. P -waves are small in amplitude. LS-SVM successfully detects these P waves as depicted in Fig. 5.(e) respectively.

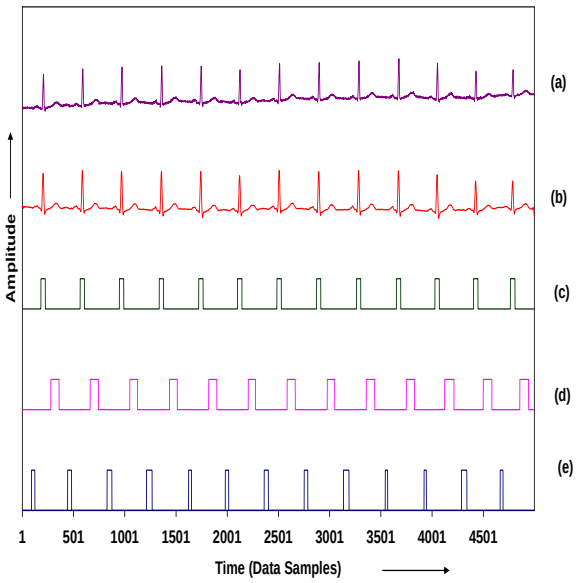

Fig 5 Detection of P -wave in record MO1_019
(a) Raw ECG (b) Filtered ECG (c) QRS detection (d) T wave detection (e) P wave detection by LS-SVM

- **Case II:** Fig. 6 shows P wave detection in record MO1_016 with the help of lead V_5. T-waves are quite large and P-waves are normal in this case. The algorithm accurately detects P -waves but algorithm fails to detect one P-wave in this case, as case of false negative (FN).

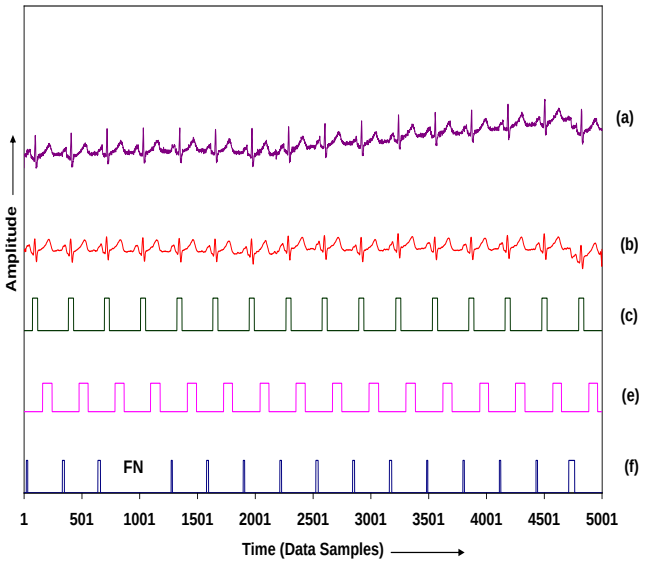

Fig 6 Detection of P -wave in record MO1_016
(a) Raw ECG (b) Filtered ECG (c) QRS detection (d) T wave detection (e) P wave detection by LS-SVM

VII. CONCLUSION

A new method for the detection of P-waves in simultaneously recorded 12-lead ECG signal using least square support vector classifier is described in this paper. The method has been exhaustively tested using the data-set 3 of the CSE multi-lead measurement library covering a wide

variety of T-wave morphologies. A significant detection rate of 92.42% in the case of P-wave detection The percentage of false positive detections and false negative detections is 1.5% and 7.58% respectively. The proposed method accurately detects normal, inverted and biphasic P-waves. It also detects the P-waves present before the first and after the last detected QRS-complex of the ECG recording.

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