IMPLEMENTATION OF FUZZY LEAST SQUARE SUPPORT VECTOR MACHINES FOR SIMULTANEOUS 12-LEAD QRS DETECTION

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Abstract: Electrocardiogram (ECG) is an important bioelectrical signal used to assess the cardiac state of a person. The QRS complexes are the dominant feature of the ECG. This paper presents an application of Fuzzy Least Square Support Vector Machines for the detection of QRS complexes in the 12 lead ECG.

I. INTRODUCTION

Computer-aided feature extraction and analysis of ECG signal for cardiac disease diagnosis has become the necessity in the present time. The number of cardiac patients has increased too large and the number of cardiac specialists is so limited that it has become difficult to provide effective cardiac care without the help of computer-based expert system. The ECG is characterized by a recurrent wave sequence of P, QRS and T-wave associated with each beat. Accurate determination of the QRS-complex is essential for computer-based ECG analysis. Once the positions of the QRS-complexes are found, the locations of other components of ECG like P, T-waves and ST-segment etc. are found relative to the position of QRS, in order to analyze the complete cardiac period. In this sense, QRS-detection provides the fundamental basis for almost all automated ECG analysis systems. The rapid development of powerful microcomputers has promoted the widespread application of software for QRS-detection algorithms in cardiological devices. Beginning almost 35 years ago, software based QRS-detection has replaced to a great extent the hardware based QRS-detectors. Numerous QRS-detection algorithms, such as derivative based algorithms, algorithms based on digital filters, wavelet transform, artificial neural networks, genetic algorithms, syntactic methods, Hilbert transform etc. are reported in literature for the accurate and reliable detection of the QRS-complexes in the ECG signal. But, still there is scope to further carryout the work on more efficient and reliable methods that can increase the percentage of accurate and reliable QRS-detection without leaving much doubt for automated systems. This paper describes FLS-SVM based algorithm for the detection of QRS-complexes in the simultaneously recorded 12-lead Electrocardiogram. Three different criteria namely absolute slope, entropy and combined entropy are used in the present work to generate feature signal. The FLS-SVM is used as a classifier to delineate QRS and non-QRS-regions.

II. PREPROCESSING OF ECG SIGNAL

A recorded ECG signal may contain noise from various sources. Therefore, before any kind of processing these noises should be minimized. This section describes the techniques used for the removal of power line interference, baseline wander and enhancement of the ECG signal using absolute slope, entropy and combined entropy criteria. A raw ECG signal of a patient is acquired. The finite impulse response (FIR) notch filter proposed by Alste and Schilder[1] is used to remove baseline wander. The adaptive filter to remove baseline wander is a special case of notch filter, with notch at zero frequency (or dc). This filter has a "zero" at dc and consequently creates a notch with a bandwidth of $(\mu/\pi)*f_s$, where f_s is the sampling frequency of the signal and μ is the convergence parameter. Frequencies in the range 0-0.5 Hz are removed to reduce the baseline drift. The convergence parameter used is 0.0025. The filter proposed by Furno and Tompkins [2] is used to remove 50Hz power line interference. The absolute slope at every sampling instant of the filtered ECG signal is calculated and these are clustered into two classes, namely QRS-class and non-QRS-class using Fuzzy C-mean (FCM) of clustering algorithm. Absolute slope is used as an important feature because absolute slope of the ECG signal is much more in the QRS-region than in the non-QRS-region. The probability, $P_i(x)$ of absolute slope at each sampling instant belonging to each of the two classes is calculated using (1).

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

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 [3]. The entropy $h_i(x)$ at each sampling instant for QRS and non-QRS-class is calculated using (1). These entropies are then normalized.

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

The combined entropy, $h_c$is then calculated by using (2). Thereafter it is also normalized.

$$h_c(x) = (1 - h_{2n}(x))^* h_{1n}(x) \quad (3)$$

Thus, from a single filtered ECG signal, one absolute slope curve; two normalized entropy curves, one from the QRS-entropies and other from the non-QRS-entropies; and one combined entropy curve are obtained. Similar procedure is applied for remaining leads of a subject and for all the subjects from the CSE ECG data-set 3. Fig. 1 shows the

results of the preprocessing stage of lead IIof record MO1_119 of the CSE ECG data-set 3. As depicted in Fig. 1(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. 1(c). Fig. 1(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. 1(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.
The two entropy curves, $h_1(x)$ and $h_2(x)$, shown in Fig. 1(d) and (e) are normalized in order to obtain normalized entropy $h_{1n}(x)$ and $h_{2n}(x)$. Now if the curve, showing the product $h_c(x) = (1- h_{2n}(x))* h_{1n}(x)$ called combined entropy is obtained, it has much lower values in QRS-region and much higher values in non-QRS-region thus giving even better information compare to h_{1n} (x) and h_{2n} (x) curves shown in Fig. 1(d) and (e). This can be seen in the combined entropy curve shown in Fig. 4.1(f). This makes the task of FLS-SVM classifier even easier for more reliable detection of QRS-complexes and drastic reduction in percentage of false positive and false negative detections as can be seen in the later part of this report. In the present work, FLS-SVM algorithm is trained and tested separately using absolute slope, entropy and combined entropy criteria for the detection of QRS-complexes in the simultaneously recorded 12-lead ECG signal.

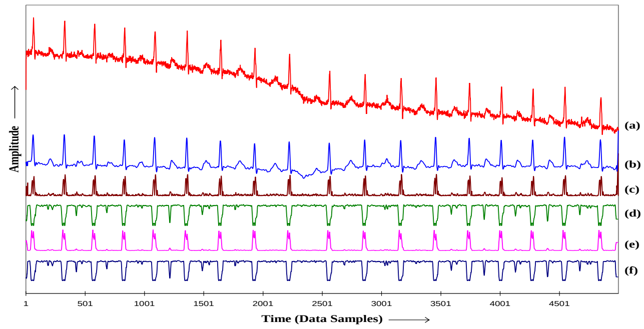

Fig. 1 Preprocessing of ECG signal (a) Raw ECG of lead II of record MO1_119 of CSE ECG data-set 3, (b) Filtered ECG, (c) Absolute slope curve, (d) Entropy QRS, (e) Entropy non-QRS, (f) Combined entropy

III. IMPLEMENTATION OF FUZZY LEAST SQUARE SUPPORT VECTOR MACHINE

1)LS-SVMlab

Support vector machine (SVM) is a learning system for training linear learningmachines in the kernel-induced feature spaces, while controlling the capacity to preventover fitting by generalization theory. It can be formulated as a quadratic programming problemwith linear inequality constraints. The least squares support vector machine (LSSVM)is a least squares version of SVM, which considers equalityconstraints instead of inequalities for classical SVM. As a result, the solution of LS-SVMfollows directly from solving a system of linear equations, instead of quadratic programming. Implementation of FLS-SVM for QRS-detection in twelve-lead ECG signal is done by using LS-SVMlab toolbox [4]. It contains MATLAB implementations of LS-SVM algorithm, which is updated by introducing Fuzzy parameter in it i.e the membership function u_i, The choice of fuzzy parameters u_i is determined based upon the error variables $\xi_i = \alpha_i/\gamma$ resulting from the LS-SVM case and the standard variance robust estimation value $\hat{s}$ of ξ_i in LS-SVM, and its value [5] is

$$\hat{s} = 1.48\, MAD(\xi_i)$$

where MAD denotes media absolute deviation, and constant c_1=2.5, c_2=3, which can be used for classification, regression, time-series prediction and unsupervised learning.

2) Parameter Selection

The type of kernel function, its parameters and margin-loss trade-off *C* should be determined to find the optimal solution. It is not known beforehand which values of *C*, the type of kernel function and its parameter are the best for this problem of QRS-detection. The objective is to obtain best kernel function, its parameters and margin-loss trade-off *C* so that the classifier can accurately predict unknown data (testing data). In the present study four-fold cross-validation approach is used to select the kernel function, to tune its parameters and margin-loss trade-off *C* [6]. The optimum values of the parameters with the cross-validation accuracy for the three criteria used for the generation of feature signal are displayed in Table 1.

Table 1 Optimum values of various parameters with the cross-validation accuracy for various criteria used for feature signal generation

S. No.	Criteria	Regularizing Parameter (gam) (γ)	Kernel parameter (sig2) (σ)	No. of training instances	Cross validation Accuracy (%)
1	Slope	10	4	9747	99.14
2	Entropy	10	4	9747	99.44
3.	Combined Entropy	10	4	9747	99.66

IV. EXPERIMENTAL RESULTS

This section describes the results obtained during the testing of FLS-SVM based algorithm using three criteria namely absolute slope, entropy and combined entropy. The proposed algorithm for QRS-detection in simultaneously recorded ECG signal is done using data-set 3 of CSE multi-lead measurement library [7]. This data-set contains original 12-lead simultaneous ECG recordings of 125 patients covering a variety of pathological cases. Detection is said to be true positive (TP) if the algorithm correctly identifies the QRS-complex and it is said to be false negative (FN) if the algorithm fails to detect the QRS-complex. False positive (FP) detections are obtained if a non-QRS-wave is detected as a QRS-complex. Following cases demonstrates the effectiveness of the FLS-SVM based algorithm using signal absolute slope as a feature.

1) QRS-Detection using Absolute Slope as a Feature

The algorithm, when tested using the optimum values of the parameters (γ =10, σ = 4) gives detection rate of 99.82%. The percentage of false negative detection is 0.18% and of false positive detection is 1.61%. The false positive detections are mainly due to prominent absolute slope of P and T-wave in some cases. There are total 1488 QRS-complexes in the 125, 12-lead simultaneously recorded original ECG recordings of the standard CSE ECG data-set 3. The proposed algorithm fails to detect only three QRS-complexes of record MO1_075. Any further attempt to identify/remove this false negative by way of adjusting the parameters of the FLS-SVM detracts the over all detection rate of the algorithm.

Following cases demonstrates the effectiveness of the FLS-SVM based algorithm using signal absolute slope as a feature.

Case I: Fig. 2 shows 12-lead ECG signal of record MO1_108 of CSE ECG data-set 3 and beneath it a square wave representing the locations of the QRS-complexes as detected by the FLS-SVM. It can be seen clearly that the morphology of QRS-complexes in the respective leads of ECG signal is consistent; hence all the QRS-complexes have been successfully detected by the FLS-SVM.

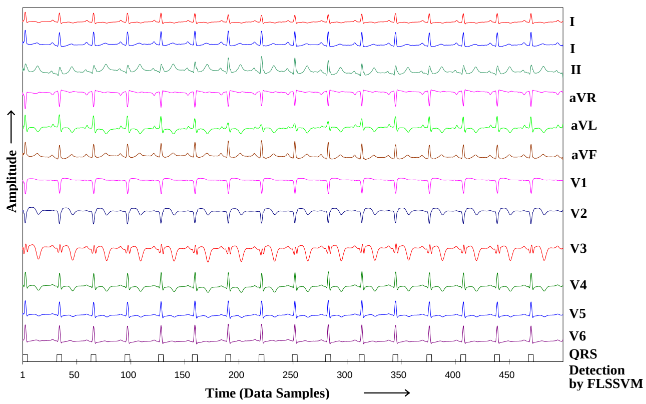

Fig. 2 Detection of QRS-complexes in record MO1_108 using absolute slope as feature

Case II: Fig.3 shows QRS-detection of record MO1_075. As depicted in this figure, out of thirteen QRS-complexes, the algorithm fails to detect second, seventh and eleventh QRS-complex due to its lower absolute slope compare to other QRS-complexes. This is the only 12-lead ECG out of 125 ECGs of data-set 3 in which three false negatives (FN) are encountered, demonstrating the strength of FLS-SVM.

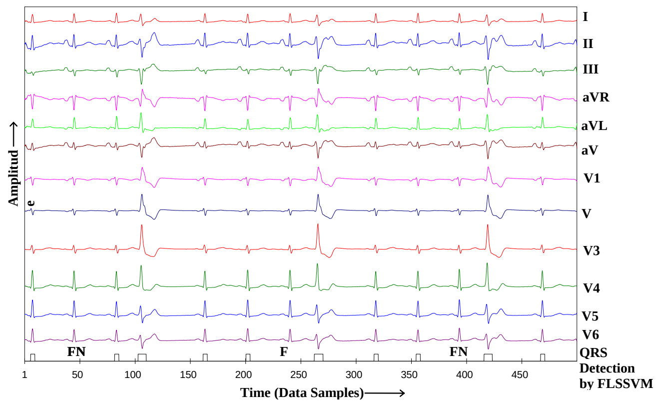

Fig. 3 Detection of QRS-complexes in record MO1_075 using absolute slope as feature

2) QRS-Detection using Entropy as a Feature

The QRS-detection algorithm using entropy criteria, gives detection rate of 99.93%, when tested with the optimum values of the parameters (*γ =10, σ = 4*). The percentage of false negative detection and false positive detection is reduced to 0.06% and 0.87% respectively. The false positive detections are due to peaky P and T-wave in some cases. There are total 1488 QRS-complexes in the 125, 12-lead simultaneously recorded original ECG recordings of the standard CSE ECG data-set 3. The proposed algorithm fails to detect only one QRS-complex of record MO1_045. This false negative detection is due to higher QRS-entropies and lower non-QRS-entropies in the QRS-region in most of the leads. Any further attempts to detect this particular QRS-complex by adjusting the parameter of FLS-SVM detract the overall detection rate. The three QRS-complexes in record MO1_075, giving false negative detections using absolute slope criteria, as discussed in earlier, are identified correctly using entropy criteria showing the effectiveness of entropy over absolute slope feature.

Following cases demonstrates the usefulness of the FLS-SVM based algorithm using signal entropy as a feature.

Case I: Fig. 4 shows 12-lead ECG signal of record MO1_020 and beneath it a square wave representing the locations of the QRS-complexes as detected by the FLS-SVM. It can be seen clearly that the morphology of QRS-complexes in the respective leads of ECG signal is consistent; hence all the QRS-complexes have been successfully detected by the FLS-SVM.

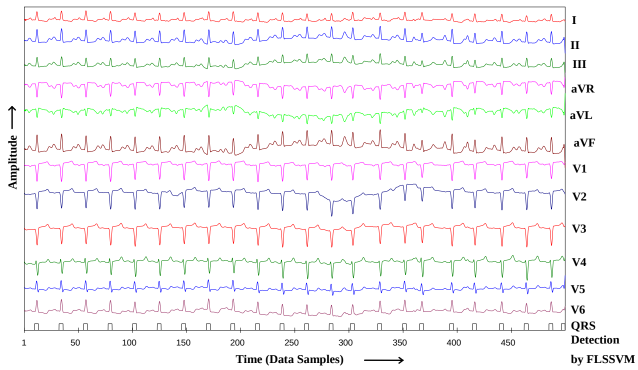

Fig. 4 Detection of QRS-complexes in record MO1_020 using entropy as feature

Case III: QRS-detection of record MO1_075 is displayed in Fig. 5. The amplitude of the fourth, eighth and twelve QRS-complexes in most of the leads is large as compared to other QRS-complexes. All these QRS-complexes along with the other QRS-complexes very small in amplitude are precisely identified by the algorithm showing its effectiveness.

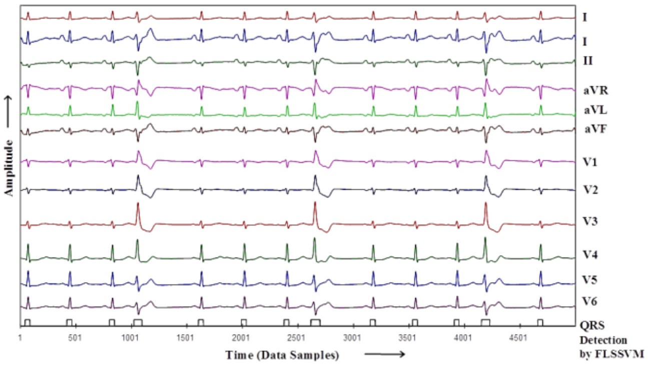

Fig. 5 Detection of QRS-complexes in record MO1_075 using entropy as feature

3) QRS-Detection using Combined Entropy as a Feature

Algorithm for the detection of QRS-complexes in 12-lead simultaneously recorded ECG using combined entropy criteria gives a maximum detection rate of 100% with a very low percentage of false positive detection, when tested with the optimum values of the parameters (γ =10, = 4). The percentage of false positive detection is 0.54%. These results demonstrate that combined entropy criterion is found to be effective compared with absolute slope and entropy criteria.

The cases discussed below shows the competence of the FLS-SVM based algorithm with a combined entropy criteria.

Case I: Fig. 6 shows 12-lead ECG signal of record MO1_003 of CSE ECG data-set 3 and beneath it a square wave representing the locations of the QRS-complexes as detected by the FLS-SVM. In this case, the morphology of QRS-complexes in the respective leads of ECG signal is consistent. Hence all the QRS-complexes have been successfully detected by the FLS-SVM.

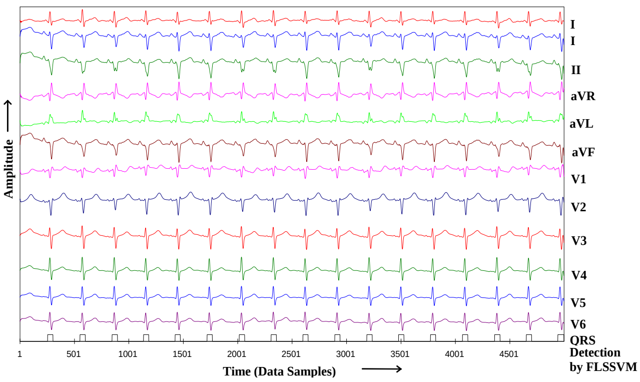

Fig. 6 Detection of QRS-complexes in record MO1_003 using combined entropy as feature

Case II: In the record MO1_044 morphology of the QRS-complexes is consistent in respective leads of the record as shown in Fig. 7. T-waves are of larger amplitude in some leads. These T-waves are rightly not detected as QRS-complexes by the algorithm due to their smaller pulse duration of trains of 1's.

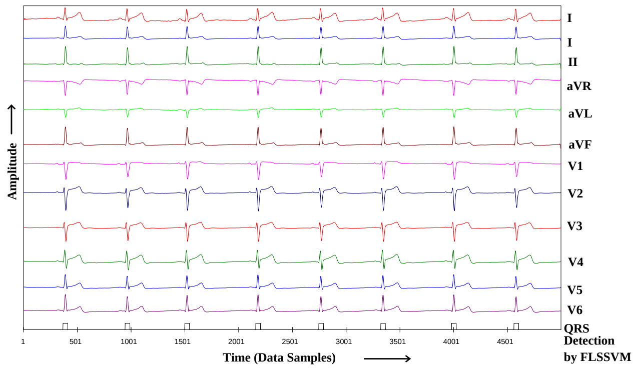

Fig. 7 Detection of QRS-complexes in record MO1_044 using combined entropy as feature

Table 2 Performance comparison of the proposed 12-lead algorithm

S. No.	Criteria	DR (%)	FP (%)	FN (%)
1	Absolute slope	99.75	1.61	0.26
2	Entropy	99.93	0.87	0.06
3	Combined Entropy	100	0.54	0.00

V. CONCLUSION

Application of FLS-SVM has been effectively employed in the present chapter for the detection of QRS-complexes in simultaneously recorded 12-lead ECG signal. Experimental results of the algorithm using data-set 3 of the CSE multi-lead measurement library demonstrate that the performance of the FLS-SVM based algorithm is found to be better compared to the performance of the methods reported in the literature. The performance of the computerized ECG processing systems relies heavily upon the accurate and reliable detection of the cardiac complexes and mainly upon the detection of QRS-complexes. The FLS-SVM based algorithms are a step towards this direction.

REFERENCES

[1] Alste Van J.A. and Schilder T.S.,"Removal of baseline wander and power line interference from the ECG by an efficient FIR filter with a reduced number of taps",IEEE Transactions on Biomedical Engineering, vol. 32, no. 12,pp.1052-1059, 1985.

[2] Furno G.S. and Tompkins W.J.,"A learning filter for removing noise interference", IEEE Transactions on Biomedical Engineering, vol. 30, no. 4, pp. 234-235, 1983.

[3] Tou J.L. and Gonzalez R.C., "Pattern Recognition Principles", Addison-Wesley Publishing Company MA, 1974

[4] Brabanter K. De, Karsmakers P, Ojeda F., Alzate C., BrabanterJ.De, Pelckmans K., De Moor B., Vandewalle J., Suykens J.A.K. "LS-SVMlab Toolbox User's Guide", ESAT-SISTA Technical Report 10-146, September 2010.

[5] Xie J., "Structural Damage Detection Based on Fuzzy LS-SVM Integrated Quantum Genetic Algorithm**",** Applied Mechanics and Materials

Vols. 20-23 (2010) pp 1365-1371.
[6] Ghosh D.C., Chakraborty M. and Das T., "QUANTITATIVE DETECTION OF VENTRICULAR TACHYARRHYTHMIA: A FRACTAL APPROACH", International Journal of Engineering Sciences & Emerging Technologies (IJESET), Volume 6, Issue 2, pp: 154-161, October 2013.
[7] Willems J.L., "The CSE Multilead atlas measurement results data set 3", Common Standards for Quantitative Electrocardiography, Leuven, Belgium, 1988.

