LS-SVM based Algorithm for the Identification of QRS complexes in Single-lead ECG using Entropy Criterion

Swati Sharma, S.S. Mehta, *Member IAENG,* Shubhi Kulshrestha

***Abstract*— An Electrocardiogram (ECG) is a bio-electrical signal that provides important information regarding the performance of the heart. The ECG is the most useful and feasible diagnostic tool for initial evaluation, early risk stratification and triage for cardiac ailments. The identification of QRS-complexes using LS-SVM as classifier has been presented in the paper. Entropy of the ECG is an important discriminating feature. Using LS-SVM as a classifier, the QRS-complexes have been identified with an accuracy of 99.96 % with 0.04% of false negative (FN) and 0.69% of false positive (FP) respectively.**

***Index Terms* — ECG, QRS-complex, LS-SVM, entropy**

I. Introduction

Computer-aided feature extraction and analysis of ECG signal for cardiac disease diagnosis has become the necessity of the day. The number of cardiac patients has increased many folds in comparison with limited number of cardiac specialists and it has become difficult to provide effective cardiac care without the help of computer-aided expert systems. 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 like P, T-waves and ST-segment etc are found with respect to it. 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.

Least Square Support Vector Machine (LS-SVM) based classification methods have established their impact in the field of pattern recognition research. LS-SVM based algorithm for the detection of QRS complexes has been presented in this paper. The entropy of the ECG signal has been used as the discriminating feature in the present work. The LS-SVM is then used as a classifier for the accurate and reliable detection of the QRS-complexes.

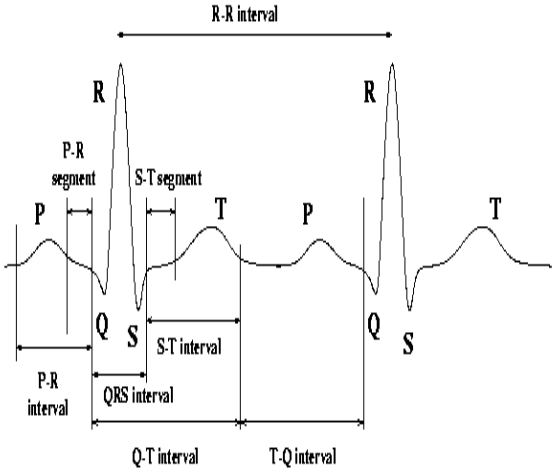

Fig.1 ECG signal and its components

II. Least-square support vector machine

Least Square Support Vector Machine (LS-SVM) is re-formulations of the standard Support Vector Machine (SVM). LS-SVM classifier proposed by Suykens and Vandewalle [21] 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.

Here a modification to the Vapnik SVM classifier formulation has been made which leads to solving a set of linear equations, which for many practitioners in different areas is easier to use than QP solvers. The following SVM modification was originally proposed by Suykens:

Manuscript received May 14, 2015. This work was supported by the grant received from AICTE, New Delhi INDIA.

Swati Sharma is working as Associate Prof. in the department of Electrical Engg in Jodhpur National University, Jodhpur, INDIA. (e-mail: er.swati.sharma15@gmail.com)

S.S. Mehta obtained his PhD from IIT Roorkee, INDIA and presently working as Professor in Electrical Engineering Department, Jai Narain Vyas University, Jodhpur, INDIA (e-mail: ssmehta_58@rediffmail.com)

Shubhi Kulshrestha is M.E. Student at Electrical Engineering Department, Jai Narain Vyas University, Jodhpur, INDIA (e-mail: shubhi.kulshrestha@gmail.com)

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

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

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

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.

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

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

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

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 (LS-SVM) 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. In the present work the implementation of LS-SVM for QRS-detection in single-lead ECG signal has been 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.

III. Entropy as a Feature Signal

The probability $P_i(x)$ of absolute slope at each sampling instant belonging to QRS and non- QRS region is calculated using equation (8).

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

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

ISBN: 978-988-14047-2-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

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.

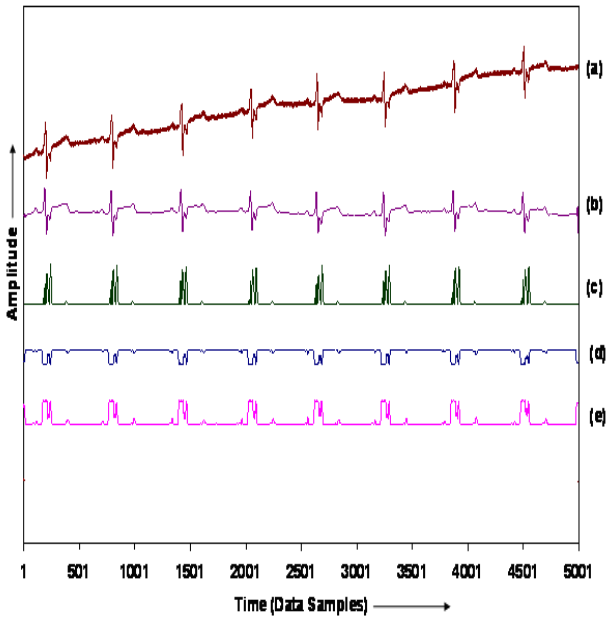

Fig. 2 Preprocessing of ECG signal (a) Raw ECG of lead aVF of record MO1_014 of CSE ECG data-set 3, (b) Filtered ECG, (c) Absolute slope curve, (d) Entropy QRS, (e) Entropy non-QRS

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-based 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.

V. ALGORITHM FOR QRS- COMPLEX DETECTION IN SINGLE LEAD ECG SIGNAL

For single lead QRS detection using entropy criteria, the input vector $\mathbf{x}_i$ to the LS-SVM classifier is a set of normalized entropy values. During the training of LS-SVM, two synchronized sliding windows of size of ten sampling instants are moved over both the entropy curves from the training set. A window size of ten is selected because too small and too large size of the window leads to under-capturing and over capturing of the ECG signal respectively. The first pattern vector is formed by taking twenty normalized entropy values (ten belonging to QRS and ten belonging to non-QRS) from first to tenth sampling instant. The windows are then moved forward by a step of one sampling instant and the second pattern vector is formed by taking another set of twenty normalized entropy values but now from second to eleventh sampling instant. This way, sliding windows of size ten sampling instant and a jump size of one sample are moved over the normalized entropy values from the training set. When the window lies in the QRS region, the desired output of the LS-SVM is set to 1 and when it lies in the non QRS region, the desired output is set to -1. The ECG portions, when the window lies partially in QRS as well as in non-QRS-regions are not included in the training set.

During testing, a set of twenty calculated normalized entropy values (ten belonging to QRS and ten belonging to non QRS) of a particular lead of a subject, from a standard CSE ECG database, are used at an instant to form the input vector for the LS-SVM. The first pattern vector is formed by taking twenty normalized entropy values (ten belonging to QRS and ten belonging to non QRS) from first to tenth sampling instant. The windows are then moved forward by one sampling instant and again a set of twenty entropies, are taken to form next input pattern vector. In this way, two synchronized sliding windows of size of ten sampling instants are moved over both the entropy curves. A train of 1's is obtained at the output of LS-SVM, when the windows traverse through the QRS region and -1 for the non QRS region. Those trains of 1's whose duration turns out to be more than the average pulse duration are identified as QRS regions and the other ones are identified as non-QRS regions.

In some cases, when the P or T-waves are peaky in nature, the LS-SVM gives a train of 1's in P and T regions but of smaller duration as compare to that of the QRS-complex. In order to differentiate between trains of 1's for QRS-complex and that for peaky P or T-waves, an average width or duration of all the trains of 1's is calculated. Those trains whose duration is greater than average pulse width are picked up as QRS-complexes by the algorithm and those whose duration is smaller than the average pulse width are discarded. This reduces the number of false positive detection of QRS-complexes to a great extent.

In the present work four-fold cross-validation approach is used to select the kernel function, to tune its parameters and margin-loss trade-off γ. In this, the training data is divided into four subsets of equal size. Sequentially one subset is tested using the classifier trained on the remaining subsets. Thus, each instance of the whole training set is predicted once so the cross validation accuracy is the percentage of data which are correctly classified.

ISBN: 978-988-14047-2-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

Table 1 Optimum value of various parameters with the cross validation accuracy for the entropy criteria used in single lead ECG Signal

Regularizing Parameter (gam) (γ)	Kernel parameter (sig2) (σ)	No. of training instances	Cross validation Accuracy (%)
10	0.2	9827	98.56

VI. Result and Discussion

The performance of the proposed LS-SVM based algorithm for QRS-detection is evaluated using 1500, single lead ECG recordings from the dataset-3 of the CSE multi-lead measurement library [25]. 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 non-QRS-wave is detected as a QRS-complex.

Case I: Fig. 3 show results obtained at the preprocessing stage and QRS-detection in lead aVF of record MO1_002. As depicted in fig. (b), the preprocessor removes noise and baseline wander present in the signal. The P-waves are prominent in this case. It can be seen from Fig. (c) and (d) that in the QRS-region, the entropy belonging to QRS-class is low i.e. uncertainty of the occurrence of QRS is low or in other words certainty of the occurrence of QRS-region is high. Similarly, in this region entropy belonging to non-QRS is high i.e. uncertainty of the occurrence of non-QRS is high or in other words certainty of non-QRS is low. Hence all the QRS-complexes have been correctly identified by the LS-SVM as shown in Fig. (e). Moreover, the P-waves though prominent in nature are not detected as QRS complex by the algorithm.

Case II: Fig. 4 shows results obtained in lead aVR of record MO1_024. As depicted in fig. (b), the preprocessor removes noise and baseline wander present in the signal. It can be seen from Fig. (c) and (d) that in the QRS-region, the entropy belonging to QRS-class is low i.e. uncertainty of the occurrence of QRS is low or in other words certainty of the occurrence of QRS-region is high. Similarly, in this region entropy belonging to non-QRS is high i.e. uncertainty of the occurrence of non-QRS is high or in other words certainty of non-QRS is low. Similar characteristics are seen in T-wave regions. But they are not picked up as QRS complexes owing to lesser durations of trains of 1's in these regions. Hence all the QRS-complexes are correctly identified by the LS-SVM as shown in Fig. (e).

VII. Conclusion

A simple but effective method using LS-SVM has been presented in this paper for the detection of the QRS-complexes in Electrocardiograms. Digital filtering techniques effectively remove the noise and power line interference present in the ECG signal. The performance of the proposed LS-SVM for QRS-detection and delineation is evaluated using 1500, single lead ECG recordings from the dataset-3 of the CSE multi-lead measurement library [25]. The algorithm has been exhaustively tested using the data-set 3 of CSE multi-lead measurement library covering a wide variety of QRS-complexes, P and T-wave morphologies

In single lead average detection rate (DR) of 99.96% has been obtained with the false negative and false positive percentage of 0.04% and 0.69% respectively. The performance of the algorithm compares favorably with other QRS-detection algorithms. The proposed simple statistical method gives a new direction in the area of ECG signal processing. It can be said that LS-SVM can be seen as very promising techniques to solve ill-posed problems. Furthermore, these lead to robust models in cases of spectral variations due to nonlinear interferences. 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 LS-SVM based algorithm is a step towards this direction.

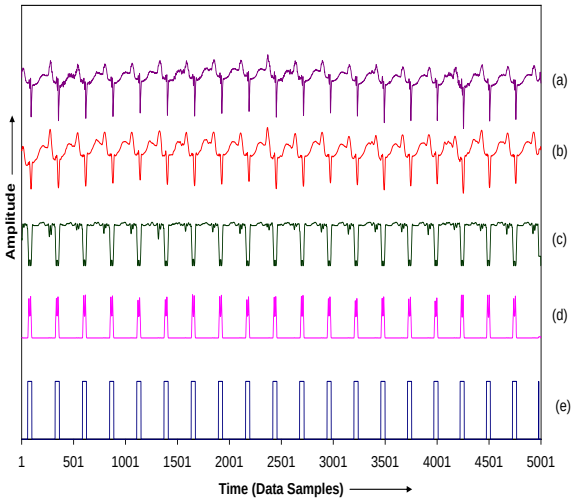

Fig. **3** Detection of QRS-complexes in lead aVF of record MO1_002 (a) Raw ECG, (b) Filtered ECG, (c) Entropy QRS, (d) Entropy non-QRS, (e) QRS-detection by LS-SVM

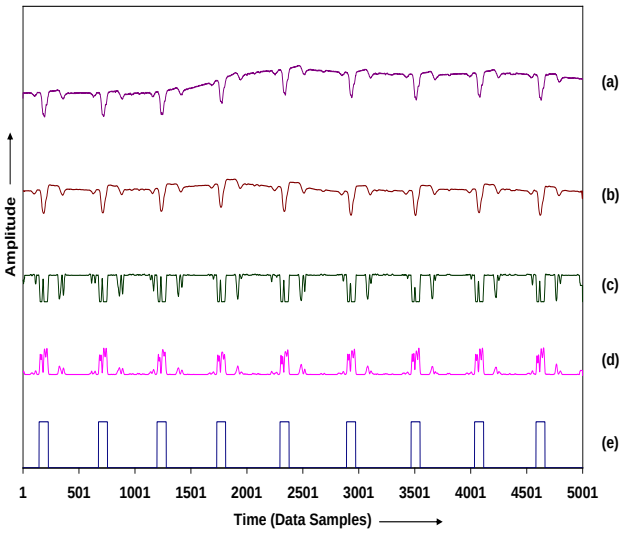

Fig. 4 Detection of QRS-complexes in lead aVR of record MO1_024 (a) Raw ECG, (b) Filtered ECG, (c) Entropy QRS, (d) Entropy non-QRS, (e) QRS-detection by LS-SVM

ISBN: 978-988-14047-2-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

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] An Senjian, Liu Wnaquan and Venkatesh Svetha, "Fast cross-validation algorithms for least squares support vector machine and kernel ridge regression", Pattern Recognition, ScienceDirect, pp. 2154-2162, ELSEVIER 2007.

[3] Chang C.C. and Lin C.J., "LIBSVM: A library for support vector machines", Technical report, National Taiwan University, Taiwan, 2004.

[4] Clifford. Gari D., Azuaje Francisco, McSharry. Pattrick E., "Advanced Methods and Tools for ECG Data Analysis", Artech House, INC., 2006.

[5] 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.

[6] Gestel T. Van, Suykens J.A.K., Lanckriet G., Moor B. De and Vandewalle J., "Bayesian Framework for Least-Squares Support Vector Machine Classifier, Guassian Process and Kernel Fisher Discriminant Analysis", Neural Computing, No. 14, pp. 1115-1147, 2002.

[7] Hingorani P., Natekar M., Deshmukh S, Deshmukh R.D., Kothari S., Narula D. and Lokhandwala Y., "Morphological abnormalities in baseline ECGs in healthy normal volunteers participating in phase I studies", Indian J Med Res 135, pp 322-330, March 2012.

[8] Juan LI Li, Hong-Ye SU and Jian CHU, "Generalized Predictive Control with Online Least Square Support Vector Machine", Acta Automatica Sinica, Vol. 33, No. 11, November 2007.

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

[10] Karpagachelvi S., Arthanari M., Sivakumar M., "ECG Feature Extraction Techniques - A Survey Approach", (IJCSIS) International Journal of Computer Science and Information Security, Vol. 8, No. 1, pp: 76-80, April 2010.

[11] Kuh Anthony, "Analysis of Detectors for Support Vector Machines and Least Square Support Vector Machine", NSF Grant, IEEE, 2002.

[12] Lin C., Kail G., Tourneret J.Y., Mailhes C., and Hlawatsch F., "P and T-wave Delineation and Waveform Estimation in ECG Signals Using a Block Gibbs Sampler", in Proc. IEEE ICASSP 2011 Prague, Czech Republic, May 2011, pp. 537-540 Copyright 2011 IEEE.

[13] Ligayat N.S., "Development Of Classification Techniques For The Delineation Of ECG Components", Ph.D Thesis, Department of Electrical Engineering, J.N.V. University, Jodhpur, 2008.

[14] Macfarlane P.W, "A brief history of computer–assisted electrocardiography", Methods of Information in Medicine, vol. 29, no. 4, pp. 272-281, 1990.

[15] Malgina Olga, Milenkovic Jana, plesnik Emil, Zajc Matej and Tasic Jurij F., "ECG Signal Feature Extraction and Classification Based on R Peaks Detections in the Phase Space" , IEEE GCC Conference and Exhibition, pp. 381-384, Feb 2011.

[16] Pan J. and Tompkins W.J., "A real time QRS-detection algorithm", IEEE Transactions on Biomedical Engineering, vol. 32, no. 3, pp. 230-236, 1985.

[17] Pasolli Edoardo and Melgani Farid, "Active Learning Methods for Electrocardiographic Signal Classification", Information Technology in Biomedicine, Vol. 14, No. 6, pp. 1405-1416, November 2010.

[18] Pipberger H.V., Arms R.J. and Stallman F.W., "Automatic screening of normal and abnormal ECG by means of a digital electronic computer", Proceedings of the Society for Experimental Biology and Medicine, vol. 106, pp. 130-132, 1961.

[19] Pipberger H.V., McManus C.D. and Pipberger H.A., "Methodology of ECG interpretation in the AVA program", Methods of Information in Medicine, vol. 29, no. 4, pp. 337-340, 1990.

[20] Samsudin Ruhaidah, Saad Puteh and Shabri Ani, "Hybridizing GMHD and Least Squares Support Vector Machine for Forecasting Tourism Demand", pp. 274-279, IJRRAS 3, June 2010.

[21] Suykens J.A.K. and Vandewalle J., "Least Square Support Vector Machine Classifier", Neural Processing Letters, 9, pp. 293-300, 1999.

[22] Suykens J.A.K., Brabanter J. De., Lukas L. and Vandewalle J., "Weighted least square support vector machines: robustness and sparse approximation", Neurocomputing 48, pp. 85-105, ELSEVIER 2002.

[23] Suykens J.A.K., Brabanter J. De., Lukas L. and Vandewalle J., "Least Square Support Vector Machine", World Scientific Publishing Co.Pte.Ltd, 2005.

[24] Willems J.L., "The CSE Multilead atlas measurement results data set 3", Common Standards for Quantitative Electrocardiography, Leuven, Belgium, 1988.

[25] Willems J.L, Abreu-Lima C., Arnaud P., Brohet C.R., Denis B., Gehing J., Graham I., Herpen van G., Machado H., Michaelis J. and Moulopoulous S.D., "A reference database for multilead electrocardiographic computer measurement programs", J.Amer. Coll. Caediol., vol. 10, pp.1313-1321, 1987.

[26] Willems J.L., Arnaud P., Bemmel J.H.V., Degani R., Mcfarlane P.W. and Zywietz C., "Common standards for quantitative electrocardiography: Goals and main results", Methods of Information in Medicine, vol. 29, no. 4, pp. 263-271, 1990.

[27] Xingli Bai and Zhengiun Tian, "Medical Images Classification Based on Least Square Support Vector Machines", Henan Foundation and Cutting-edge Technology, IEEE, 2009.

[28] Zhenghzhong Gao, Fanxue Kong, Xu Zhang, "Accurate and Rapid QRS Detection for Intelligent ECG Monitor", Third International Conference on Measuring Technology and Mechatronics Automation, pp. 298-301, 2011.

ISBN: 978-988-14047-2-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)