Journal of Theoretical and Applied Information Technology

www.jatit.org

IDENTIFICATION AND DELINEATION OF QRS COMPLEXES IN ELECTROCARDIOGRAM USING FUZZY C-MEANS ALGORITHM

S.S. MEHTA[1], C.R.TRIVEDI[2], N.S. LINGAYAT[3]

1 Electrical Engineering Department, J.N.V, University, Jodhpur. Rajasthan, India
2 Electrical Engineering Department, SSPC, Visnagar, GTU, Gujarat, India
3 Electrical Engineering Department, Dr. B.A. Technological University, Lonere, Maharasthra, India
email: ssmehta_58@rediffmail.com , chrg.trvd@gmail.com, nslingayat@yahoo.com

ABSTRACT

Over the past few years, there has been an increased trend toward processing of the electrocardiogram (ECG) using microcomputer. The system based on microcomputer can perform the needed medical services in extremely efficient manner. In fact, many systems have already been implemented to perform signal processing task such as 12-lead ECG analysis. All these applications require an accurate detection of QRS complex of ECG. Thus QRS complex detection is an important part of many ECG signal processing system. This paper presents application of Fuzzy C-Means algorithm (FCM) for detection of QRS complex in ECG signal. The performance of the algorithm is validated using original 12-lead ECG recording from the standard ECG data base. Significant detection rate is achieved. The onset and offset of the QRS complexes are found to be within tolerance limit given by CSE library.

Keywords: *ECG, QRS complex, FCM, Delineation*

1. INTRODUCTION

Correct detection of QRS-complexes forms the basis of most of the algorithms used in automated processing and analysis of ECG. The other waves like T and P waves are detected by identifying their position relative to QRS complex.

The ECG recording may contain various challenging problems such as segment with high noise content, sudden change in QRS amplitude and morphology, or muscle and electrode artifact which are not often detected correctly. Hence reliable and correct detection of QRS complexes, under various backgrounds, is very important in any algorithm used for ECG analysis. The correct performance of these systems depends on several important factors such as quality of ECG signal, the applied detection rule, the learning and testing dataset used.

Fig.1 displays typical ECG cycle. To facilitate the analysis, the horizontal segment of this waveform preceding the P wave is designated as baseline or isopotential line. The P wave represents depolarization of atria musculature. The QRS complex is mainly due to depolarization of the ventricle. The T wave is the wave of ventricular repolarization. The U wave if present is generally believed to be the result of after potential in ventricular muscle.

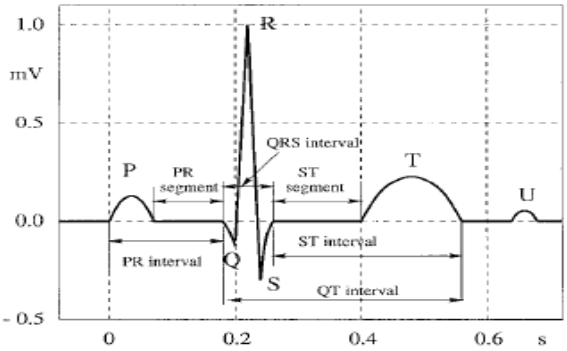

Fig.1 ECG signal

Various methods, for QRS detection are found in the literature, method based on digital filter [6, 22], mathematical transformation [2, 4, 11, 19, 20], pattern recognition [9, 28, 24,], artificial neural networks [31, 13, 25], genetic algorithm [14, 15], heuristic method [7, 23,] and statistical methods [16, 17, 18]. This paper presents an application of Fuzzy C-Means algorithm (FCM) [29] for the detection of QRS complexes, using the entropy criteria for the generation of the feature signal. This method is suitable for the detection of all kind of morphologies of QRS complexes. It not only detects the QRS complex but also locates their

onset and offset accurately, within the tolerance limits specified by the physicians in CSE library.

2. OVERVIEW OF FUZZY C-MEANS

Pattern recognition techniques can be classified into two broad categories: unsupervised techniques and supervised techniques. These two types of techniques are complementary. For example unsupervised clustering can be used to produce classification information needed by the supervised pattern recognition technique. The Fuzzy C-Means algorithm is an unsupervised fuzzy clustering algorithm [29]. Conventional clustering algorithm finds "hard partition" of a given dataset based on certain criteria that evaluate the goodness of partition. By "hard partition" we mean that each datum belong to exactly one cluster of the partition. While the soft clustering algorithm finds "soft partition" of a given dataset. In "soft partition" datum can partially belong to multiple clusters. A soft partition is not necessarily a fuzzy partition, since the input space can be larger than the dataset. However, most soft clustering algorithms do generate a soft partition that also forms fuzzy partition.

A type of soft clustering of special interest is one that ensures membership degree of point x in all clusters adding up to one, i.e.,

$$\sum_{j} \mu_{c_j}(x_i) = 1 \qquad \forall x_i \in X$$

(1)

A soft partition that satisfies this additional condition is called a constrained soft partition. The Fuzzy C-Means algorithm, which is best known fuzzy clustering algorithm, produces constrained soft partition. In order to produce constrained soft partition, the objective function J_1 of hard c-means has been extended in two ways:

(1) The fuzzy membership degree in cluster has been incorporated in the formula.

(2) An additional parameter m has been introduced as a weight exponent in fuzzy membership.
The extended objective function, denoted by J_m, is:

$$J_m(P,V) = \sum_{i=1}^{k} \sum_{x_k \in X} (\mu_{C_i}(x_k))^m \left\| x_k - v_i \right\|^2$$

(2)

where P is fuzzy partition of dataset X formed by C_1, C_2, ….., C_k and k is number of clusters. The parameter m is weight that determines the degree to which partial members of cluster affect the clustering result. Like hard c-means, fuzzy c-means also tries to find good partition by searching for prototype v_i that minimizes the objective function J_m. Unlike hard c-means, however, the fuzzy c-means algorithm also needs to search for membership function μ_{C_i} that minimizes J_m. A constrained fuzzy partition {C_1, C_2, ….., C_k } can be local minimum of the objective function J_m only if the following conditions are satisfied:

FCM (X, c, m, ε)
X: unlabeled dataset
c: the number of cluster to be formed.
m: the parameter in objective function.
ε: threshold for the convergence criteria.

1. Initialize the prototype $V = \{v_1, v_2, \ldots, v_k\}$
2. Repeat steps 3,4 and 5 until, $\sum_{i=1}^{C} \left\| v_i^{previous} - v_i \right\| \le \varepsilon$
3. $V^{previous} \leftarrow V$
4. Compute the membership function using equation 3.
5. Update the prototype, v_i in V using equation 4.

$$\mu_{C_i}(x) = \frac{1}{\sum_{J=1}^{k} \left(\frac{\left\| x - v_i \right\|}{\left\| x - v_j \right\|^2} \right)^{\frac{1}{m-1}}}$$

$$1 \le i \le k, x \in X \qquad (3)$$

$$v_i = \frac{\sum_{x \in X} \mu_{C_i}(x)^m x}{\sum_{x \in X}^{n} \mu_{C_i}(x)^m} \qquad 1 \le i \le k$$

(4)

Based on this theorem, FCM updates the prototypes and membership function iteratively using equation 3 and 4 until a convergence criterion is reached. Here it is worth mentioning few important points regarding the FCM algorithm: (1) It guarantees converge for $m > 1$. (2) It finds local minimum of the objective function J_m. (3) The result of applying FCM to a given dataset depends not only upon the choice of parameter m and c, but also on the choice of initial prototype.

3. ALGORITHM FOR QRS DETECTION

In this section, it is described how the proposed algorithm can be applied for the detection of QRS complex. Fig.2 displays the result of each step of the proposed method when applied to single lead ECG recording to clearly demonstrate how the algorithm works and its effectiveness in the identification of QRS complexes. The algorithm is as follows.

Step 1: A raw digital ECG signal is acquired as shown in fig. 2(a).

Step 2: A raw ECG signal is often contaminated by disturbances such as power line interference and base line wander. The finite impulse response (FIR) notch filter proposed by Van Alste and Schilder [1] is used to remove base line wander. The adaptive filter used to remove base line wander is special case of notch filter, with notch at zero frequency (or dc). The bandwidth of the filter is $(\mu/\pi)*f_s$, where f_s is the sampling frequency of the signal and μ is the convergence parameter. In this case, the sampling frequency is 500 Hz and the value of the convergence parameter is 0.0025. Frequencies in the range 0-0.5 Hz are removed to reduce the base line drift. The filter proposed by Furno and Tompkinson [8] is used to remove 50 Hz power line interference. Fig. 2(b) displays the filtered ECG signal after removal of power line interference and baseline wander.

Step 3: The gradient at every sampling instant is calculated to enhance the signal in the region of QRS-complex. The various slopes obtained at different sampling instant are divided in to two classes namely QRS-class and non-QRS class. Now mean and standard deviation are calculated for each class and probability of each sample belonging to QRS and non-QRS class is calculated.

Step 4: The entropy is used as a suitable criterion in the design of optimum feature selection. Entropy is a statistical measure of uncertainty. Features that reduce the uncertainty of a given situation are considered more informative than those that have the opposite effect. After calculating probability, entropies for the QRS and non-QRS class are calculated using the equation:

$h_i(x) = -p_i(x)\ log_e\ p_i(x);$

i = 1, 2; x = 1, 2, ……, *n* (5)

where *n* is the number of samples present in the ECG recording. Here *n*=5000 for CSE database ECG recordings of ten seconds duration sampled at 500 Hz. The entropies are then normalized. Fig. 2(c) and 2(d) display the entropies in the non-QRS and QRS region.

Step 5: The values of QRS entropy are used to form input vector A_1. Apply Fuzzy C-means algorithm to obtain two cluster centers C_1 and C_2. Calculate the average value of the two cluster centers $C_{average}$. Cluster center whose value is greater than $C_{average}$ is designated as C_1 and other C_2. Calculate the distance of first element of vector A_1 from both cluster center C_1 and C_2. If it is closer to cluster center C_1 then assign value 0 to sign vector Y_1, otherwise assign value 1. Repeat the above step for all elements of QRS entropy vector.

Step 6: Take the values of non-QRS entropy vector in vector A_2 and repeat the procedure as in step 4. Calculate the distance of first element of non-QRS entropy vector from both cluster center C_1 and C_2. If it is closer to cluster center C_1 assign value 1 to sign vector Y_2, otherwise assign 0 values to the sign vector. Repeat the above procedure for all elements of non-QRS entropy vector.

Step 7: The vector Y has value of 1 only where both the sign vector Y_1 and Y_2 has value of 1. It is displayed in Fig. 2(e). It is observed that continuous train of 1's is observed in QRS regions and 0's in non-QRS region.

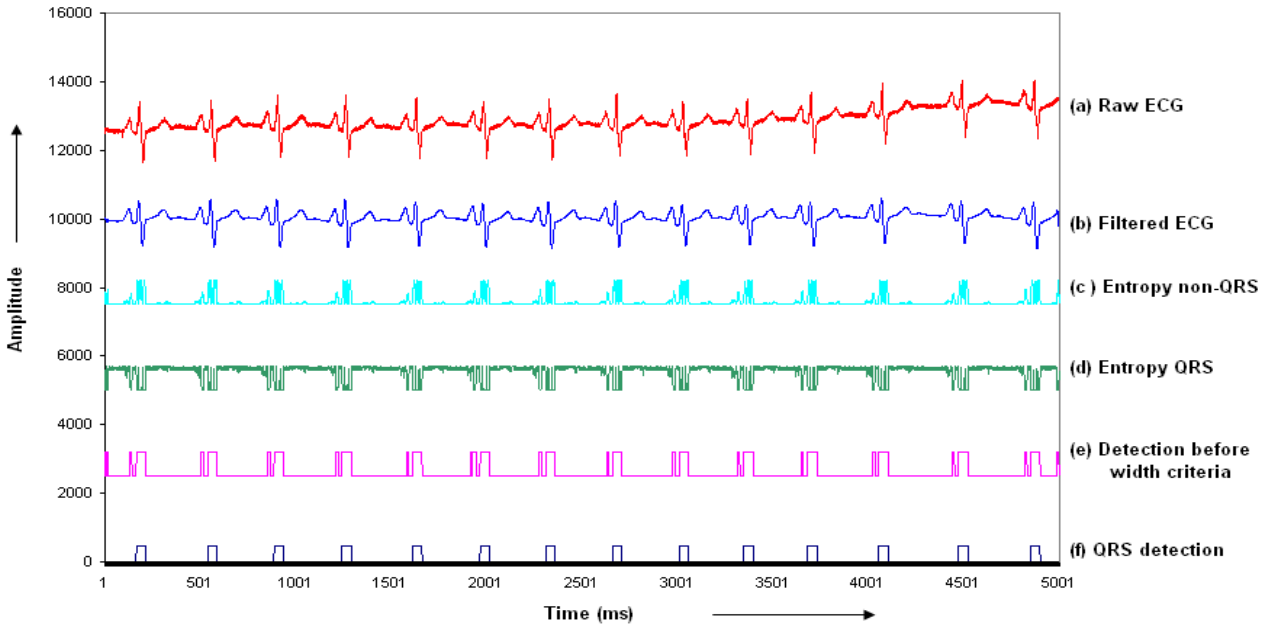

Fig.2 Results obtain at each step of algorithm

Step 8: A continuous train of 1's is picked and using their duration, average pulse duration of all the trains of 1's is evaluated. The train of 1's whose duration turns out to be more than average pulse duration is identified as QRS complex and other ones are discarded. This criterion is known as average pulse width criterion. The location of QRS complexes, after applying average pulse width criteria is shown in Fig. 2(f).

Step 9: The above steps are repeated for all the twelve leads.

4. PERFORMANCE EVALUATION AND DISCUSSION

The validation of the proposed algorithm for the QRS complex detection is done using 125 original, 12 lead ECG record of data set 3 of CSE ECG data base [30]. The data base 3 covers wide variety of the pathological case. Every record picked from CSE ECG data base is of 10 s duration sampled at 500 samples per second thus giving 5000 samples. Detection is said to be true positive (TP) if the algorithm correctly detects the QRS complex, it is said to be false positive (FP) if component other than our interest is detected and it is said to be false negative (FN) if the algorithm fails to detect the component of our interest. The result using the proposed FCM algorithm on CSE database for 12-lead is given in Table 1.

Fig.3 displays performance of the algorithm for the record M01_47. Here, the lead aVL of the record has been selected to clearly demonstrate the effectiveness of the algorithm. As depicted in fig. 3(a), the preprocessor removes power line interference and base line wander. The QRS (non QRS) entropy is minimum (maximum) in the region where QRS complex (non-QRS) is present as shown in Fig. 3(b) and 3(c). The FCM algorithm correctly detects all the sixteen QRS complexes present in the record. Similarly, Fig. 4 shows lead aVR of record MO1_117 where the algorithm has correctly identified nine QRS-complexes out of twelve. The amplitude and hence the slope of the third, seventh and eleventh QRS complexes is quite low in comparison with the other ones. Hence the algorithm has failed to detect these three QRS-complexes marked False Negatives (FN) in the figure.

Lead	Total QRS	QRS Detected	FP	FN	%QRS Detected
L1	*1488*	*1471*	*22*	*17*	*98.86*
L2	*1488*	*1481*	*38*	*7*	*99.53*
L3	*1488*	*1467*	*31*	*21*	*98.59*
AVF	*1488*	*1461*	*60*	*27*	*98.19*
AVL	*1488*	*1465*	*27*	*23*	*98.45*
AVR	*1488*	*1477*	*16*	*11*	*99.26*
V1	*1488*	*1477*	*37*	*11*	*99.26*
V2	*1488*	*1483*	*44*	*5*	*99.66*
V3	*1488*	*1478*	*69*	*10*	*99.33*
V4	*1488*	*1475*	*6*	*13*	*99.13*
V5	*1488*	*1462*	*37*	*26*	*98.25*
V6	*1488*	*1462*	*2*	*26*	*98.25*

Table 1 Lead wise test results

5. DELINEATION

Delineation determines characteristic point (onset and offset) of QRS complexes in ECG signal. The procedure begins by applying single lead QRS detector to recognize beat activity in each lead, after that wave's onset and offset are searched in each lead. The method performance has been evaluated with referee's annotation and combine program median provided in CSE multilead measurement database.

The time difference of QRS onset and offset between automatic (proposed FCM algorithm) and referee cardiologist annotation/combine program median is calculated, which is known as error. The mean (m) is calculated as average of error. Standard deviation S in ms is calculated. In order to assess the agreement between automatic (proposed FCM algorithm) and referee cardiologist annotation/combine program median for QRS onset and offset Bland-Altman analysis [3] is done.

Fig. 5-6 displays Bland-Altman plot of QRS onset and offset respectively, for comparing the performance of FCM with combine program median given by CSE. In case of QRS onset the standard deviation is ± 12.45 ms and in case of QRS offset the standard deviation is ± 14.55 ms, which is within the acceptable limits. Thus FCM based algorithm not only detects the QRS complexes of ECG, but also delineate them accurately.

6. CONCLUSION

This paper represents new method for the QRS complex detection in ECG signal using Fuzzy C-Means algorithm. The method has been comprehensively tested using the CSE ECG database covering wide variety of QRS complexes. A considerable detection rate is obtained. The delineation results show that the standard deviations of the error are within the tolerance limit.

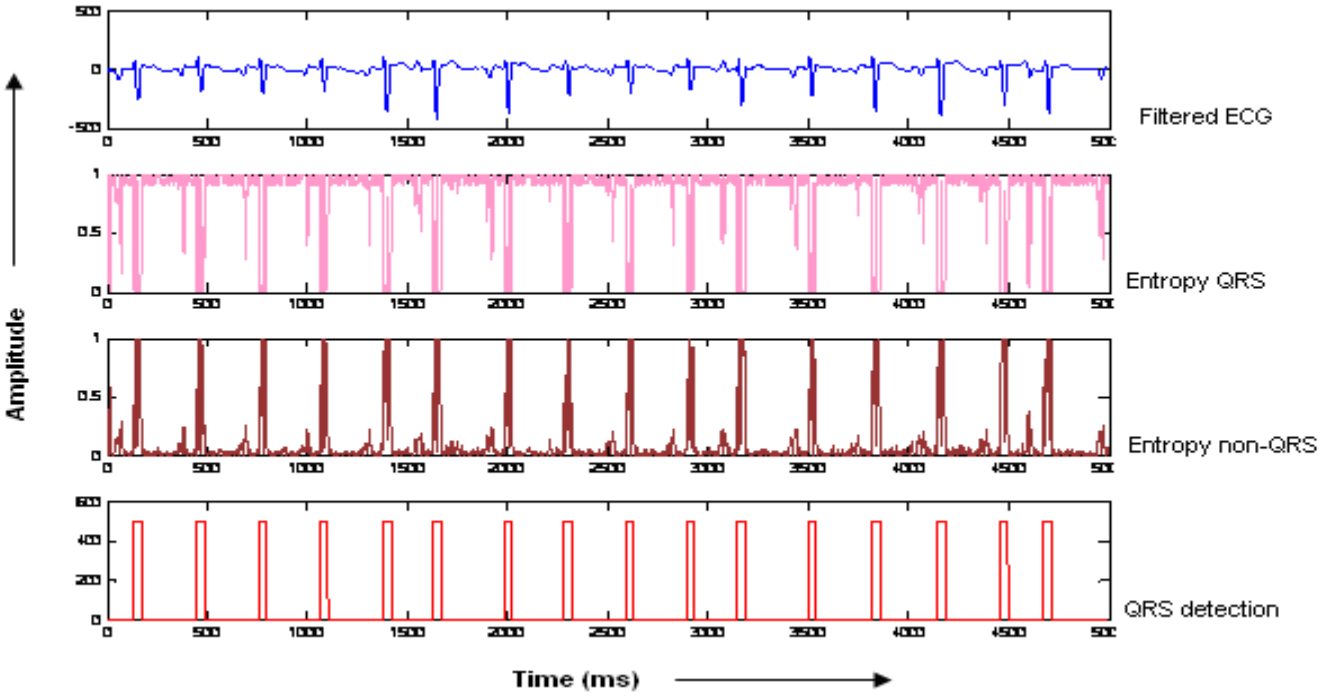

Fig. 3 Detection of QRS complexes in lead aVL of record M01_47

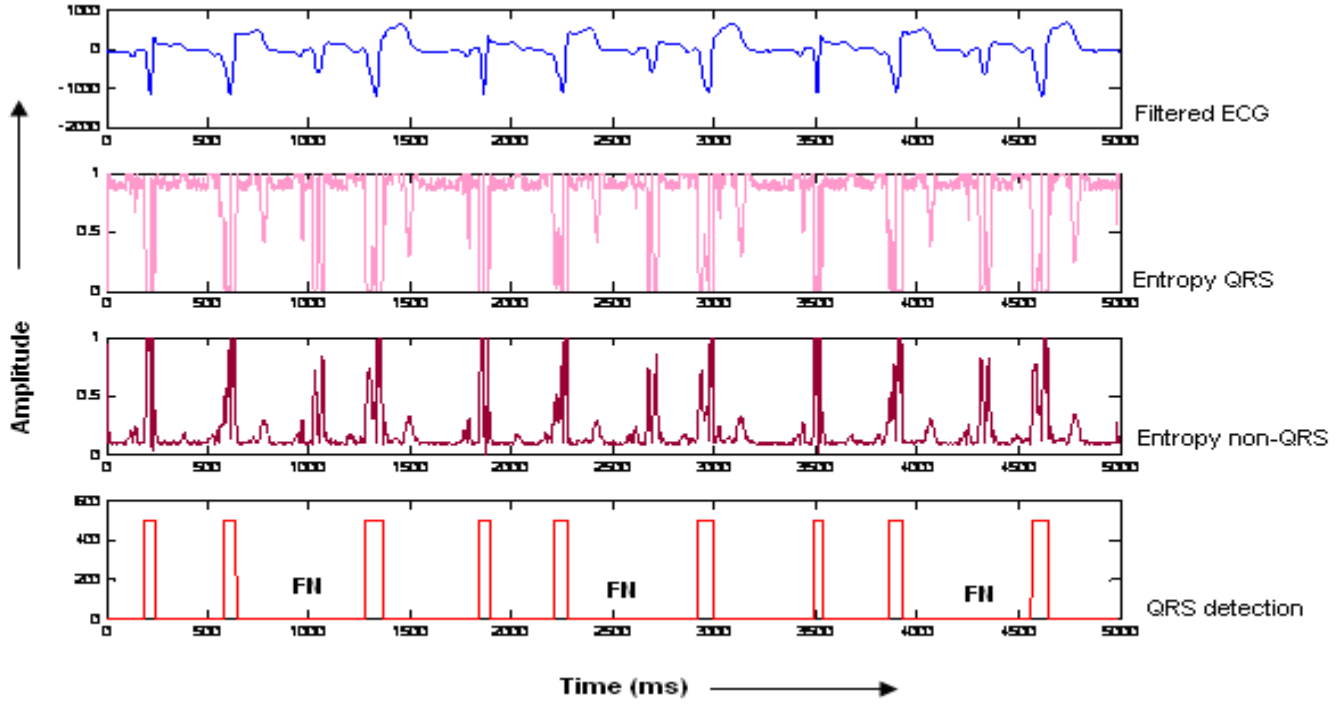

Fig. 4 Detection of QRS complexes in lead aVR of record M01_117

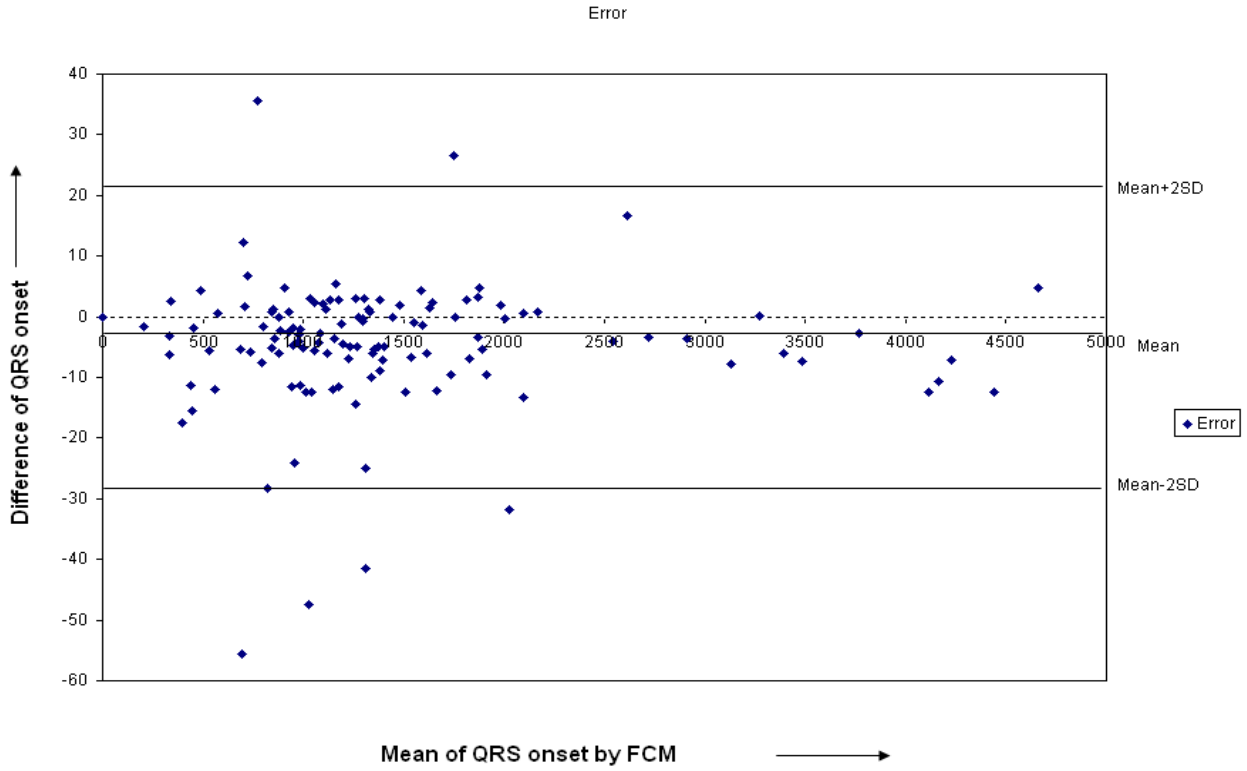

Fig. 5 Bland-Altman plot for QRS onset

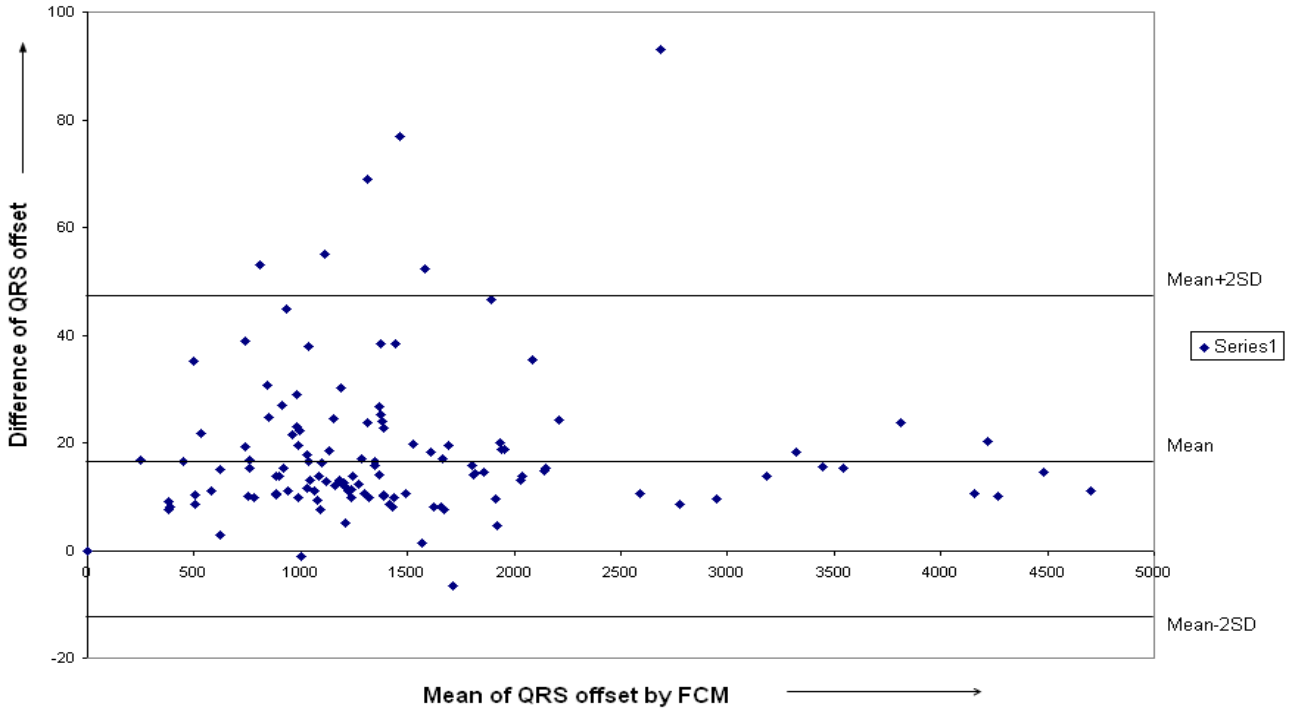

Fig. 6 Bland-Altman plot for QRS offset

REFERENCES

[1] Alste Van J. A., and Schilder T. S., "Removal of base-line wander and power line interference from the ECG by an efficient FIR filter with a reduced number of taps," *IEEE Trans. Biomed. Eng*., vol. 32, pp. 1052- 1059, 1985.

[2] Benitez D., Gaydecki P. A., Zaidi A., and Fitzpatrick A. P., "The use of Hilbert transform in ECG signal analysis," Comp. in Bio. and Med., vol. 31, pp. 399-406, 2001.

[3] Bland J. M., Altman D. G., "Statistical Methods for assessing agreement between two methods of clinical Measurement ," Lancet, pp. 307-310, 1986.

[4] Chen S. W., Chen H. C. and Chan H. L., "A real time QRS detection method based on moving-averaging incorporating with wavelet denoising," Comp. Methods and Progs. in Biomed., vol. 82, pp. 187-195, 2006.

[5] Chouhan V. S. and Mehta S.S., "Detection of QRS-complexes in 12-lead ECG using adaptive quantized threshold," International Journal of Computer Science and Network Security, vol. 8, no.1, pp. 155-163, 2008.

[6] Engelse W. A. H. and Zeelenberg C., "A single scan algoriothm for QRS detection and feature extraction," Computer in Cardiology, IEEE compu. Soc., pp. 37-42, 1979.

[7] Fraden J. and Neurman M. R., "QRS wave detection," Med. & Bio comp., vol. 18, pp. 125-132, 1980.

[8] Furno G. S., and Tompkins W. J., "A learning filter for removing noise interference," IEEE Trans. Biomed. Eng., vol. 30, pp. 234-235, 1983.

[9] Gritzali F., "Towards a generalized scheme for QRS Detection in ECG Waveforms," Signal Processing, vol. 15, pp. 183-192, 1988.

[10] Kohler B. U., Henning C. and Orglmeister R., "The principles of software QRS detection," IEEE Eng. in Med. and Bio, pp. 42-47, 2002

[11] Kyrkos A., Giakoumakis E. A. and Carayannis G., "QRS detection through time recursive prediction technique", Signal Processing, vol. 15, pp. 429-436, 1988

[12] Mehta S.S., Sexana S.C. and Verma H.K, "Computer-aided interpretation of ECG for diagnostics," International Journal of System Science, vol. 27, pp. 43-58, 1996.

[13] Mehta S.S., Dave V., Vyas S.D. and Chouhan V.S., "Detection of QRS-complexes in 12-lead ECG using Error Back Propogation neural network," Int.Cong. on Bio. and Med. Engg., Singapore, 2002.

[14] Mehta S. S, Bansal S. K., Lingayat N. S., "Application of Genetic Algorithm for ECG Pattern Recognition," UGC National Conference on Advances in Computer Integrated Manufacturing (NCACIM), Jodhpur, India, 2007.

[15] Mehta S. S, Bansal S. K., Lingayat N. S., "Detection of QRS complexes in Pricordial Leads of ECG using Genetic Algorithm," National Conference on Information Technology Engineering Perspective and Practices, Tapar Institute of Technology, Patiala, India, 2007.

[16] Mehta S. S. and Lingayat N. S., "Development of Entropy based algorithm for cardiac beat detection in 12-lead electrocardiogram," Sig. Proc., vol. 87, pp. 3190-3201, 2007.

[17] Mehta S. S. and Lingayat N. S., "Combined Entropy based method for detection of QRS complexes in 12-lead electrocardiogram using SVM," Comp. in Biol. And Med, vol. 38, pp. 138-145, 2008.

[18] Mehta S.S. and Lingayat N. S., "ECG Pattern Classification using Support Vector machine 12-lead Combined Entropy," The Sixth International Conference on Advances in Pattern recognition, Indian Statistical Institute, Kolkota, India, 2007.

[19] Mehta S. S., Lingayat N. S., "Development of SVM based classification techniques for the Delineation of wave components in 12-lead electrocardiogram," Biomedical Signal Processing and Control, 2008 (Article in Press).

[20] Murthy I. S. N. and Prasad G. S. S. D., "Analysis ECG from pole zero models," IEEE Trans. Biomed. Eng., vol. BME-39, no.7, pp. 741-751, 1992.

[21] Murthy I. S. N. and Niranjan U. C., "Component wave delineation of ECG by filtering in the fourier domain," Med.& Bio. Eng. and Compu., vol.30, pp. 169-176, March 1992.

[22] Okada M., "A digital filter for the QRS complex detection," IEEE Trans. Biomed. Eng., vol. BME-26, no.12, pp. 700-703, Dec. 1979.

[23] Pan J. and Tompkins W. J., "A real time QRS detection algorithm," IEEE Trans. Biomed. Eng., vol. 32, pp. 230-236, 1985.

[24] Sornmo L., Pahlm O. and NyGards M., "Adaptive QRS detection: A study performance," IEEE Trans. Biomed. Eng., vol. BME-32, no. 6, pp. 392-401, 1985.

[25] Suzuki Y., "Self organizing QRS wave Recognition in ECG using Neural networks,"

IEEE Trans. Biomed. Eng, vol. 6, pp. 1469-1477, 1995.

[26] Trahanias P. and Skordalakis E., "Syntactic pattern recognition of the ECG," IEEE Trans. on Pattern Analysis and Machine Intelli.,vol.PAMI-12, no.7, pp. 648-657, 1990.

[27] Trahanias, P. E., "An approach to QRS complex detection using mathematical morphology,"
IEEE Trans. Biomed. Eng., vol. 40, pp. 201-205, 1993.

[28] Trahanias, P. E., and Skordalalkis, E., "Bottom up approach to the ECG pattern-recognition problem", Med. Bio. Eng. and Compu, 27, 221-229. 1989

[29] V. Deelport and D liesch "Fuzzy C-means algorithm for code book design in vector quantization", Electronic letter 1994, vol. 30, no.13.

[30] Willems J.L., Arnaud P., Bemmel J. H. V., Bourdillon P. J., Degam R., Denis B., Graham I., Harms M.A., Mcfarlane P.W., Mazzacca G., Meyer J. and Zywietz C., "Establishment of a reference library for evaluating computer ECG programs", Computers in Biomedical Research vol. 18, pp. 439-457, 1985.

[31] Xue Q., Hu Y.M. and Tompkins W.J., "Neural network based adaptive matched filtering for QRS detection," IEEE Trans. Biomed. Eng., vol.-39, pp. 317-329, 1992.

BIOGRAPHIES

Sarabjeet S. Mehta received the B.E. degree in Electrical Engineering and M.E. degree in Control System from J. N. Vyas University, Jodhpur, India in 1980 and 1987 respectively. He received Ph.D. degree in Electrical Engineering from Indian Institute of Technology, Roorkee, India in 1994. Presently he is Professor in Electrical Engineering Department, J. N. Vyas University, Jodhpur, India. His research interests include pattern recognition, artificial neural networks, biomedical engineering and soft computing.

Chirag R. Trivedi received the B. E. degree in Electrical Engineering from North Gujarat University, Patan, India in 1997. He is Lecturer in Electrical Engineering at Swami Sachchidanand Polytechnic, Visnagar, Gujarat, India. He had submitted his dissertation for award of M.E degree in Electrical Engineering Department, MBM Engineering College, J. N. Vyas University, Jodhpur. He is working in the area of ECG signal processing.

Nitin S. Lingayat received the B.E. degree in Electrical Engineering from the University of Poona, Pune, India in 1992 and the M.Tech. degree from Indian Institute of Technology Bombay, Mumbai in 1998. He received Ph.D degree in Electrical Engineering from MBM Engineering College, J. N. Vyas University, Jodhpur in 2008. He is Head, Electrical Engineering Department, Institute of Petrochemical Engineering of Dr. B.A. Technological University, Lonere, Maharashtra, India. He is working in the area of biomedical signal processing.