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ST WINDOW PARAMETER IDENTIFICATION IN ARBITRARY ECG SIGNAL POST FACTO ISOELECTRICLINE DETECTION

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ABSTRACT

ECG signal processing has attracted tremendous focus in the recent past for attaining fully automated intelligent cardiac care systems development. Out of the several challenges posed in this path, one of the primary goal is directed towards error free isoelectric line detection. Isoelectric line detection in ECG continues to be an error prone process mainly because of wide variability of ECG shape and low frequency noise. To reduce the error gap, here a coupling scheme is suggested using accurate R-peak detection and associated process. Having obtained the baseline, we introduced the method for detection of ST segment parameters which can lead to various successful diagnostic estimation.

Keywords: *ECG, isoelectric line, ST segment, J-point.*

I. INTRODUCTION

The initial detection of ischemia is generally carried out using ECG signal analysis. Occurrence of ischemia can lead to changes in QRS complex and T - waves may be inverted. ST segment elevation or depression and peaking of T - waves also may occur. In ECG signal the time between ventricular depolarization and repolarization is represented by ST segment. Voltage difference across the boundary between ischemic cells and not resulted by ischemic cells generates the ST segment changes [1]. Magnitude of these ST segment elevation/ depression need not be identical in each lead due to the variances in distance of each lead recording from ischemic region. A direct measurement of ST segment shift in ECG signal can give an indication of location, size and position of ischemia [1] As shown in Fig. 1 ST elevation/ depression is calculated with respect to the baseline.

Moridani and Majid Pouladian has used wavelet transform method to develop an algorithm which can distinguish ischemia episode from non-ischemia episodes [3].

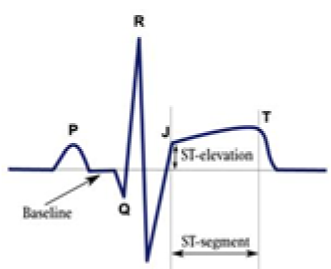

Figure 1. A typical ECG signal

Papaloukas et.al. used knowledge-based method to find ischemic signals in long duration ECG signals [4]. Same authors have given another approach to ischemia detection using neural network [5]. In this method the neural network was trained using a Bayesian regularization method. Principal component analysis (PCA) was also used to reduce dimension. This method of beat classi¿cation was providing 90% sensitivity. MLP neural network, Adaptive Backpropagation Neural Network, PCA neural networks were also used for ischemia detection [6-7]. Another method by José García et.al. used the differences between the ST segment or ST-T complex and an

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average pattern segment. The RMS series of differences were filtered, and a decisive algorithm was used to find the ischemic episodes Support vector machines were also used effectively for ischemia detection [9].

In rule-based methods where medical knowledge is directly transformed to rules generally provides less computational time and an easy explanation of diagnostic decisions [10-11]. But, the success rate depends on the appropriate selection and combination of the rules. It also depends upon the methods used for the extraction of feature values. Parameter accuracy is the main concern here. In rule-based method mainly used parameters are ST deviation from isoelectric line, ST segment slope, ST level and ST integral, ST elevation /depression and T-inversion, and ST segment frequency characteristics. The accuracy of isoelectric line plays a crucial role in determining ischemia episodes.

ECG signal ST segment changes can be analyzed to study electro-physiologic changes during ischemia. As a standard the ST segment elevation is measured as the voltage difference between the value of ECG signal at point 60 or 80 milliseconds after the J-point and the isoelectric line. Between depolarization and repolarization of the atria and ventricles there will be a region of electrical inactivity which is reflected as isoelectric line in ECG signal. The beginning and end of five major waves of ECG is represented by isoelectric line. PR segment is usually used for the isoelectric line estimation, which is 40 milliseconds before the R-peak. But this method entirely depends on the need for an accurate R-peak. Due to wide variability of ECG waves, there can be a discernible period of inactivity in PR segment and the 40ms point measured may be on P-wave or Q-wave, which will give random isoelectric line measurement. Presence of noise in this segment can also leads to wrong baseline reference. One solution to this problem may be to consider all inactive regions, P-R, S-T and T-P segments instead of only PR segment.

II. RESEARCH BACKGROUND

There are many approaches applied for the detection of isoelectric line. Onur Guven et.al. used the method of known nominal characteristics of ECG waveforms [12]. After the accurate detection of R- peak in ECG waveform, three isoelectric points J1, J2, J3 is detected where the derivative is becoming zero. J2 is estimated in ST segment approximately 60ms after R-peak. J1 and J3 are in PR and TP segments, where the derivative is zero. Another method used is to divide the total amplitude between maximum and minimum R-peak to equal amplitude levels and find the number of points in each level. The value of the level with highest number of points is considered as the isoelectric line.

A novel method to find accurate isoelectric line and ST segment parameters is presented through this paper. This method includes four stages, first part is pre-processing of ECG signal and the second part is to find exact location of R-peak. The next step is to divide ECG wave into windows between each R-peak and to find the isoelectric line for each window and the fourth stage extracts the ST segment parameters.

III. RESEARCH METHODOLOGY

Physionet data source provided the annotated ECG signals for testing [13]. ECG signals from European ST-T Database and Long-Term ST Database were used for the testing of algorithm.

A. Baseline Drift Reduction

Initial processing of the ECG signal is required to remove the noise artifacts. Baseline drift noise having a low frequency range (below 0.5Hz) is the main affecting noise in ECG automated detection. To eliminate this noise median filters of frequency 200millisecconds and 600 milliseconds is used [14]. To eliminate QRS complexes and P waves median filter of 200milliseconds is used. The resulting signal is processed with 600 milliseconds filter to remove T waves. The second filter output contains the baseline drift of the ECG signal. This drift signal is subtracted from the original signal to get ECG signal without drift. The baseline drift eliminated ECG signal for ST-T database signal 108, V1 lead is shown in Fig 2.

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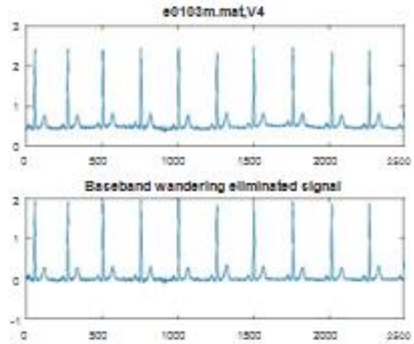

Figure 2. Base Band wandering eliminated signal

A. *R- peak detection*

R - peak detection was carried out using Continues Wavelet Transform(CWT) with a pattern adapted wavelet. Pattern adapted wavelet which resembles a cycle of QRS signal was developed using the method of least square optimization [15]. Matlab® Wavelet toolbox command 'pat2cwav' was used for this purpose. An approximation to the given pattern in the interval [0 1] is given by 'pat2cwav' function by least squares fitting. This adaptive wavelet for QRS signal is given in Fig 3.

As high value of T- wave can lead to a false detection, it is better to remove it before the R- peak detection. From the previously processed signal, T -wave can be removed using the same 600 milliseconds median filter. After T- wave elimination the signal is squared. Squaring helps in using the same adaptive wavelet for all waveforms available from different ECG leads. This process also enhances the R- peaks from P-waves. Another advantage is that, even in high noise signals also R -peaks can be detected [16].

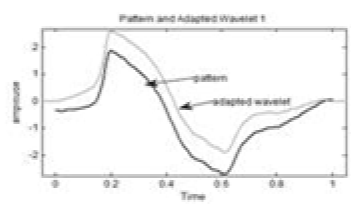

Figure 3. Adapted wavelet

R- peak detection was carried out in seven major steps.

Firstly, the ECG signal after filtering was subjected to two level
CWT using adaptive wavelet. After that series of minimum maximum pairs were isolated. Minimum – maximum pairs with absolute values less than threshold is removed. 30 percentage of the maximum of CWT coefficient is the assigned as threshold value. A heuristic estimation method is used to arrive at the threshold value, which provided the highest detection. Higher threshold values lead to misses in R- peak detection and lower value was giving false detection. Next step is to find the zero crossing points in between this minimum – maximum pairs which corresponds to R-peaks. The following steps are to remove the false detection. The peaks which are occurring within less than 120milliseconds are removed. Similar process is carried out with the coefficients of second level of CWT and compared with the first level detection. For ECG signals with less R_R interval a reduction from 120 milliseconds may be required. The R peak detection is shown in Fig.

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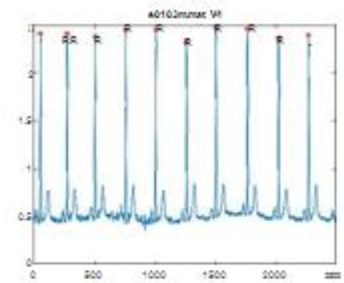

Figure 4. R-peak detected signal

C. Isoelectric line estimation

In isoelectric line estimation there are four major segments. First part is to take current ECG window whose isoelectric line must be determined. For our analysis we considered the points between two R-peak as the current window. Second step is to find active zones in the current window keeping an approximated baseline calculated from previous windows and by selecting a low threshold of 10%. If the percentage of active zones is more than 80% of the ECG window, a new baseline is calculated using histogram and checked again for the percentage of active zones. If the criteria are still not met the threshold value is increased to 20% and the process is repeated. Once the criteria are met the approximated baseline is considered as the isoelectric level for the present window [17].

D. Active zones in ECG window

Here the concept used is to divide the signal window into sensible sections or zones and assigning a value to each zone. Before the division the signal is filtered using a Gaussian filter to reduce the number of zones to limited value. As the filter should be localized in time and frequency, a gaussian filter with a ı of 25 milliseconds is used. A typical Gaussian filter equation is given (1).

ξ (1)

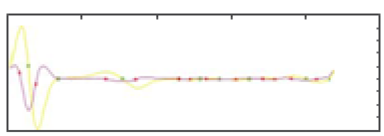

Figure 5. Active zones selection in one ECG cycle

Once these zones are chosen, a value must be assigned to each to represent its activity level. The values assigned are the amplitude values of the actual ECG signal before filtering, at the zero crossing of the first derivative of the filtered signal located on the time scale. The actual importance value assigned to the zones, are precisely located at the corresponding points in time on the actual ECG signal. This eliminates the error seen at high frequencies in the Gaussian filtered trace. Since the active zones values are taken from arbitrary zero these vales must be corrected.

The active zones are chosen by considering whether their importance value is greater than a chosen threshold or not. Since low frequency noise can affect the importance value, they must be scaled and centralized. Importance values must have transformed into percentages of the maximum excursion point in the window, which is usually an R wave average

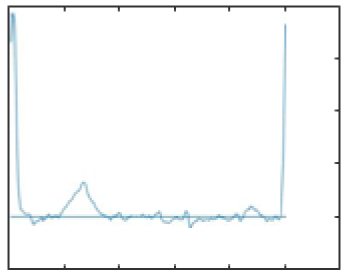

Figure 6. ECG window isoelectric line detection

over three preceding windows. The absolute values of these scaled numbers are then taken, so that maximums and minima are treated equally by the algorithm. Scaled importance value is calculated as in (2).

S.I.V(I, j) = abs [(IV (I, j) – base estimate (I))/ mean (max

(window (i-3: I))]   (2)

where S.I.V(I, j) – Scaled Importance Values in zone j, of heartbeat I; IV- Importance value, I = 1, 2, …n (i) and n(i) is the number of zones in window (i), i = 1,2… N-1, and N is the number of heartbeats. In these calculations base estimate is usually the previous window baseline value except for first one where it is considered as zero. A zone is considered as active provided the scaled importance value is above the threshold. Once the inactive zones are selected, the baseline must be calculated by considering all the points within the inactive zones as an ensemble. Median of these inactive points gives the isoelectric estimate. If over 80% of the window is active, the algorithm will not accept the baseline measurement, and will look for a better approximation. For this a new approximate baseline is calculated from histogram. If this step can give a satisfactory inactive region that value will be taken. Else threshold is increased to 20% and the procedure is repeated. In histogram the isoelectric line will correspond to the bin with the highest frequency owing to the zero gradient in these areas. Baseline estimation for one ECG window is given in Fig. 6. In ECG the J - point is the junction between QRS complex end and the ST segment beginning. That is where the repolarization phase of the ECG signal starts. J-point the distinctive deflection occurring after the QRS wave. In this research work along with R- peak P, Q, S, T peaks were also identified [17] before the J-point detection. The J-point is the first deflection after the S-point. From S-point 80 millisecond durations are searched for the first inflation. After the correct identification of J - point, J60 point value is taken and compared with isoelectric line value to find the ST elevation / depression at that point.

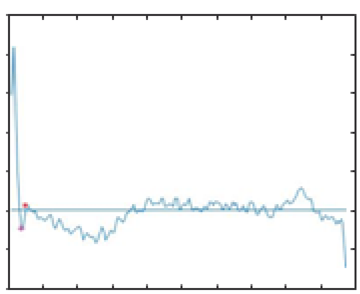

Figure 7. S &J point detection in one cycle of e0104

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IV. RESULT

European ST-T Database and Long-Term ST Database was used to test the algorithm. ST-T database consists of 90 annotated records sampled at 250 samples per second and stored by 12-bit resolution over a nominal 20 millivolt input range. Long term ST-T database contains 96 data records sampled at 250Hz with 12-bit resolutions. In both databases it was possible to detect the isoelectric line and J-point correctly. Exceptions were only few signals with very low signal to noise ratio where R- peak detection was not proper.

V. CONCLUSION

R-peak detection using adaptive wavelet provided an accuracy of 99.9%. Along with good R-peak detection and the proposed algorithm, isoelectric line detection could provide great accuracy. J–point detection and ST segment elevation / depression value measurement was accurate and compared with the annotations of database. The research paves the way for automatic detection of ischemia with higher accuracy.

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