Proceedings of the 26th Annual International Conference of the IEEE EMBS
San Francisco, CA, USA • September 1-5, 2004

Laplacian ECG Moment Of Activation Detection Algorithm During Pacing

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Abstract—**Laplacian ECG (LECG) is a new technique for detecting cardiac electrical activity. An algorithm was designed utilizing ECG QRS complexes to determine where cardiac activity was likely present in the LECG. The recurrent property of ECG is exploited by this new algorithm for the detection of the QRS complexes by cross (auto) correlation. Further, the algorithm calculates the time offset of the LECG signal from the ECG peak. This offset is termed the moment of activation (MoA) and is determined automatically. LECG body surface isochronal maps depict information about cardiac activation patterns. Besio [1] related the ECG QRS complex to the LECG isochrones by mapping the body surface MoAs. We now report on an algorithm to increase the efficiency of this method.**

Keywords—ECG, Laplacian ECG, mapping, QRS

I. Introduction

Developments in computerized patient monitoring systems over the recent years have had remarkable demands on automatic ECG analysis systems. Whilst researchers have refined and enhanced the way in which automatic detection and classification of cardiac arrhythmia is performed, diagnostic errors can still occur. One source of error is often attributed to the variability of the signal characteristics between patients.

The QRS complex is an important part of the ECG signal carrying a number of clinically significant parameters of cardiac arrhythmia. Detecting where in time this QRS complex occurs has significant importance in diagnosis of cardiac arrhythmias. QRS complex detection is difficult because, QRS complexes vary physiologically from one subject to another. This algorithm is adaptive to small signal changes, in detecting the QRS complexes, in spite of their physiological variability from subject to subject.

Laplacian ECG (LECG) is a new high resolution technique for detecting cardiac electrical activity. The electrical activity that we record on the body surface must travel through the volume conductor of the body. Due to this, the signal is attenuated, the potentials on the surface resulting from internal sources are blurred. LECG records the second order spatial derivative, which enhances information that may not be apparent in normal ECG. It sharpens the image.

Since ECG is recorded close to the heart it mostly records electrical activity of the heart, but it is also susceptible to global electrical activity in the body. The LECG signals that we record are recorded from an array of LECG sensors located over the heart area. They are extremely localized sensors and are similar to looking at the electrical cardiac activity through a pipe. When the heart depolarizes it spreads over the surface of the heart. When this activity is below a sensor, it is detected. This depolarization wavefront will be detected at different times under each Laplacian sensor.

This algorithm utilizies ECG-QRS complexes to determine when cardiac activity was present below the Laplacian sensor. The offset of the LECG signal in time from the ECG peak is termed the moment of activation (MoA) and is determined by this algorithm and shown in Fig. 1. Body surface LECG isochronal maps depict information about cardiac activation patterns and has clinical significance. Besio [1] related the ECG QRS complex to the LECG isochrones by mapping the body surface MoAs. Besio had a semi automated method for finding MoA that required hours to generate body surface maps. This is not practical to take so much time and is subject to user intervention. This algorithm determines the MoA's automatically decreasing the time taken to generate body surface isochornal maps and removing operator subjectivity.

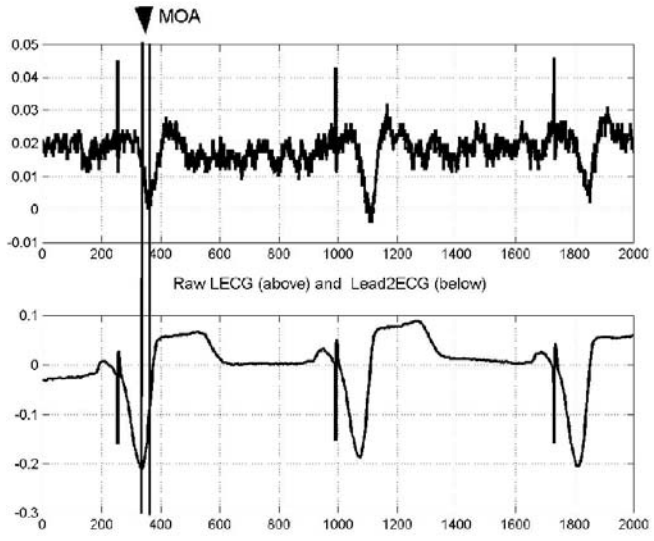

Fig.1 Moment of Activation (MoA), shown with the vertical lines. For this research is the difference in time between the ECG R-wave peak and the detection of the depolarization activity directly below the LECG sensor on the body surface.

The duration of the QRS complex is one of the main characteristics of the ECG signal and is used in analysis and classification. This duration is approximately 100ms [6] in the human heartbeat and varies from one subject to another.

The strength of the signal also varies from subject to subject [6].

The ECG signal is characterized by its recurrent behavior with each beat. This recurrence is approximately every 800ms in the healthy human heartbeat and varies for different subjects. Laplacian ECG MoA maps vary from subject to subject and have been shown to poses clinical significance [1]. By utilizing a database of MoA maps, subjects can be screened for cardiac diseases.

J. Pan and W. J. Tompkins [3] were the first people to address the software QRS detection. They concentrated more on the enhancement of the QRS complex. Their approach recognizes QRS complexes based upon digital analyses of slope, amplitude, and width of the QRS complex. Since then there have been other solutions reported [2, 3, 7, 8, 9, 10]. All those solutions use slope, amplitude, and width of the QRS-wave and these features vary a lot from subject to subject. None of those solutions reported are adaptive to these physiological variations, or reported results while pacing. Due to these limitations we developed an adaptive algorithm that will detect the QRS complex during pacing. Moreover none of the above solutions will be able to find MoA's since they are intended for QRS detection and not for comparing temporal data from various leads.

II. Methodology

Algorithm Overview

All data were recorded under the guidelines of our institutional review board approved protocol. The algorithm was implemented in Matlab. Laplacian ECG was recorded from active Laplacian sensors placed at thirty-five different recording sites on the surface of human subjects chests. For each subject there are five sets of recordings corresponding to thirty-five locations. All these data sets are of 30 second duration and each set of recordings consists of eight channels of data corresponding to seven Laplacian and one Lead II ECG. The Lead II ECG in each set was used for synchronization between the five sets of recordings. These signals are bandpass filtered and sampled at 1000 samples per second.

The premise is to find the time instances of all the QRS complexes in the Lead II ECG and to use these QRS complexes as templates to determine where over time in the Laplacian channel the cardiac activity has occurred. The difference in time instances among these channels, Lead II ECG and Laplacian ECG – is what is required, the MoA.

The algorithm uses the following techniques:

- Differentiation: Detects the first QRS peak by differentiation of the signal and applying a threshold. Then that QRS complex will be used as a template.
- Cross-correlation: Detects the remaining QRS peaks and MoAs using cross correlation. The ECG signal is characterized by recurrence of the QRS complex (which represents the signal produced by the ventricles for each depolarization) with a frequency of 70-80 beats per minute for a healthy human heart. The recurrent (periodic) property of the ECG is exploited by our algorithm for the detection of the QRS complexes.

The correlation between two signals (cross correlation) is the standard approach to feature detection [4, 5]. We utilized the cross correlation as a match filter for automatically detecting the QRS peaks and MoA's.
The cross correlation function used is:

$$\frac{\sum (X_i - M_x)(Y_i - M_y)}{\sum [X_i - M_x]^2 \sum [Y_i - M_y]^2} \qquad (1)$$

where X and Y are the two signals of interest and M is the mean of the signal.

Algorithm

The algorithm starts by differentiating the first 800 points of the signal and thresholds the differentiates to find the location of the highest differentiate. This point of highest differentiate is taken as the R-wave. If the algorithm finds more than one location with the same high differentiates then the algorithm processes each such point in minute detail to find the location which has the maximal differentiate. This point is the R-wave peak. An 800 point window will be centered on this peak. This is the first heartbeat. Only the first QRS complex is detected by differentiation and the rest are detected using autocorrelation.

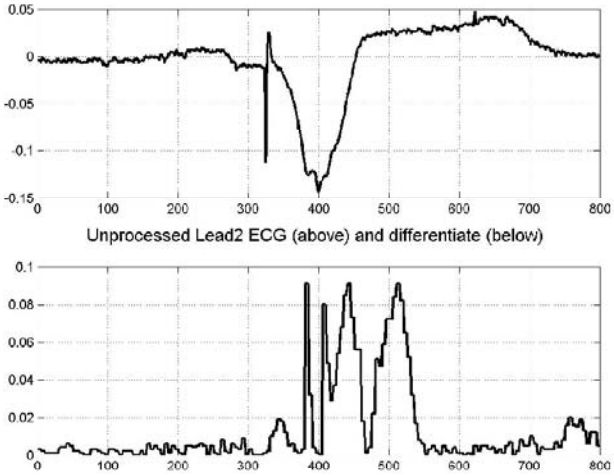

Fig.2. An 800 point window with corresponding differentiate taken every 5 points. The double peaks are from the two steep slopes. Note the pacer spike in the top panel.

After finding the greatest differentiate, a 200 point window centered around the location with the highest differentiate will be sliced and used as a template. This template is used

as a match filter for detecting the remaining QRS waves in the recording. This template is cross-correlated with the signal in 800ms windows. The algorithm takes the location with the highest correlation coefficient as the R-wave peak. For each new QRS complex that the algorithm detects, two tasks are performed. Two windows are sliced for analysis both centered at the time instance of the R-wave peak. The first is an 800-point window in the Laplacian ECG and the other a 200-point window in the Lead II ECG. The 200-point window is used to update the template by ensemble averaging. The 200-point window is an adaptive mechanism used to update the match filter template by ensemble averaging.

Surface recordings are subject to noise contamination. Prior to determining the temporal location of the Laplacian signal, when the cardiac activity occurred, the Laplacian signal must be filtered. A Weiner adaptive filter similar to one used by Bertrand et. al. [11] is implemented to process the Laplacian signal and a schematic diagram of it is shown in Fig. 3. The transfer function used for the filter is:

$$H = \frac{N}{N-1}\left(\frac{S_{\bar{x}}}{\bar{S}_x} - \frac{1}{N}\right) \qquad (2)$$

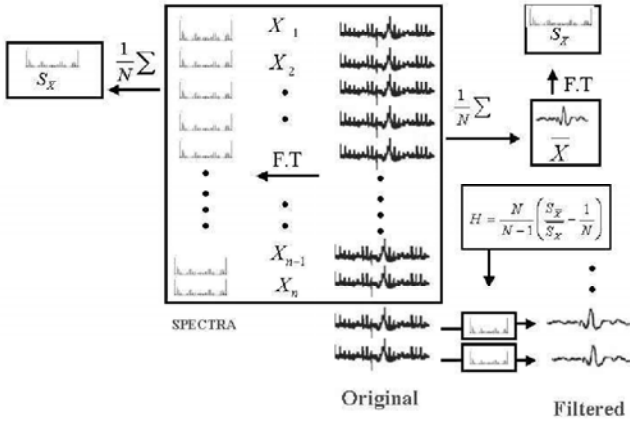

Fig.3. Adaptive Weiner filter schematic. The epochs are averaged and the spectrum of the average is found $S_{\bar{x}}$ and then the average of the spectrum of the epochs is taken. The filter is then applied to the new epoch.

The ECG QRS complexes are then used to cross correlate the filtered Laplacian ECG to determine MoAs. These MoAs are then used to produce isochronal maps, which represent the timing of electrical activity below the surface of the 35 Laplacian recording sites. Fig. 4 is such a isochronal MoA map. This is a body surface map of a person with the pacemaker active. The contours show one area of early activity and two later areas.

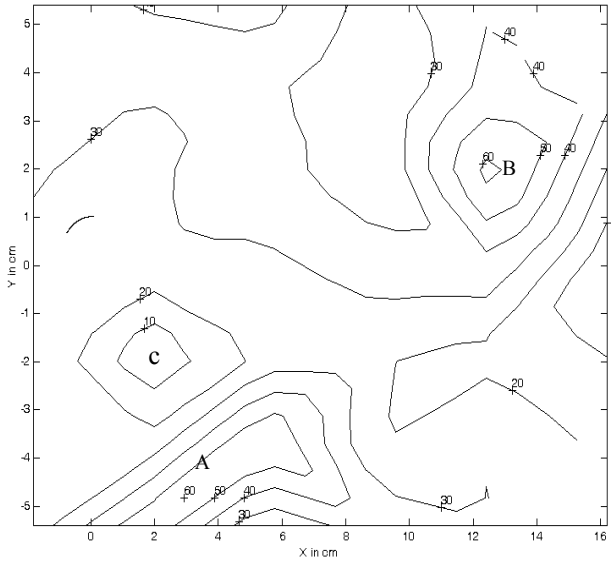

Fig.4. MOA contour map showing the timing of the cardiac activation as it was sensed on the body surface. These times are relative to the Lead II R-wave peak. Areas (A) and (B) are later (60ms) and area (C) is the earliest (10ms).

III. Results

The efficiency of the algorithm has been tested on two sets of data. The first set is simulated data, using the same QRS complex repeatedly, but varying the amount of noise and the time location of the complexes. The level of white noise was varied from zero percent to seventy-five percent of the full QRS magnitude. The MoAs were recognized correctly 100% of the time with noise levels below ten percent. For a typical offset of 10ms the MoA means for 10, 25, 50, and 75 percent noise levels are 9.979, 10.007, 10.007, and 10.245 and the standard deviations are 0.059, 0.186, 0.263, and 0.498 respectively. The second set of data was recorded from subjects with active pacemakers. The pacemaker caused much artifact that would not normally be discriminated from QRS complexes with common threshold detection methods. Four typical subjects were tested and the pattern matching algorithm correctly detected 2587 out of 2604 QRS complexes in our dataset for a percentage correct of 99.34.

IV. Discussion and Conclusion

The algorithm is robust, detecting MoAs correctly even with up to 70% additive noise. The algorithm has high detection and low false positive rates even during pacing. This algorithm is adaptive to small variations in the signal. Presently the algorithm can detect QRS complexes that are 400ms apart and not more than 1200ms apart with high efficiency. Future work will allow for detection of QRS complexes that are out of the above range. The algorithm

can be made adaptive to variable heart rate by adjusting the size of the windows automatically.

ACKNOWLEDGMENT

The authors would like to give their appreciation to the Louisiana Tech University Center for Entrepreneurship and Information Technology (CEnIT) and the Louisiana State Board of Regents for their generous support of this research.

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