A WAVELET-BASED MULTI-CHANNEL ECG DELINEATOR

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Abstract: Detecting peaks and boundaries of ECG characteristic waves supplies fundamental features for extracting clinically useful information.
In this paper, an accurate threshold-independent multi-lead ECG delineation system is presented. Detection of QRS complexes, P and T waves is based on wavelet transform using Haar function as prototype wavelet and analyzing the first scale details coefficients.

The delineator is performed on certain selected channels. Afterwards, a method, using a special histogram-based estimation, yields the exact positions of the significant points in all multi-channel ECG signals. The algorithm is applied on MIT-BIH Arrhythmia database signals and on multi-channel ECG signals measured at our institute.

The single-channel delineation method was tested on MIT-BIH Arrythmia database signals. Sensitivity and positive predictivity were greater than 99.84% and 99.89% respetively for more than 15,990 beats. Furthermore, an overall mean error of less than two sampling intervals (1 ms) is obtained comparing the manual and the automatic method, whereas the standard deviation does not exceed three sampling intervals.

Introduction

ECG delineation, specially the QRS complex detection, has always been a subject of major importance in research. An extensive review of approaches proposed in the last decade can be found in [1]. One can find in the literature many different delineation approaches based on mathematical models, like the signal envelope, matched filters, ECG slope criteria, second-order derivatives, low-pass differentiation, the wavelet transform, non-linear time-scale decomposition, adaptive filtering, artificial neural networks or hidden Markov models [2].
Extensive research has been made in the field of ECG delineation using Wavelet Transform (WT). Wavelet Transform (WT) provides a description of the signal in time-scale domain, allowing the representation of the temporal features of a signal at different resolutions; therefore, it is a suitable tool to analyze the ECG signal, which is characterized by a cyclic occurrence of patterns with different frequency content (QRS complexes, P and T waves) [1].

In [2][3][4][5], the Dyadic Wavelet Transform (DyWT) has been proposed. A spline wavelet, which is a derivative of a smoothing function, has been used as the prototype mother wavelet. The implementation is carried out by means of digital filters. The WT at a particular scale is proportional to the derivative of the filtered version of the signal with a smoothing impulse response at that scale. Therefore, the zero-crossings of the WT correspond to the local maxima or minima of the smoothed signal at different scales, and the maximum absolute values of the WT are associated with maximum slopes in the filtered signal.

In [3], first modulus maximum lines corresponding to R waves are searched across four different scales, namely, 2^1, 2^2 ,2^3 and 2^4, using different threshold for different scales (based on the corresponding rms value). For a valid R wave, the *Lipschitz regularity* [1] must be greater than zero. Also, the R wave corresponds to a positive maximum-negative minimum pair at each characteristic scale. After applying certain definite criteria, the isolated and redundant modulus maximum lines were rejected. Finally the R peaks were located at the zero-crossing points between the positive maximum-negative minimum pairs at scale 2^1. On the right and left of each detected R peak, the local modulus maxima lines were taken care of for the delineation of the rest of the wave peaks and boundaries.

In [2], the same procedure of [3] is extended and evaluated on several manually annotated databases. They also generalize the filter coefficients (for DyWT) for different sampling frequencies of the ECG. Moreover, they consider more morphological variations for T wave in addition to those listed in [3].

In [4], only the QRS complex detection is accomplished, as they are more interested in the heart rate variability. The main use of the property is that the absolute value of DyWT has localized maxima across several consecutive scales at the instant of occurrence of transients. Applying a definite threshold criterion, the peaks are located in a particular scale. Then the next higher scale is scanned in the same way. If the number of peaks in both cases does not agree, computation is carried out for the next scale. Finally, for acceptance as QRS locations, three consecutive scales should agree on the same no. of peaks and also the corresponding peak locations in different scales must be within tolerable time deviation.

In [5], an on-line QRS detection algorithm was developed based on the Haar Wavelet and implemented as a recursive filter. They also use magnitude threshold to determine the location of R peaks.

Relatively little has been published on ECG and QRS detection in multi-channel electrocardiograms. A QRS-detction and delineation algorithm for 64-lead

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surface ECG recordings was described in [6] . The algorithm is used mainly for QRS detection and based on three signals, derived from the multi-channel ECG recording.

Materials and Methods

Wavelet-Based Marks Extraction: Electrocardiogram signal, by its very nature is non-stationary. It is characterized by a cyclic occurrence of patterns with different frequency contents (QRS complexes, P and T waves) [7]. Each of these patterns represents a certain distinct event. The QRS complex occurs as a high frequency, high amplitude spike of very small duration in the ECG cycle. On the other hand, P wave or T wave has got relatively low frequency contents, leading to their smoother appearance.
The Wavelet Transform provides a description of the signal in the time-scale domain allowing the representation of the temporal features of the signal at different resolutions.
In Discrete Wavelet Transform (DWT), time-scale representation of a digital signal is obtained using *digital filtering* techniques. By implementing Mallat algorithm for DWT, the signal to be analysed is passed through special filters with different cut-off frequencies at different scales, figure 1.
Applying Mallat algorithm using Haar wavelet in our approach, the first level details coefficients, were obtained and analysed.
Haar function has a step nature, which is very sensitive to any slope change in the signal under study.
Haar Wavelet function $\psi(x)$ and Haar scaling function $\phi(x)$ are defined mathematically as follow:

$$\begin{aligned} \psi(x) &= 1 \quad \text{if } 0 \le x \le 0.5 \qquad \phi(x) = 1 \quad \text{if } x \in [0,1] \\ &= -1 \quad \text{if } 0.5 \le x \le 1 \qquad\quad = 0 \quad \text{if } x \notin [0,1] \\ &= 0 \quad \text{if } x \notin [0,1] \end{aligned} \tag{1}$$

A first-level Mallat decomposition algorithm is applied on some signals with specific shape (e.g. a straight line with a constant slope, a triangular wave, a cosine wave etc). Reconstructing back with all approximation coefficients set to zero, the First Level Details Signal (FLDS) is obtained.
Samples of FLDS are of the same amplitude and alternating signs as long as the slope remains constant, that is, straight line with a constant slope, figure 2.
When the slope of the signal is zero, FLDS samples have zero magnitude.
When there is a direction change in the original signal, e.g. triangle signal, two consecutive samples of FLDS are of same sign. In other words, when the slope changes its sign from positive to negative for instance, it reflects two consecutive positive samples in FLDS and vice versa in the case of negative to positive slope change, figure 3.
Direction Change Mark (DCM) is defined as a time vector whose length comprise the same number of samples as the original signal or FLDS and whose elements are all zero in magnitude except at the direction changing points. Whenever there are two positive consecutive samples in FLDS, the element of DCM corresponding to the first sample will be '+1'. On the other hand, two consecutive negative samples of FLDS will reflect a '–1' in the corresponding element of DCM. Therefore, a '+1' in DCM will signify a positive peak in the original signal and a '–1' will represent a negative peak, figure 3.

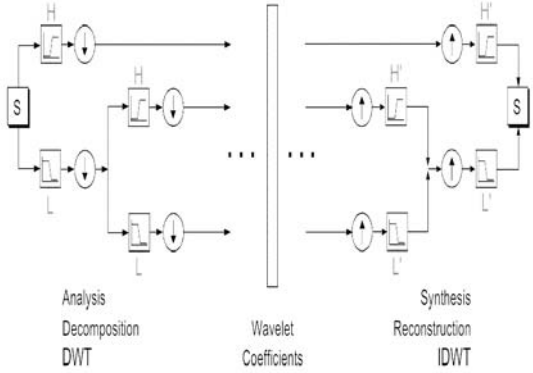

Figure 1: Mallat algorithm for DWT, where H and L denote the Analysis high-pass and low-pass filter respectively. H' and L' denote the Synthesis high pass and low pass filters respectively and the arrow up and down denote up and down sampling by factor of two [9]

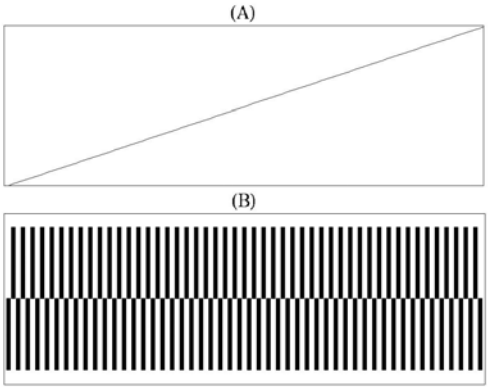

Figure 2: A) straight line with a constant slope B) FLDS samples with same amplitude and alternating signs

Direction Change Sharpness (DCS) is also defined as a time vector having exactly the same span as DCM, but its elements are all zero except at those positions where DCM has a non-zero value. In other word, when DCM has a '+1' or '-1', the corresponding sample of FLDS is tracked and then, the absolute difference in magnitude between this sample and the following one is calculated and given as a value to the corresponding position of DCS, figure 3.

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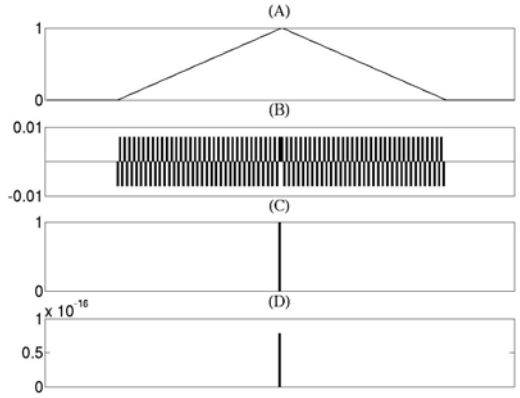

Figure 3: A) triangle signal B) FLDS samples C) DCM samples D) DCS samples. DCM and DCS samples are all zero except the samples that correspond to the direction of change in the original signal

Figure 4 shows also FLDS, DCM and DCS for a real ECG signal.

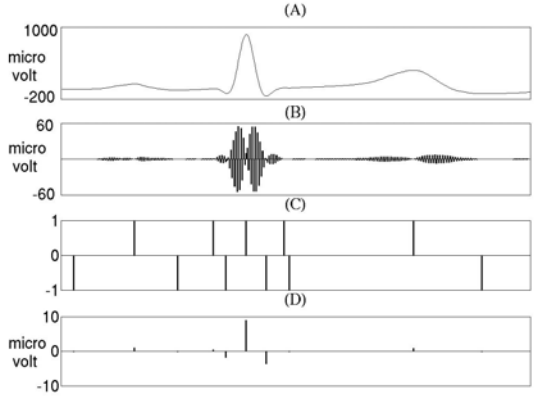

Figure 4: A) An ECG cycle taken from a 64-channel ECG signal B) FLDS samples C) DCM samples D) DCS samples

It can be seen that eleven direction changing points are marked in DCM corresponding to a QRS complex and both of P and T waves, namely, P onset, P peak, P offset, Q onset, Q peak, R peak, S peak, S offset, T onset, T peak and T offset.

Single-Channel Delineation Strategy: First, we start with the delineation strategy on a single channel ECG data. Then, it will be modified for multi-channel delineation. Signals should undergo a zero-shifted low-pass Butterworth digital filter of second order and 50 Hz cut-off frequency in order to get rid of the high-frequency artefacts in the ECG and to assure an accurate detection for P waves. Furthermore, A new robust DWT-based approach has been devised on all ECG signals to eliminate the baseline wander and low-frequency disturbances from the signals as part of conditioning phase before delineation process [8], figure 5.

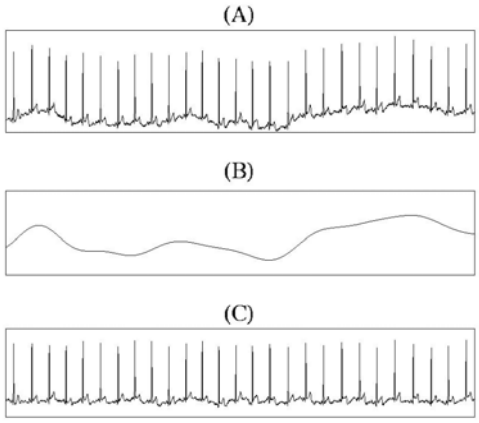

Figure 5: A) ECG signal taken from 64-channel ECG signal and distorted by baseline wander B) Estimated and extracted Baseline wander C) Filtered ECG

R peak detection: After proper conditioning of the ECG signal, a fixed length window is made to run over the whole data set in a constant Increment Step (IS). The Windows Length (WL) should be less than one R-R interval and more than half of the R-R interval.
The instant of occurrence of the max/min value of DCS (positive/negative R peaks) is noted inside each window. If the window encompasses any R peak, then it will cause the sharpest direction change in the ECG, and hence the max/min value in the corresponding sample of DCS. If the channel is known to have positive R peaks, the time of occurrence of the highest DCS value for each and every window will be accumulated in a vector called Extreme Direction Change Sharpness (EDCS). If the ECG channel contains negative R peaks, the time of occurrence of the lowest values of DCS will be accumulated in EDCS. When the same R peak is enveloped by 'n' consecutive windows, the same value will occur consecutively n times in the EDCS vector. Detecting n time accumulation in the EDCS, R peak will be localized. The position of R peak will be at the last sample of the first scanning window encompassing the existence of R peak, figure 6.
R peak localization solely depends on the elements of EDCS, which are in turn determined by the samples of DCS.

In order to enhance the DCS samples corresponding to R peak locations, a modified DCS signal is derived. First of all, ECG signal was up-sampled and down-sampled. Two DCS signals were first computed. The first, 'DCS up', is the DCS of the original ECG after multiplying the number of samples by the factor of two and the second, 'DCS dn', is the DCS of the original ECG after dividing the number of samples by factor of two. Given that the DCS signal computed from the original ECG signal is denoted as DCS normal, the modified DCS signal, 'DCS md', is given as follows:

$$DCS\_md = DCS\ up + DCS\ normal + DCS\ dn \quad (2)$$

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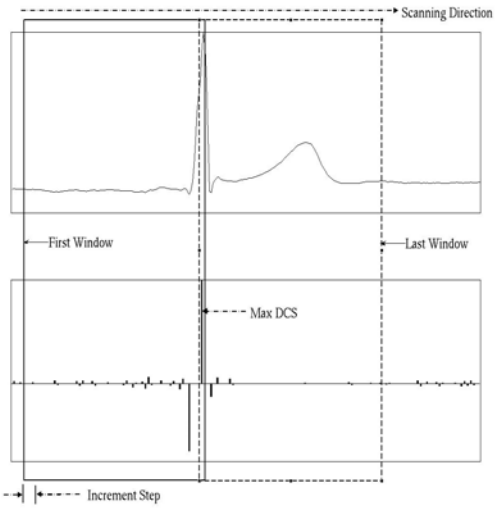

Figure 6: A Scanning window running over an ECG Cycle, accumulating the number of appearance of the same maximum value in the DCS signal at each step and localizing R peak as the number of appearance reaches the ratio of window length over the increment step duration

Up sampling is accomplished by means of interpolation and down sampling by discarding every alternate sample.
Figure 7 shows the enhancement of 'DCS md' in comparison to 'DCS normal' corresponding to R peak locations.

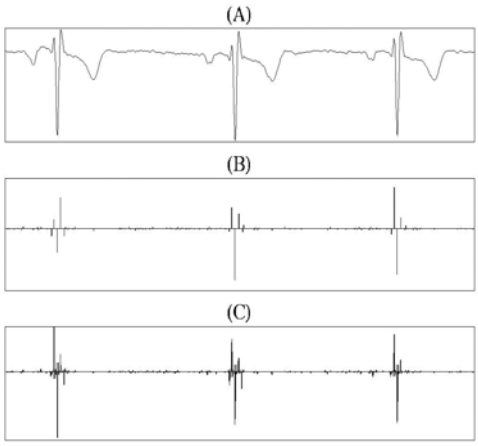

Figure 7: A) An ECG cycle taken from a 64-channel ECG signal B) DCS normal C) DCS md
'DCS md' improve the amplitude of 'DCS normal' at the significant points of the original signal

In the case of exercise ECG, the number of beats per minute is not stable any more and hence the beat-to-beat variation in R-R intervals is quite high. Therefore, ECG signal is split in segments with an overlap between two consecutive segments. In each segment, R peak detection will be carried out as already described. The average value of the R-R interval obtained from the previous segment is taken care of to determine the window length (WL) for the segment following.

Q and S waves delineation: Had the Q wave been positive (negative-positive slope changing), its corresponding Q onset and Q peak would have caused a '-1' and '+1' respectively in DCM vector. In case of negative Q wave (positive-negative slope changing), the corresponding values of DCM at Q onset and Q peak positions would be '+1' and '-1' respectively. The same methodology is applicable on S peak and S offset.
The immediate two non-zero values ('+1' or '-1') of DCM signal followed by the detected R peak in each heart beat indicate the positions of S peak and S offset in that ECG cycle. Whereas, the two non-zero values ('+1' or '-1') of DCM signal immediately localized before R peak position indicate the positions of Q peak and Q onset.

P and T waves delineation: Positive P and T waves have '+1' values corresponding to T and P peaks in the DCM vector and '-1' values for P and T onsets as well as P and T offsets and vice versa in the case of negative P and T waves.
Detecting Q onset, P peak is located by applying a search window spanning half of the previous R-R interval and detecting the highest positive or negative DCS values. Afterwards, The position of P onset and P offset is considered the location of the immediate right and left, '-1' or '+1' DCM values, from P peak (depend on P wave type). T wave is delineated exactly in the same manner of the former strategy for P wave, but in this case the search window starts at S offset position and is given the length of the half of the following R-R interval.

Multi-Channel Delineation Strategy: R peak detection, in this case, is carried out simultaneously on 'n' several channels. For every heartbeat n number of R location in different channels is obtain and a histogram from those values is calculated. The integral mean of the most frequent occurrence in the histogram represents the final decision of R peak location in multi-lead delineation. The general rule is to find out the value with highest frequency of occurrence. If more than one value is found to satisfy the same condition, the integral mean of them is taken as the final decision.
After computing the final decision regarding the R peak location in Multi-Channel ECG, T wave, P wave as well as Q and S wave are delineated in all channels.
The same kind of histogram-based method, used to get the final delineation result for R peak, is used again to get the final location for Q onset, Q peak, S peak, S offset, T peak, T onset, T offset, P peak, P onset and P offset.
The locations of each significant point, taken from many selected channels, are used as input for the histogram in order to take the final result.
The channels for delineation should be selected judiciously so as to ensure prominent wave-shapes.

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Considering the multiple channel result, the number of false positive or false negative detections is decreased.

Results

Comparing the automatic delineation result against manual delineation, the performance of the delineation algorithm is examined.
The mean and the standard deviation of the difference between manual & automatic delineation (in terms of number of samples) as well as the Sensitivity (Se) and the Positive Predictivity (P+) are used in the validation procedure.
The Sensitivity (Se) and the Positive Predictivity (P+) are given as follows:

$$Se = \frac{TP}{TP + FN} \times 100\% \qquad P+ = \frac{TP}{TP + FP} \times 100\% \qquad (3)$$

Where TP, FN and FP are referred to True Positive, False Negative and False Positive respectively.
The algorithm of single-channel R peak detection was tested on several records taken from MIT-Arrhythmia database. The output of our algorithm was compared with the manual annotation provided with each record, table 1.

Table 1: The results of applying single-lead delineation algorithm based on our approach on some records of MIT-Arrhythmia database

Record No.	**100**	**101**	**103**	**113**
Channel No.	1	1	1	1
Samples taken	650000	650000	650000	650000
FN	0	3	0	3
FP	1	4	0	4
TP	2271	1863	2084	1791
Se	100	99.84	100	99.83
P+	99.96	99.78	100	99.78
M.E.	-1.9	-0.48	-2.23	-1.74
S.D.	2.46	1.18	2.31	1.38
Record No.	**115**	**122**	**100**	**103**
Channel No.	1	1	2	2
Samples taken	650000	650000	650000	400000
FN	1	6	1	0
FP	6	5	0	0
TP	1953	2469	2271	1294
Se	99.95	99.75	99.95	100
P+	99.69	99.8	100	100
M.E.	-3.16	-3.95	0.736	-2.97
S.D.	3.54	5.87	2.4	3.08

The overall Sensitivity (Se) and Predictivity (P+) obtained for MIT-Arrhythmia Database are found to be 99.84% and 99.89%, respectively. Furthermore, the mean error and standard deviation are -1.96175 (sample), 2.7775 (sample) respectively.

The algorithm is also applied on several 64-channel and 32-channel ECG data sets with more than five-minute duration each and 1 kHz sampling rate.
So far, the delineator is able to delineate all heartbeats. Moreover, the output of our algorithm, applied on five-minute 32-channel ECG segment, was compared with the manual estimation.
The manual annotation is applied on the channels, taken part in multi-lead delineation processes, and done manually by the authors.
The mean error and the standard deviation are calculated for every detected point in all chosen channels.
Thereafter, the overall mean error and standard deviation are derived, table 2.

Table 2: The results of applying multi-lead delineation algorithm on a five-minute 32-channel ECG signal with 1kHz sampling rate.

	P on	**P pk**	**P off**	**Q on**	**Q pk**	**R pk**
M.E.	-0.48	-1.83	-4.52	3.52	1.17	-0.52
S.D.	3.96	3.39	3.29	1.04	1.03	0.59
	S pk	**S off**	**T on**	**T pk**	**T off**	**Overall**
M.E	0.26	0.09	1.08	0.78	0.09	**-0.03**
S.D.	0.75	0.42	1.12	0.95	1.59	**2.83**

Where on=onset, off=offset, pk=peak and the unit is 'sample'.

Discussion

This method is stated on using the simplest Wavelet prototype and dealing only with the first level Details coefficients allowing a relatively fast delineation process for multi-channel ECG. Furthermore, it provides an accurate detection for the significant points without using any kind of threshold techniques.

Conclusion

Haar Discrete Wavelet transform and the histogram-based technique used in this approach allow for perfect P, QRS and T detection and delineation either in multi-channel ECG data or even in single-channel ECG, Figure 8.

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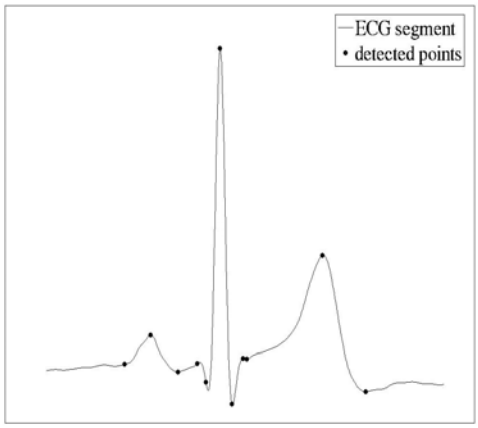

Figure 8 shows a Lead II heart cycle derived from the 64-channel ECG along with its corresponding delineation results computed by the mean of our Multi-lead delineation approach. The multi-channel ECG signal is recorded with 2 KHz sampling rate

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