Wavelet-Based Denoising and Beat Detection of ECG Signal

Miad Faezipour, Tarun M. Tiwari, Adnan Saeed, Mehrdad Nourani and Lakshman S. Tamil
Quality of Life Technology Lab
The University of Texas at Dallas, Richardson, TX 75083
{mxf042000, tmt061000, axs055200, nourani, laxman}@utdallas.edu

***Abstract*— This paper presents the design and implementation of an automatic ECG beat detection system. We proposed modifications to the existing Pan-Tompkins algorithm by introducing only one set of adaptive threshold computations to reduce the amount of data processing significantly. LabVIEW signal processing tools were used to test the performance of wavelet based analysis for denoising and feature extraction of the ECG signal. Our design achieved an overall accuracy of 99.51% when applied on the MIT/BIH Arrhythmia Database, which is far better than the old method of digital filtering.**

***Index Terms*— ECG feature extraction, wavelet denoising, LabVIEW.**

I. INTRODUCTION

A. Background

Bringing real-time arrhythmia assessment process to the patient's home has been a long time research. Almost all type of arrhythmia detectors need accurate detection of the *Electrocardiogram* (ECG) beats [1]. ECG signal is represented by the bioelectrical activity of the heart representing the cyclical contractions and relaxations of the human heart muscles. ECG devices with varying number of electrodes can be used to pick up ECG signals.

During the recording process, noise affect the signal heavily and ECG signals collected from different people are heterogeneous, while some cardiac causes are reflected by the variation in peak to peak distance between the ECG beats. Once the ECG signal has been picked up, effective pre-processing is required for beat detection, as efficient identification of the ECG beats is necessary for correct analysis of arrhythmia.

The ECG signal requires pre-processing before entering the beat detection stage. ECG pre-processing generally takes care of denoising the ECG signal. In ambulatory ECG, all forms of noise may occur simultaneously and unpredictably. Different kind of noise include baseline wandering, EMG noise, motion artifact, power line interference and electrode pop or contact noise [1] [2]. The baseline wandering and the power line interference are the most substantial noise and can strongly affect ECG signal analysis. Baseline wandering (or trend) usually comes from respiration and lies between 0.15Hz-0.3Hz. Other than these two noise elements, remaining are wideband and usually a complex stochastic process which also distort the ECG signal and affect the analysis. The power line interference is a narrow-band noise centered at 60Hz (or 50Hz in European standards) with a bandwidth of less than 1Hz [2]. Usually the ECG signal acquisition hardware can remove the power line interference, but the baseline wandering and other wideband noise are not easy to be suppressed by hardware equipment. Instead, we need some software schemes which are powerful, and feasible for offline ECG signal processing.

Several works have been done in the area of ECG beat detection. However, many of them are not suitable when high reliability is needed. There are some commercially available tools which are possible to use at home, but their performance is not very satisfactory. Pan and Tompkins developed a method to detect the beats in a ECG signal that successfully performed 99.32% detection when tested on the MIT-BIH open-source arrhythmia database [1]. There is room for possible improvement in the existing algorithm with the development of the *Wavelet Transform* [3]. We identified the possible enhancements in the algorithm to reduce the complexity of the algorithm and to increase the SNR of the ECG signal before detection. We also used LabVIEW graphical programming language which could help us create such applications that can be used in a computer running on general purpose processors. The software application could take the ECG signal, denoise it and do the correct beat detection efficiently. Possible enhancements included reducing the number of fiducial marks and reducing the number of thresholds, that could reduce the complexity of the algorithm to a large extent.

B. Main Contribution and Paper Organization

An efficient method to accurately derive the QRS complexes of an ECG signal is introduced in this paper. We propose modifications to the existing Pan-Tompkins QRS Detection algorithm by using only one threshold derived from denoised ECG signal instead of using one more deduced from the moving window integration of the ECG Signal. This significantly reduced the number of comparisons that was required to decide whether a fiducial mark would be a QRS complex or not. In our implementation, we use wavelet-based tools available in LabVIEW. LabVIEW's Wavelet Detrend Tool is used to reduce the baseline wandering in ECG signal. Wavelet Denoising is then applied for high frequency denoising. This method performs much better in case of non-stationary ECG signal and would result in an SNR gain when using the wavelet denoising method. With the help of LabVIEW's Wavelet Based Multi-Scale Peak Detection Tool, we reduce false fiducial marks identified by the highest squared slope during the rising part of the moving window integration wave.

The rest of this paper is organized as follows. In Section II, we take a glance at prior work related to ECG pre-processing and beat detection techniques. Our method for pre-processing and ECG feature extraction is described in Section III. In Section IV, we provide simulation results and evaluate the performance of our system in terms of false positives, false negatives and total error. Finally, concluding remarks are in Section V.

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II. Prior Work

Jiapu Pan and Willis J. Tompkins of the University of Wisconsin were perhaps the first to develop a real time QRS detection algorithm on a Z-80 microprocessor [1]. They performed denoising of the ECG signal using a band pass filter which was built using cascaded high pass and low pass filters. Pan and Tompkins detected the fiducial point by finding the highest squared slope during high spectral energy of ECG waves, which resulted in much more number of fiducial points than the actual QRS complexes. They applied two adaptive thresholds, and chose the highest among the two thresholds extracted from the ECG signal and the integration of the ECG signal. A search-back algorithm was also applied if no QRS complex candidates were found within a certain time interval. They demonstrated a very good performance of 99.325% when tested against the MIT-BIH arrhythmia database [4]. However, their technique required larger amount of processing than what is actually needed.

As for pre-processing of the ECG signal, noise cancellation requires different strategies for different noise sources. Authors in [5] performed the noise reduction using an adaptive filter with constant or unity reference input, which was used to cancel baseline wander. However, this filter is not reliable for applications that require diagnostic ECG analysis.

Nonlinear filtering is a common approach to detect QRS complexes [1] in considerably less time and can be easily implemented. However, the main drawback of these algorithms is the frequency variation in QRS complexes which adversely affects their performance. These methods can result in higher false positives and false negatives because the frequency band of QRS complexes generally overlaps with the frequency band of noise.

The authors in [3], [6], [7], and [8] analyzed the *Wavelet Transform* method for denoising of ECG signal. This technique decomposes the signal into various components that appear at different scales. It also uses a linear operation which makes it suitable to preserve the important phase information of the signal. Authors in [9] propose to use the cubic spline wavelet and interpolation for accurate QRS detection. They conclude that wavelet functions that support symmetry and compactness achieve the highest accuracy on the ECG readings in MIT-BIH arrhythmia database. Though the wavelet transform approach does not discriminate between the noise and signal coefficients of the wavelet decomposition at low SNRs, it is still an attractive solution for non-stationary signals as it maintains the signal behavior.

III. ECG Signal Processing

For ECG signal processing, we use LabVIEW and related toolkits [10]. LabVIEW has wavelet analysis tools that are highly efficient for ECG denoising and feature extraction [2].

A. Pre-processing

The LabVIEW Advanced Signal Processing Toolkit (ASPT) provides the *WA Detrend* Virtual Instrument (VI) which can be used to remove the low frequency baseline wandering (or trend) of a signal. In the WA Detrend VI, we suggest using the *sym5* wavelet as it resembles the QRS wave of ECG more

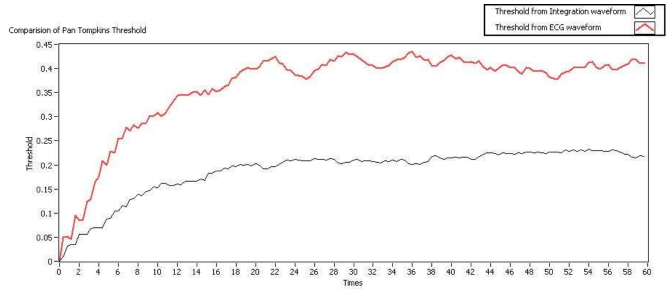

Figure 1. Comparison of Pan-Tompkin's two thresholds.

than the other type of wavelets. An internal parameter called *trend level* is required for baseline removal [2]. The trend level is calculated as follows:

$$LEVEL_{Trend} = \left\lceil \frac{\log_2 2t}{\log_2 N} \right\rceil \quad (1)$$

where t is the sampling duration and N is the number of sampling points in t time.

After we suppress baseline wandering, the ECG signal becomes more stationary and explicit than the raw ECG signal. The remaining noise are complex stochastic processes with wideband nature, and cannot be efficiently suppressed or removed by the conventional digital filter approach [7]. To suppress the wideband noise, we chose to use the Wavelet Denoise VI module from LabVIEW [2]. This VI first decomposes the ECG signal into several sub-bands by applying the wavelet transform, and then modifies each wavelet coefficient by applying a threshold or shrinkage function, and finally reconstructs the denoised signal. In our design, we used *undecimated wavelet transform (UWT) sym5* with single level and soft thresholding for the wavelet denoising VI block setup. These settings perform perfect denoising on the original ECG signal, and smoothen the signal without suppressing ECG features such as the P and T waves. For effective feature extraction, we apply a wavelet denoise VI with *UWT sym5* and multiple levels on the detrended signal to make only the QRS complexes of the signal more distinct.

B. Feature Extraction

The technique we deployed for ECG feature extraction is a hybrid approach of Pan and Tompkin's adaptive thresholding [1] combined with wavelet peak and valley detection [2], in which we achieved significant improvement compared to both approaches.

After detrending the signal and applying the wavelet denoising VI, the resulting signal would result in a zero DC offset. We mark peaks that are above zero and valleys that are below zero by the help of WA Multiscale Peak/Valley Detection VI in LabVIEW. Then, we apply an approach similar to Pan and Tompkin's method, but with some modifications, to dynamically set a threshold for beat detection. The peaks and valleys that were detected from the peak/valley detector VI now become candidates for *signal* peaks in Pan-Tompkin's algorithm [1].

In our implementation, only one set of threshold extracted from the denoised ECG can be applied, because the threshold

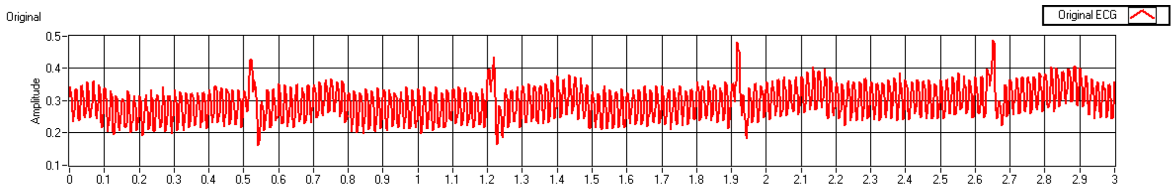

Figure 2. Raw ECG signal.

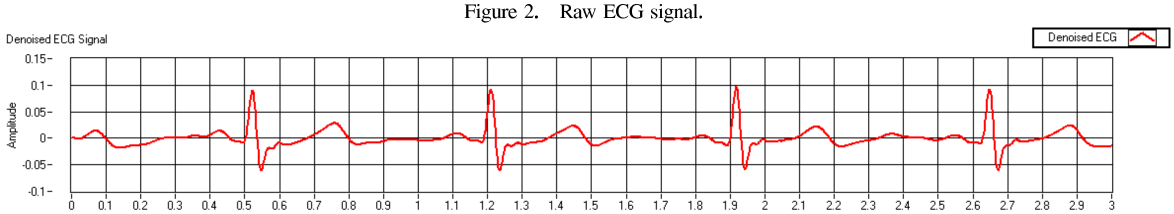

Figure 3. ECG signal after wavelet denoising.

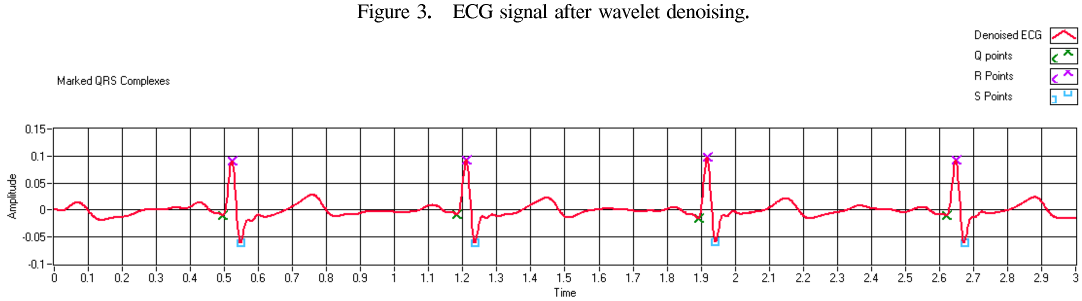

Figure 4. QRS complexes marked on denoised ECG.

calculated from integration waveform was found to be always lower than the other threshold, as seen in Figure 1. Therefore, no integrator is required in our technique. This lowers the amount of processing to a large extent.

Let us consider *Peaks* as the array of peaks that LabVIEW peak detector VI has found. The equations for adaptive thresholding are as follows:

$$\begin{cases} PEAK = Maximum(Peaks) \\ NPK = Minimum(Peaks) \\ SPK = 0.125 \times PEAK + 0.875 \times SPK \\ THR = NPK + 0.25(SPK - NPK) \end{cases} \tag{2}$$

A signal peak that is larger than the threshold THR is considered a QRS complex, where the R point is detected. Each time a beat (R point) is found, we intentionally move the starting point of the sliding window to a point that is $360ms$ apart from the previous R point detected, as R-R intervals cannot be less than this timeframe physiologically [1].

Similar to Pan-Tompkins approach, a search back algorithm is required if a beat is not found within a certain time interval. We maintain only one R-to-R average (instead of two) for the search back algorithm, that being the average of the eight most recent R-R intervals found. If n is the index of the current beat, R-to-R average is computed as follows:

$$RR_{Avg} = \begin{cases} \frac{1}{n-1}\sum_{i=0}^{n-2} RR_{(n-i)} & 2 \leq n \leq 7 \\ \frac{1}{8}\sum_{i=0}^{7} RR_{(n-i)} & n \geq 8 \end{cases} \tag{3}$$

If no beat has been detected within 116% of the current R-to-R average, the search back algorithm is applied. This is a percentage that has been found empirically [1]. In the search back algorithm, we lower the threshold by a certain amount and start looking for a QRS complex from the last R point detected. Since our denoising technique pretty much only keeps the QRS complex of the signal and suppresses the P and T waves, a very low threshold can be used in this search back stage. The threshold we have applied in the search back algorithm is as follows:

$$THR_{new} = \frac{THR_{old}}{8} \tag{4}$$

If a signal peak (SPK) exceeds this new threshold, we consider it as a beat (R point). The new signal peak SPK and threshold THR should then be updated accordingly.

Table I summarizes the differences between our design and Pan-Tompkins algorithm.

TABLE I
COMPARISON OF OUR AND PAN-TOMPKIN'S ALGORITHMS.

Pan-Tompkin's Algorithm	**Our Algorithm**
Digital Filter Denoising	LabVIEW's Wavelet Detrending and Denoising
Integration waveform required	No Integrator required
Two Threshold computations	Only one Threshold
PEAKI and *NPKI* computed recursively in each window	*PEAK* and *NPK* computed only once by LabVIEW's WA Peak Detector
Two RR_{Avg} values required	Only one RR_{Avg} required
Search back algorithm for 166% of RR_{Avg}, $THR/2$	Search back algorithm for 116% of RR_{Avg}, $THR/8$

To find the Q and S points of the ECG waveform, we apply this underlying concept that a Q point is the maximum valley location right before an R point, and an S point is the minimum valley location right after a detected R point. As mentioned earlier, the valley locations are found using the WA peak/valley detector with zero as the threshold. Since the signal has been detrended to zero baseline wandering, this would locate all valleys that are below zero. When an R point is found, we search through the valley location array, and mark the maximum and minimum locations before and after that R point as Q and S points, respectively.

IV. Experimental Results

A. Denoising and Feature Extraction Simulation

We have implemented our design in LabVIEW 8.5 graphical programming environment [10] and have tested for various ECG waveforms. Figure 2 shows a raw ECG signal captured with a sampling frequency of 500Hz. Figures 3 and 4 show respectively, after applying our denoising and beat detection technique, the ECG signal that has been denoised and the ECG signal with Q, R and S points.

B. Performance Evaluation

Our algorithm when evaluated against MIT-BIH arrhythmia database [4] achieved an overall performance of 99.51% for one minute time frame of the readings. Table II depicts the performance of our algorithm when implemented in LabVIEW.

False positives (FP) and false negatives (FN) have been reflected in the table as erroneously detected beats and missed beats, respectively. The overall error is calculated as follows:

$$Error = \frac{FP + FN}{Total\ \#\ of\ Beats} \quad (5)$$

Our algorithm performed poorly on those readings (e.g. dataset 200) that had inverted waves and did not look like the *sym5* wavelet. Nevertheless, we achieved 99.93% accuracy for the first 23 readings that resemble normal ECG patterns, while Pan-Tompkins achieved 99.17% accuracy for the same datasets [1].

V. Conclusion

We introduced and efficient algorithm designed for ECG denoising and feature extraction. Our design is a hybrid of the wavelet-based approach and Pan and Tompkins QRS detection algorithm, using which we have achieved 99.51% accuracy when tested on MIT-BIH arrhythmia database. This design is highly efficient for applications such as ECG beat classification that require precise feature extraction.

TABLE II
Performance Evaluation of our QRS detector on MIT-BIH Arrhythmia Database.

Data #	# of Beats	# of FP	# of FN	Not Detected	Error
100	74	0	0	0	0%
101	71	0	0	0	0%
102	73	0	0	0	0%
103	70	0	0	0	0%
104	74	0	0	0	0%
105	83	0	0	0	0%
106	67	0	0	0	0%
107	71	0	0	0	0%
108	58	1	0	1	1.72%
109	91	0	0	0	0%
111	69	0	0	0	0%
112	85	0	0	0	0%
113	58	0	0	0	0%
114	54	0	0	0	0%
115	63	0	0	0	0%
116	78	0	0	0	0%
117	50	0	0	0	0%
118	73	0	0	0	0%
119	65	0	0	0	0%
121	60	0	0	0	0%
122	87	0	0	0	0%
123	49	0	0	0	0%
124	49	0	0	0	0%
200	86	4	3	7	8.14%
201	90	1	0	1	1.11%
202	53	0	0	0	0%
203	102	2	1	3	2.94%
205	89	0	0	0	0%
209	93	0	0	0	0%
210	92	0	0	0	0%
212	90	0	0	0	0%
213	110	0	0	0	0%
214	75	0	0	0	0%
215	112	0	0	0	0%
217	72	0	0	0	0%
219	73	0	0	0	0%
220	72	0	0	0	0%
221	78	0	0	0	0%
222	75	0	0	0	0%
223	80	0	0	0	0%
228	70	1	1	2	2.86%
230	79	0	0	0	0%
231	63	0	0	0	0%
232	56	2	0	2	3.57%
233	104	1	1	2	1.92%
234	92	0	0	0	0%
Total	# of (Beats) 3619	# of FP (Beats) 12	# of FN (Beats) 6	Beats Not Detected 18	Overall Error 0.49%

References

[1] J. Pan and W. J. Tompkins, "A Real-Time QRS Detection Algorithm," *in IEEE Transactions on Biomedical Engineering, vol. 32, no. 3, pp. 230-236*, Mar. 1985.

[2] LabVIEW for ECG Signal Processing, *http://zone.ni.com/devzone/cda/tut/p/id/6349.*

[3] C. Li, C. Zheng and C. F. Tai, "Detection of ECG Characteristic Points Using Wavelet Transforms," *in IEEE Transactions on Biomedical Engineering, vol. 42, no. 1, pp. 21-28*, Jan. 1995.

[4] MIT-BIH Arrhythmia Database, *www.physionet.org/physiobank/database /mitdb/.*

[5] N. V. Thakor and Y. S. Zhu, "Applications of Adaptive Filtering to ECG Analysis: Noise Cancellation and Arrhythmia Detection," *in IEEE Transactions on Biomedical Engineering, vol. 38, no. 8, pp. 785-794*, Aug. 1991.

[6] J. P. Martinez, S. Olmos and P. Laguna, "Evaluation of a Wavelet-Based ECG Waveform Detector on the QT Database," *in Computers in Cardiology, pp. 81-84*, Sep. 2000.

[7] P. M. Agante, J. P. Marques de Sa, "ECG Noise Filtering Using Wavelets with Soft-Thresholding Methods," *in Computers in Cardiology, pp. 535-538*, Sep. 1999.

[8] J. S. Sahambi, S. N. Tandon and R. K. P. Bhatt, Using Wavelet Transforms for ECG Characterization: An On-line Digital Signal Processing System," *in IEEE Engineering in Medicine and Biology Magazine, vol. 16, no. 1, pp. 77-83*, Jan-Feb 1997.

[9] H. A. N. Dinh, D. K. Kumar, N. D. Pah and P. Burton, "Wavelets for QRS Detection," *in Proceedings of the 23rd IEEE EMBS International Conference, pp. 1883-1887*, Oct. 2001.

[10] National Instruments, "User Manuals for LabVIEW Toolset Version 8.5.1", 2008.