# P AND T WAVE DETECTION ON MULTICHANNEL ECG USING FRI

*Amrish Nair and Pina Marziliano*

School of Electrical and Electronic Engineering
Nanyang Technological University, Singapore

## ABSTRACT

This paper proposes a new method for detecting P and T waves in multilead ECG based on the Finite Rate of Innovation(FRI) technique [8]. A simple QRS detection scheme will be presented followed by a novel P and T wave detection algorithm. The novelty here is the modelling of the P and T wave using a Gaussian kernel. Using a 2D wavelet decomposition, the approximation coefficients are windowed based on the QRS locations. The FRI method is then used to identify the Gaussian distribution present in the window which will in turn provide the locations of the P and T wave. This method was tested on more than an hour of clean and noisy data and shows good performance in the noisy case.

## 1. INTRODUCTION

Electrocardiograms are electrical signals representing the impulses generated by the heart. The ECG signal is represented by the P, QRS and T waves, as seen in Figure1, and describes the atrial and ventricular contraction and relaxation, respectively.

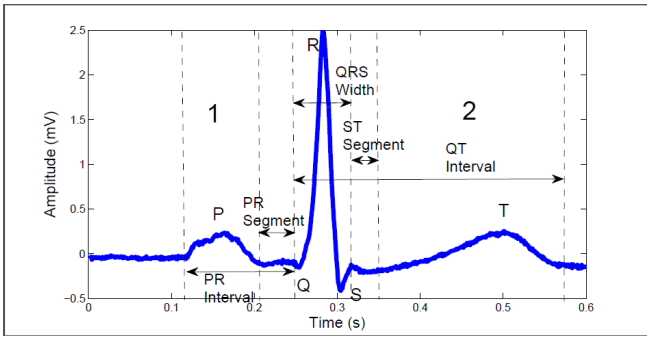


**Fig. 1**. ECG Waveform

The various morphologies of the P and T wave indicate the presence of cardiac conditions or abnormalities associated with the atria and ventricles. By identifying the locations of the P and T waves, this would enable clinicians to better identify the presence of these waves especially in noisy signals. This would be useful especially in channels with low amplitude P and T waves, respectively.

Various methods have been used to detect the P and T waves: First and Second Derivative [1], slope [9], ICA based techniques [4] and energy signature [7] methods have been used. Our method has an added advantage in that all the channels are compressed into one set of approximation coefficients from which the P and T waves can be detected. This simplifies the process and is fast in its implementation. The P and T waves which are less prominent in some channels can also be detected much more easily this way.

This paper is arranged as follows. Section 2 describes the methodology used to detect the P and T waves. Section 3 describes the data collection experiments and the results obtained. Section 4 concludes the paper.

## 2. METHODOLOGY

We present in detail the proposed P and T wave detection algorithm described in Figure 2. Consider a multichannel ECG signal, $x[m,n]$ where $m$ is the channel number and $n$ represents the index of the data points. The signal $x[m,n]$ will first undergo QRS detection so as to define the windows, $\tau_P$ and $\tau_T$, which contain the P and T waves.

In [8], a sampling and reconstruction scheme was presented for a class of parametric signals containing a finite number of degrees of freedom, termed as signals with a Finite Rate of Innovation(FRI). It proved that a stream of K weighted Diracs, $x(t) = \sum_{k=1}^{K} c_k \delta(t - t_k)$ where $t \in [0, \tau]$, could be perfectly reconstructed from uniform samples taken at the rate of innovation, $\rho = \frac{2K}{\tau}$. In this paper $\tau$ is defined as the windows, $\tau_P$ and $\tau_T$, which will be further discussed in Section 2.3.1.

The P and T waves within the windows $\tau_P$ and $\tau_T$ are modelled as Gaussian filtered Diracs and FRI is then used to retrieve the location and amplitude parameters.

### 2.1. QRS detection

The proposed QRS detector is based on the energy method developed by J.F.Kaiser [2] and Pan and Tompkins [5]. In this section, the QRS detection is applied to each channel individually, hence the signal $x[n]$ is used without reference to the

This work was funded by Qualcomm Inc., San Diego, USA.

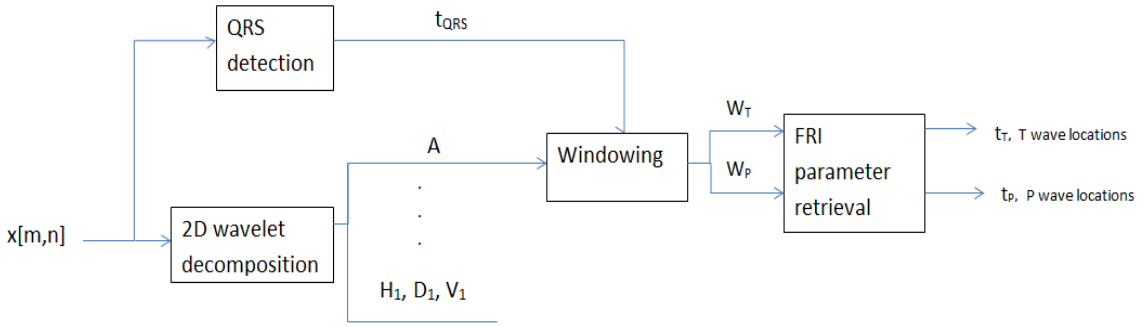


**Fig. 2**. Multichannel P and T wave detection algorithm using the FRI method

channel number $m$. The method in [2] was modified to take the width of the QRS in account which can be represented by

$$E[n] = x[n]^2 - x[n - (\frac{w}{2} f_s)]x[n + (\frac{w}{2} f_s)], \quad (1)$$

where $w$ is the maximum width in seconds of the QRS complex and $f_s$ is the sampling frequency. Equation (1) behaves like the lowpass filter in [5]. In this paper, a value of $w = 0.10sec$ [3] was used to account for a large variety of QRS complexes. The energy signal, $E[n]$, is then thresholded to identify the QRS locations, $t_{QRS}$. Assuming a maximum heart rate of 200 beats/min, if peaks were less than $60/200$ secs apart, the highest valued peak will be chosen and the rest will be rejected.

If two or more channels identify a similar QRS location within an error threshold, the location is confirmed. The average of all the similar locations is then taken as the QRS location. If only one channel identifies a location, then the location is rejected.

### 2.2. 2D wavelet transform

The ECG signal, $x[m, n]$, is then decomposed using a 2D wavelet decomposition. The Biorthogonal 5.5 wavelet was found appropriate for ECG signals [6].The wavelet is then used to decompose $x[m, n]$ which yields the approximation, horizontal, vertical and diagonal coefficients which are denoted by the variables $A, H, V$ and $D$, respectively.

The bandwidth of $x[m, n]$ which is of interest is $< 30Hz$. Therefore an appropriate level of decomposition should be used given that the bandwidth of the signal reduces by half after each decomposition. The approximation coefficients, $A$, are then reshaped into a single row vector.

### 2.3. Windowing and FRI Parameter Retrieval

The QRS locations are found by applying the method in Section 2.1 on the multichannel ECG signal, $x[m, n]$. These QRS locations are then mapped onto the approximation coefficients $\hat{t}_{QRS}$, using a scaling factor $h$, followed by a shift $g$,

$$\hat{t}_{QRS} = (h \times t_{QRS}) + g. \quad (2)$$

The hat notation is used to represent the values mapped onto the approximation coefficients, $A$.

#### 2.3.1. *Windowing*

The approximation coefficients, $A$, are windowed before and after the QRS locations, $\hat{t}_{QRS}$. The windows are defined by medically accepted intervals for physiological processes [3] such as the contraction and relaxation of the atria and ventricles. The constants $w = 0.1$sec, $v = 0.08$sec, $u = 0.2$sec, $z = 0.4$sec, $s = 0.1$sec are used to denote the QRS, ST, PR, QT and P wave duration respectively [3]. The windows are defined by

$$\tau_P = [\hat{t}_{QRS} - 0.5\hat{w} - \hat{u}, \hat{t}_{QRS} - 0.5\hat{w} - \hat{u} + \hat{s}] \quad (3)$$

$$\tau_T = [\hat{t}_{QRS} + 0.5\hat{w} + \hat{v}, \hat{t}_{QRS} - 0.5\hat{w} + \hat{z}], \quad (4)$$

where $\tau_P$ and $\tau_T$ represent the windows for the P and T waves respectively. The constants $w, v, u, z, s$ are defined for a heart rate of 60 beats/min and therefore would have to be weighted depending on the instantaneous heart rate(HR) which can be calculated from the RR intervals found in Section 2.1. The values $w, v, u, z$ and $s$ are multiplied by a factor $\frac{60}{HR}$ to weigh them accordingly. These values are then mapped to the approximation coefficients using the same scaling factor and shift in Equation (2). The windows do not need to capture the entire P or T wave and only needs to contain the peak of the wave.

#### 2.3.2. *FRI parameter retrieval*

From now on, the FRI method would represent the sampling and reconstruction of signals using the Annihilating filter method found in [8]. We define the locations, $t_k$, and amplitudes, $c_k$, as the parameters to be retrieved from each window,

$\tau_P$ and $\tau_T$. Since each window only contains one Gaussian filtered Dirac, $K = 1$, correspondingly there will only be one $t_k$ and $c_k$ per window and it would need to be sampled at a minimum rate of $\rho = \frac{2}{\tau}$. In other words, a minimum of 2 uniform samples per window is needed. The samples, $y_n$ are given by

$$\begin{aligned} y_n &= \sum_{k=0}^{K-1} c_k e^{-(t_k - nT)^2/2\sigma^2} \\ &= \sum_{k=0}^{K-1} (c_k e^{-t_k^2/2\sigma^2}) e^{nt_kT/\sigma^2} e^{-n^2T^2/2\sigma^2}, \end{aligned} \quad (5)$$

where $\sigma$ represents the standard deviation of the Gaussian kernel and $n = 0, ..., N-1$. The $\sigma$ value is known *a priori*.

If we let $S[n] = e^{-n^2T^2/2\sigma^2} y_n$, $a_k = c_k e^{-t_k^2/2\sigma^2}$, $u_k = e^{nt_kT/\sigma^2}$, then Equation (5) is equivalent to

$$S[n] = \sum_{k=0}^{K} a_k u_k^n, \qquad n = 0, \ldots, N-1. \quad (6)$$

The annihilating filter method in [8] can be used to solve Equation (6) and resolve for the $u_k$ values. The $t_k$ values are then given by

$$t_k = \frac{\sigma^2 \ln u_k}{T}, \quad (7)$$

where $t_{k,P}$ and $t_{k,T}$ represent the locations in the $\tau_P$, and $\tau_T$, windows respectively. The amplitudes are then given by

$$c_k = a_k e^{t_k^2/2\sigma^2}. \quad (8)$$

The locations of the P and T waves in the approximation coefficients,$A$, can be represented by

$$\hat{t_P} = \hat{t}_{QRS} - 0.5\hat{w} - \hat{u} + t_{k,P} \quad (9)$$

and

$$\hat{t_T} = \hat{t}_{QRS} + 0.5\hat{w} + \hat{v} + t_{k,T}, \quad (10)$$

where $t_{k,P}$ and $t_{k,T}$ represent the location of the peak in the $\tau_P$ and $\tau_T$ windows respectively.

The locations in the time domain can be found by reversing the shift and scaling performed in Equation (2).

## 3. EXPERTIMENT AND RESULTS

### 3.1. Data Collection

The data used in this paper was obtained using the CleveMed BioCapture™which can record up to eight channels simultaneously. A sampling rate of 960Hz with a resolution of 12 bits/sample was used to capture the data. A three lead ECG, leads I, II and III, were captured using wet electrodes.

The subjects were made to perform various tasks which included raising of arms, picking up objects from the ground, brushing teeth, jogging, push ups and climbing stairs. A total of twenty sets of data were collected from three volunteers. These tests were designed to observe the artefacts generated on an ambulatory ECG device during the daily routine of regular people. Artefact free segments as well as segments with EMG and motion artefact were chosen to test the robustness of this algorithm.

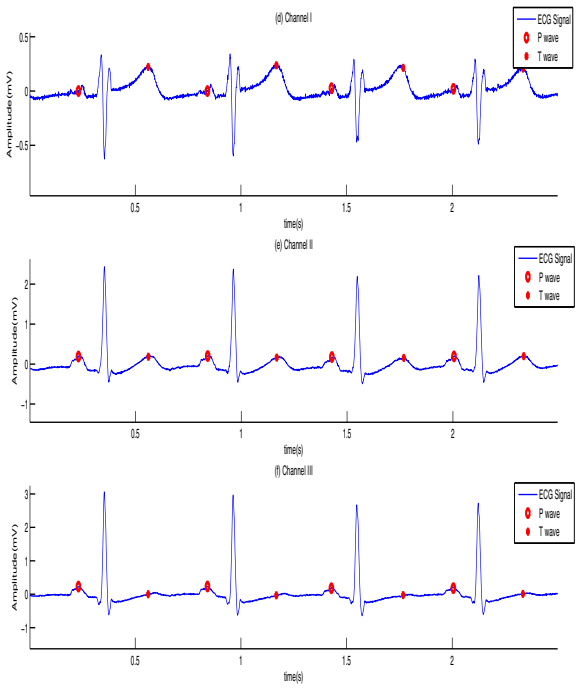


**Fig. 3**. P and T wave detection on 3 lead ECG signals

### 3.2. Results

The algorithm presented in Section 2 was tested on the data in Section 3.1. Each segment of data tested was 4096 samples long. The threshold used in Section 2.1 was $0.75\sigma_E$, where $\sigma_E$ is the standard deviation of the energy signal, $E_n$. Also, a $5^{th}$ level decomposition is used in Section 2.2 due to the 960Hz sampling rate.

The P and T wave detection was tested on clean ECG signals as well as on signals with artefacts added to them. Both baseline wander and Electromyography(EMG) artefacts were simulated and added to a clean segment of data. Baseline wander was simulated as a $4th$ order polynomial and EMG was simulated as additive Gaussian white noise at various SNR levels.

As seen in Figure 3, the method outlined in this paper can identify the P and T waves in normal ECG signals. All the P and T waves were identified accurately. This shows the validity of the assumption that all the P and T waves and QRS

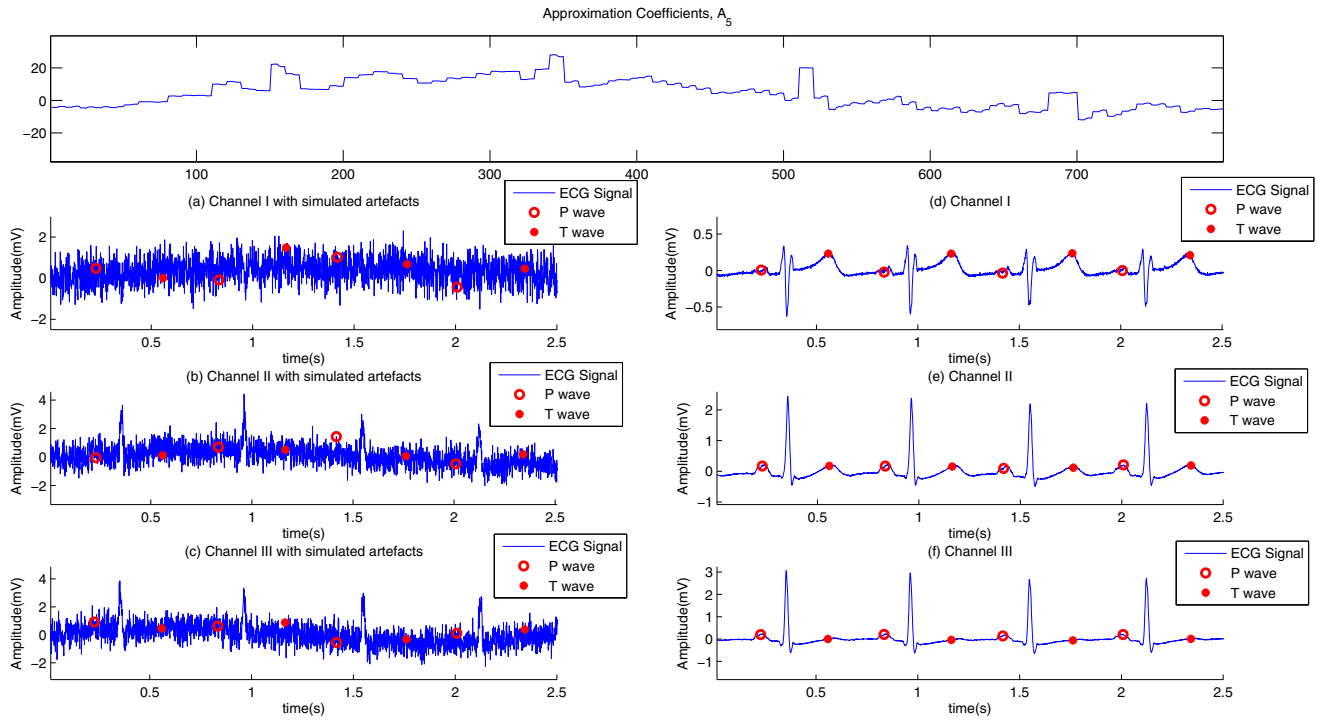


**Fig. 4**. Top: Reshaped $A_5$ coefficients, (a)-(c):P and T wave detection on ECG signal with simulated baseline wander and EMG noise at SNR 0dB, (d)-(e): Detected P and T wave instances juxtaposed onto the original, clean ECG signal

complexes occur at the same instances. This in turn validates the use of the 2D wavelet transform where the $A_5$ coefficients shows relevant information from all the channels.

In Figure 4, the case containing simulated artefacts is shown. The P and T wave detection was tested on the noisy signal and the detected P and T wave instances were juxtaposed onto the original, noiseless signal to confirm the accuracy of the detection. As can be seen, the P and T waves were detected accurately despite the noise. Also shown in Figure 4 are the approximation coefficients involved in the detection process.

The results were consistently reliable at EMG noise levels of up to 0dB and anything lower degrades the performance significantly. The determining factor for performance would be the QRS detector as the positions of the windows are dependant on that.

The multichannel nature of the method presented in this paper is advantageous in scenarios where the amplitude of the P or T wave is very low in one or more channels. As can be seen in Figure 4, where the T wave amplitude in Channel III is low, it is compensated for by the other two channels which enables accurate detection. This is on the basis that if a T wave is present in one channel, it should be present in all other channels.

## 4. CONCLUSION

The results described in Section 3.2 show the robustness of the method presented in this paper. The ability to handle intense artefacts makes this suitable for use when analyzing ECG signals from ambulatory devices such as Holter monitors. The algorithm can also be applied to the single channel case where a 1D wavelet transform is used and the results are similar.

The method presented in this paper could also be extended to detecting P waves in $2:1$ AV blocks where P waves appear without the corresponding QRS complex. The windows could be applied between QRS complexes which exhibit bradycardia, or low heart rate, which is an indication of $2:1$ AV block. The windows could be placed so that the P waves can be located for the missing QRS complexes.

One weakness of this method is that it is not real-time and has to be applied as a post processing step. Possible implementation with the real time QRS detection in [5] would be a possibility and will have to be investigated further.

## 5. REFERENCES


[1] K. Freeman and A. Singh. P wave detection of ambulatory ecg. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 1991. Vol.13*, pages 647 –648, Oct-3 Nov 1991.

[2] J.F. Kaiser. On a simple algorithm to calculate the 'energy' of a signal. In *International Conference on Acoustics, Speech, and Signal Processing*, pages 381 –384 vol.1, April 1990.

[3] R. E. Klabunde. Cardiovascular Physiology Concepts, September 2012. http://www.cvphysiology.com/.

[4] Nian-Qiang Li and Zheng-Sheng Wang. T-wave detection in electrocardiogram signal based on independent sub-band function. In *International Workshop on Intelligent Systems and Applications, ISA 2009.*, pages 1 –3, May 2009.

[5] Jiapu Pan and Willis J. Tompkins. A real-time QRS detection algorithm. *IEEE Transactions on Biomedical Engineering,*, BME-32(3):230 –236, March 1985.

[6] N. Sivannarayana and D.C. Reddy. Biorthogonal wavelet transforms for ECG parameters estimation. *Medical Engineering and Physics*, 21(3):167 – 174, 1999.

[7] T.H.C. Tat, Chen Xiang, and Lim Eng Thiam. Physionet Challenge 2011: Improving the quality of electrocardiography data collected using real time QRS-complex and T-wave detection. In *Computing in Cardiology, 2011*, pages 441 –444, Sept. 2011.

[8] M. Vetterli, P. Marziliano, and T. Blu. Sampling signals with finite rate of innovation. *IEEE Transactions on Signal Processing*, 50(6):1417 –1428, June 2002.

[9] Xiankui Wan and Du Xu. An ECG T waves detection scheme based on the compensatory criterion. In *3rd International Conference on Biomedical Engineering and Informatics (BMEI), 2010*, volume 2, pages 730 –734, Oct. 2010.