Pattern analysis of different ECG signal using Pan-Tompkin's algorithm

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Abstract—**Electrocardiogram (ECG) is one of the most important parameters for heart activity monitoring. The main objective of digital signal processing of ECG signal is to deliver accurate, fast and reliable estimation of clinically important parameters such as the duration of the QRS complex, the R-R interval, the occurrence, amplitude and duration of the P, R, and T waves. In this paper, I have measured all these parameters by using pan-Tompkins's algorithm. It is a real time QRS detection algorithm. It gives the number of QRS peaks for recorded ECG signals. Results of simulations in MATLAB are presented.**

Keywords-component; pan-tompkin'salgorithm; band-pass filter; differentiator; integrator; moving-window.

I. INTRODUCTION

In many applications for biomedical signal processing the useful signals are superposed by different components. So, extraction and analysis of the information-bearing signal are complicated, caused by distortions from interference. Using advanced digital signal processing this task can be solved. Pan-Tompkin's algorithm is a real time algorithm which is consists of band-pass filter, differentiator, integrator and moving-window. The electrocardiogram (ECG) provides a physician with a view of the heart's activity through electrical signals generated during the cardiac cycle, and measured with external electrodes. Its clinical importance in cardiology is well established, being used for example to determine heart rate, investigate abnormal heart rhythms, and causes of chest pain.

II. ECG COMPONENTS

The electrocardiogram (ECG) provides a physician with a view of the heart's activity through electrical signals generated during the cardiac cycle, and measured with external electrodes. Its clinical importance in cardiology is well established, being used for example to determine heart rate, investigate abnormal heart rhythms, and causes of chest pain. As shown in Figure 1, the most important ECG signal features in a single cardiac cycle are labeled (along with the physiological cause of that feature):

• "P" wave - due to depolarization of the atria
• "Q" wave - due to activation of the anterior septal region of the ventricular myocardium
• "R" wave - due to depolarization of the ventricular myocardium
• "S" wave - due to activation of the posterior basal portion of the ventricles
• "T" wave - due to rapid ventricular repolarization

Because the QRS complex is the major feature of an ECG, a great deal of clinical information can be derived from its features. Identification of this feature in an ECG is known in the literature QRS detection, and it is a vital task in automated ECG analysis, portable arrhythmia monitoring, and many other applications. Though trivial in an "ideal" ECG (as shown in Figure 1), the range in quality of real-world ECG signals obtained from a variety of subjects under different measurement conditions makes this task much more difficult.

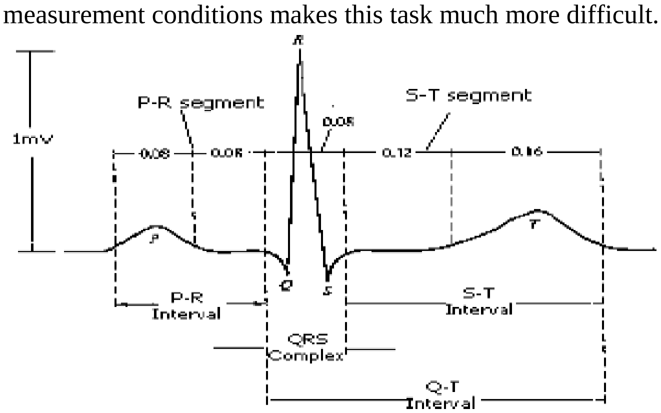

Fig. 1 An ideal ECG beat from a healthy subject (time duration equivalent to one Heartbeat).

III. PAN-TOMPKIN'S ALGORITHM DESIGN AND SIMULATION

A. BAND-PASS FILTER

The band pass filter reduces the influence of muscle noise, 60Hz interference, baseline wander, and T-wave interference. The desirable pass band to maximize the QRS energy is approximately 5-15Hz. Our filter is a fast, real-time recursive filter in which poles are located to cancel zeros on the unit circle of the z-plane. This approach results in a filter design with integer coefficients. Since only integer arithmetic is necessary, a real-time filter can be implemented with a simple microprocessor and still has available computing power left to do the QRS recognition task.

This class of filters having poles and zeros only on the unit circle permits limited pass band design flexibility. For our chosen sample rate, we could not design a band pass filter directly for the desired pass band of 5-15 Hz using this specialized design technique. Therefore, we cascaded the low-pass and high-pass filters described below to achieve a 3 db pass band from about 5-12 Hz, reasonably close to the design goal.

B. LOW-PASS FILTER

The transfer function of the second-order low-pass filter is

$$H(Z) = \frac{(1 - z^{-6})^{2}}{(1 - z^{-1})^{2}}$$

The amplitude response is

$$|\boldsymbol{H(wT)}| = \frac{\boldsymbol{sin^2(3wT)}}{\boldsymbol{sin^2(wT/2)}}$$

Where T is the sampling period the difference equation of the filter is

Y (n T) = 2 y (n T-T) – y (nT-2T) + x (n T) – 2 x (nT-6T) + x (nT-12T)

Where the cutoff frequency is about 11Hz and the gain is 36. The filter processing delay is six samples.

C. HIGH-PASS FILTER

The design of the high-pass filter is based on subtracting the output of a first-order low-pass filter from an all-pass filter (i.e., the samples in the original signal). The transfer function for such a high-pass filter is

$$H(Z) = \frac{(-1+32z^{-16}+z^{-32})}{(1+z^{-1})}$$

The amplitude response is

H (wt) = $|H(wT)| = \frac{[256+sin^2(16wT)]^{1/2}}{\cos(\frac{wT}{2})}$

The différence équation is

Y (n T) = 32 x (n T – 16T) – [y (n T – T) + x (n T) – x (n T – 32T)] .

The low cutoff frequency of this filter is about 5Hz, the gain is 32, and the delay is 16 samples.

D. DERIVATIVE

After filtering, the signal is differentiated to provide the QRS-complex slop information. We use a five-point derivative with the transfer function

H (z) = (1/8T) ($-z^{-2} - 2z^{-1} + 2z^{1} + z^{2}$).

The amplitude response is

H (w T) = (1/4T) [sin (2wT) + 2 sin (w T)].

The difference equation is

Y (n T) = (1/8T) [-x (n T – 2T) – 2x (n T – T) +2 x (n T+T) + x (n T + 2T)].

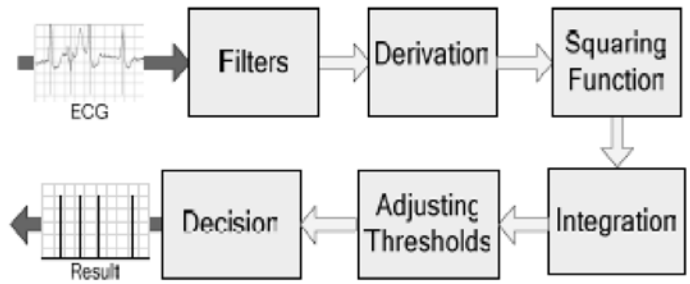

Fig. 2 A graphical representation of the algorithm, The signal passes through filtering; derivation, squaring, and integration phases before thresholds are set and QRS complexes are detected.

E. SQUARING FUNCTION

After differentiation, the signal is squared point by point.

The equation of this operation is

Y (n T) = $[\mathrm{x}\ (\mathrm{n\ T})]^2$

This makes all data points positive and does nonlinear amplification of the output of the derivative emphasizing the higher frequencies (i.e., predominantly the ECG frequencies).

F. MOVING-WINDOW INTEGRATION

The purpose of moving-window integration is to obtain wave-form feature information in addition to the slope of the R wave. It is calculated from-

Y (n T) = (1/N) [x (n T – (N-1) T) + x (n T – (N – 2) T) +………. + x (n T)]

Where N is the number of samples in the width of the integration window

Fig-5 shows the relationship between the moving-window integration waveform and the QRS complex. The number of samples N in the moving window is important. Generally, the width of the window should be approximately the same as the widest possible QRS complex. if the window is too wide, the integration waveform will merge the QRS and T complexes together. If it is too narrow, some QRS complexes will produce several peaks in the integration waveform. These can cause difficulty in subsequent QRS detection processes. The width of the window is determined empirically. For our sample rate of 200 samples /s, the window is 30 samples wide (150 ms).

F. FIDUCIAL MARKS

The QRS complex corresponds to the rising edge of the integration waveform. The time duration of the rising edge is equal to the width of the QRS complex. A Fiducial mark for the temporal location of the QRS complex can be determine from this rising edge according to the desired waveform feature to be marked such as the maximal slope or the peak of the R wave.

Table I. No. of beats present in the ECG signals

Patients Recorded ECG	Total beats	Noise peaks as QRS	QRS missed	Failed detection%
1	2272	0	0	0.000
2	2543	1	0	0.039
3	1775	2	1	0.169
4	1953	2	1	0.154
5	2278	4	0	0.176
6	1473	1	0	0.068
7	1972	2	1	0.152
8	2102	1	0	0.048
9	2649	0	0	0.000
10	3256	1	3	0.123

IV. ALGORITHM SIMULATION RESULTS

ST-segment: The ST deviation is derived 80 ms after the endpoint of the QRS complex, if the RR-interval is greater than 0.7s, and if the RR-interval is smaller than 0.7s, the amplitude is measured 60ms after the QRS complex has ended.

T-and P-wave detection: A different algorithm is used for the T-and P-wave detection, the algorithm searches for the T-wave, after a QRS complex is detected.

Table II. Step by step output of Pan-Tompkin's

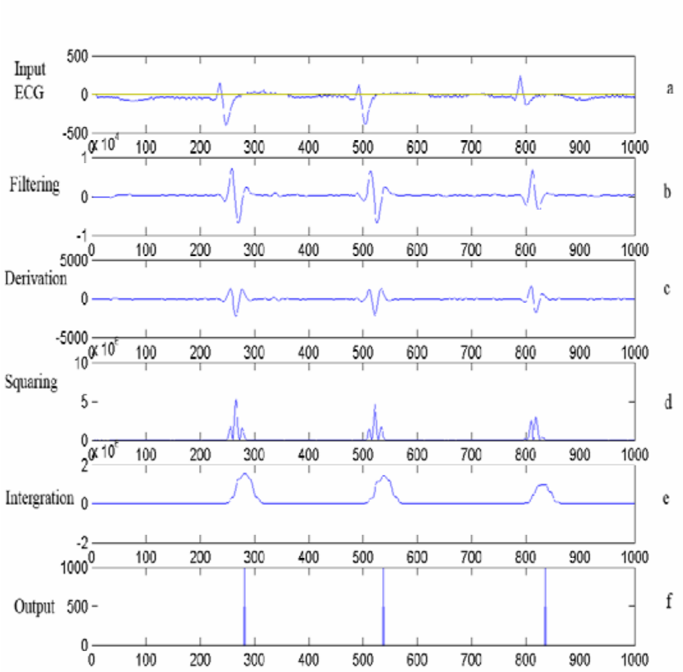

Table III. Mapping of Waveforms to different sections in the heart

Interval	*Reason for Wave generation*	*Amplitude*	*Time Interval*	*Characteristics*
P wave	**Represents Atrial Depolarization**	**Normal amplitude is 1-1.5 mm**	**<0.12 sec**	**Small, rounded and upright**
QRS complex	**Represents ventricular Depolarization**	**Normal amplitude of R-wave is 8-12 mm**	**<0.04 to 0.10sec (QRS Interval)**	**The first negative wave in the complex is the Q wave, the first positive wave in the complex is the R-wave and the first negative wave following the R-wave is the S-wave**
T wave	**Represents ventricular repolarization**	**Normal amplitude is 2 – 5 mm**	**Not Measured**	**Same polarity as QRS complex usually correlates with polarity of R-wave**
U wave	**Purkinje fiber repolarization**	**Not measured (low voltage)**	**<0.01sec**	**Usually of low voltage and same polarity as T wave when present**

V. CONCLUSION

The QRS wave detection algorithm still needs improvement before reaching sensitivity and positive productivity levels acceptable for implementation in technical applications. One reason for the unsatisfying QRS wave detection capabilities, especially the great variety of detected waveform location, is the fact that fixed thresholds have been for detection. Implementation of threshold adaptation, like the one used in QRS detection, will most likely bring significant improvement.

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