Threshold-based Detection of P and T-wave in ECG using New Feature Signal

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Summary
Detection of P and T waves is an important part in the analysis and interpretation of ECG. The presented algorithm detects and delineates both P and T-waves simultaneously. It employs a modified definition of slope, of ECG signal, as the feature for detection of ECG wave components. A number of transformations of the filtered and baseline drift corrected ECG signal are used for extraction of this new modified slope-feature. Five feature-components are combined to derive the final feature signal. Amplitude threshold of the final feature signal is employed for distinguishing P and T waves with respect to already detected QRS-complexes. P-wave detection rate of 96.95% with false positive and false negative percentage of 2.62% and 3.01% has been reported. Similarly, T-wave detection rate of 98.01% with false positive and false negative percentage of 3.08% and 1.93% has been reported.

Key words:
ECG, P and T-wave detection, threshold detection, feature signal.

1. Introduction

A standard scalar electrocardiogram consists of P-wave, PR-interval, PR-segment, QRS-complex, ST-segment, ST-interval and T-wave. The P-wave represents atrial depolarization, the QRS complex left ventricular depolarization and the T-wave left ventricular repolarization.

Different delineation approaches are found in literature. Many of these approaches delineate either P or T-waves of ECG waveforms, whereas a few approaches delineate both P and T-waves. Murthy & Niranjan [1] used discrete Fourier transform (DFT) to delineate P and T waves, while Murthy and Prasad [2] used discrete cosine transform (DCT). Thakor and Zhu [3] used adaptive filters for delineation of P-waves. Pietka [4] used a combination of syntactic methods and methods based on measurement vectors by applying the attribute grammars. Trahanias and Skordalakis [5] used attribute grammar for the detection of P and T-waves.

Li *et al*. [6] proposed a method for detecting monophasic P and T-waves. Martinez *et al*. [7] presented a generalized and robust method for delineation of P and T waves. Mehta *et al*. [8] proposed a method for the recognition of P and T waves in electrocardiograms using fuzzy theory. Carlson *et al*. [9] proposed classification method for P-wave morphology. Botter *et al*. [10] used a neural network with asymmetric basis functions to extract the features of the P waves. Yang *et al*. [11] proposed approximating functions for P waves recognition.

A fuzzy clustering technique using asymmetric basis function network approach, is presented by Geva [12]. Sovilj *et al*. [13] used multistage methodology enabled by Wavelet Transform to delineate the ECG signal and develop a sensitive and reliable P-wave detector. Wong *et al*. [14] applied Discrete Wavelet Transform (DWT) analysis, employing Haar Wavelet detecting the T-wave peak and the T-wave end.

Vila *et al*. [15] presented an algorithm for the detection of T -waves based on its mathematical modeling. Strumillo [16] proposed nested median filtering for detecting T-wave offset in ECG. Sahambi *et al*. [17], validated an algorithm for detecting the peaks, onsets and ends of monophasic P and T waves.

The detection of P and T-waves demands attention on the following aspects:

Filtering: The features extracted, for the detection of P- and T-waves in the proposed algorithm, and those for the detection of QRS- regions incorporate slope, therefore the presence of noise causing unjustifiable magnitude variations is undesirable. The filtering, using moving averages algorithm, is done prior to the QRS-detection [18]. Its performance is found to be satisfactory and no additional filtering is required prior to detection of P- and T-waves.

QRS-detection: Since the detection of P- and T-waves is done with reference to QRS onset and offset, therefore a good QRS-detection rate is a pre-requisite and is fulfilled by the algorithm for QRS-detection [19].

Removal of baseline drift: In the proposed algorithm, the feature extraction for detection of P- and T- waves uses computation of gradient, in a sliding window; therefore baseline drift causes computation of false

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gradient. For this reason, two levels of baseline drift removal are employed – one prior to the QRS-detection on the entire range of sampling instants and another in the RR-interval after the QRS-detection [20]. The first level minimizes the baseline drift, which is sufficient for the QRS-detection. The removal of baseline drift is near total after the second level, this is particularly needed for detection of low magnitude P-waves and feeble T-waves.

Feature signal for detection of P- and T-waves: The feature extracted from the ECG signal for the detection of P- and T-waves should be capable of appreciating the low slope and low magnitude of the wave components, as contrasted to QRS-complexes containing peaky waves with prominent slope and magnitude. Further, to ensure sufficient magnitude of the extracted feature, so as to meet the thresholding needs, the proposed algorithm extracts multiple feature components and combines them to attain the final feature signal (referred to as non-QRS feature signal F_{NQ}).

Search interval for P- and T-waves: Since the detection of P- and T-waves is done with reference to QRS onset and offsets, entire range of sampling instants is divided into 3 search intervals for P- and T-waves:

– First sampling instant to the first QRS-onset
– All sampling instants between each successive pair of QRS-offset and the subsequent QRS-onset, and
– Last QRS-offset till the last sampling instant.

2. Procedure

One way of looking at the ECG is the classification of the signal in two parts, namely, QRS-complexes and non-QRS regions. The QRS-complexes being the most prominent parts of the signal are detected first [19]. Already detected QRS-complexes become a reference for detection of P- and T-waves. The ECG signal part between each successive pair of QRS-offset and the subsequent QRS-onset constitute non-QRS regions.

The proposed algorithm first extracts non-QRS feature F_{NQ} for detection of P and T waves (non-QRS components). F_{NQ} is a combination of five different constituent feature components.

The algorithm then detects and demarcates non-QRS wave components in each search interval. This demarcation is interim and is done uniformly, on the basis of magnitude-threshold of the extracted non-QRS feature signal. The interim demarcation is done with rectangular marking pulses and given a common name C_{NQ}, that is, non-QRS candidates regardless of being a P-wave or a T-wave.

The algorithm then identifies the P-waves and T-waves, out of these candidates C_{NQ}, on the basis of their spatial location, in each search-interval, with respect to the QRS-onset and QRS-offset. The detected P-waves and T-waves are demarcated with marking pulses MP_P and MP_T respectively. In order to distinguish between the identified P and T-waves, two different magnitudes MP_P and MP_T are assigned to the marking pulses of P and T-waves respectively. This helps in visual distinction between the detected P and T-waves.

The present work has been tested on the entire range of dataset 3 of CSE ECG database [21], which contains 125 cases of 12-lead simultaneously recorded ECG of 10 seconds duration each, sampled at a rate of 500 samples/sec. Thus each of the 1500 (125x12) single lead records has 5000 sampling instants.

3. Procedural Steps

(A) The first set of steps aims at extracting 5 feature-components fc1 through fc5 so as to compute non-QRS feature F_{NQ} which is sum of fc1, fc2, fc3, fc4 and fc5.

– Here, fc1 is derived from conventional first derivative of ECG signal (eqn. 4)
– fc2 is derived from filtered gradient FG (eqn. 8)
– fc3 is derived from product (FG*S) of filtered gradient FG and ECG signal S, (eqn. 10)
– fc4 is derived from combination of fc1, fc2, fc3 and absolute value of ECG signal S (eqn. 12)
– fc5 is derived from another combination of fc1, fc2, fc3 and absolute value of ECG signal abs(S) (eqn. 14)

The procedures for extraction of these components is detailed below:

1. For computing the first feature-component fc1, feature signal F1 is used, which in turn, is derived from y1:

$$y1(n) = S(n) - S(n-1);\ n=1, 2, \ldots, 5000 \quad \ldots (1)$$

where, y1(n) is the first derivative of the ECG signal at n^{th} sample point,

S(n) is the magnitude of ECG signal at n^{th} sample point,

Absolute value of y1(n) is filtered for smoothing it using moving averages method with a rectangular sliding window of 11 sample points' size from (n–5) to (n+5), with center at (n) (eqn. 2):

$$F[y1(n)] = \frac{1}{11}\sum_{i=n-5}^{n+5} abs[y1(i)]$$

$$n=1, 2, \ldots, 5000 \quad \ldots (2)$$

Filtered values F[y1(n)] of eqn. (2) are normalized by using eqn. (3) to obtain F1(n) as shown in fig. 1(b).

$$F1(n) = F[y1(n)]/\max(F[y1(n)])$$

$$n=1, 2, \ldots, 5000 \quad \ldots (3)$$

2. Now, fc1(n) is derived from F1(n), by eliminating the parts of F1(n) where QRS Marking Pulses MP_Q are already demarcated [19], and doubling the remaining F1(n) for enhancing prominence of the feature-component:

$$fc1(n) = \begin{cases} 2 * F1(n), & \text{if } F_Q(n) = 0 \\ 0, & \text{if } F_Q(n) > 0 \\ 0, & \text{if } F1(n) < 0 \end{cases} \quad \ldots (4)$$

The negative values of fc1(n), if any, are discarded as indicated by the last part of eqn. (4), because they are never used. The values of fc1(n), on and above zero-line, are preserved as seen in fig. 2(d).

3. Derive transformed signal 'TS' by evaluating the following sigmoid function at the signal sample points:

$$TS(n) = 1 - \{2/(e^{2S(n)}+1)\};$$
$$n = 1, 2, \ldots, 5000 \quad \ldots (5)$$

4. Evaluate gradient 'G' of 'TS' with the following relation:

$$G(n) = TS_{max}(w_n) - TS_{min}(w_n);$$
$$n=1, 2, \ldots, 5000 \quad \ldots (6)$$

Where, w_n is a sliding rectangular window, of width 11 samples, from (n-5) to (n+5) with center at the n^{th} sampling instant. TS_{max} is the maximum value of transformed signal TS within this window and TS_{min} is the minimum value of TS within this window.

5. Filter the gradient values by moving averages method to evaluate filtered gradient 'FG' with a sliding window of 11 sample points' size from (n–5) to (n+5), with center at (n), to smoothen it:

$$FG(n) = \frac{1}{11}\sum_{i=n-5}^{n+5} G(i) \quad \ldots (7)$$

6. For computing the second feature-component fc2, the filtered gradient FG is used:

Obtain signal FGhm(n) by shifting FG(n) by half the median value 'm' of FG(n). The effect of this shifting can be appreciated in fig. 2(b) and (c).

After the shifting FGhm is closer to the zero-line of the plot, ensuring detection of genuine threshold values only. In case of QRS detection, full median is used for shifting the concerned signal [19], whereas in case of detection of P- and T-waves half median value is found to be more appropriate.

$$fc2(n) = \begin{cases} FG(n), & \text{if } F_Q(n) = 0 \\ 0, & \text{if } F_Q(n) > 0 \\ 0, & \text{if } FG(n) < 0 \end{cases} \quad \ldots (8)$$

The values of fc2(n), on and above zero-line are preserved and the negative values are discarded, using eqn. (8) as shown in fig. 2(d).

7. For computing the third feature-component fc3, Filtered Gradient FG of step 5 is used:

$$Pre\_fc3(n) = FG(n) * S(n);$$
$$n=1, 2, \ldots, 5000 \quad \ldots (9)$$

The advantage of the product of FG(n) and ECG signal S(n) is that wherever the slope of S(n) is more the product is enhanced as seen in fig 3(c)

The portion belonging to QRS region is eliminated to obtain fc3(n) from Pre_fc3 using eqn. (10):

$$fc3(n) = \begin{cases} Pre\_fc3(n), & \text{if } F_Q(n) = 0 \\ 0, & \text{if } F_Q(n) > 0 \\ 0, & \text{if } Pre\_fc3(n) < 0 \end{cases} \quad \ldots (10)$$

The negative values of Pre_fc3(n) are discarded and remaining values are preserved as fc3(n) as shown in fig. 3(d).

8. For computing the 4^{th} and 5^{th} feature-components fc4 and fc5, combinations of fc1, fc2, fc3 and absolute value of ECG signal abs(S) are used. Pre_fc4(n) signal is obtained using eqn. (11):

$$Pre\_fc4(n)=[fc1(n)+fc2(n)+fc3(n)+abs(S(n))] * abs(S(n)); \quad \ldots (11)$$

$$fc4(n) = \begin{cases} Pre\_fc4(n), & \text{if } F_Q(n) = 0 \\ 0, & \text{if } F_Q(n) > 0 \\ 0, & \text{if } Pre\_fc4(n) < 0 \end{cases} \quad \ldots (12)$$

9. A slightly different combination, by dropping the last factor of eqn. (11), is used to compute Pre_fc5(n):

$$Pre\_fc5(n)=[fc1(n)+fc2(n)+fc3(n)+abs(S(n))] \quad \ldots (13)$$

After eliminating the feature-component parts corresponding to QRS marking pulses and discarding negative values, if any, the final values of fc5(n) are preserved as shown in fig. 6(d).

$$fc5(n) = \begin{cases} Pre\_fc5(n), & \text{if } F_Q(n) = 0 \\ 0, & \text{if } F_Q(n) > 0 \\ 0, & \text{if } Pre\_fc5(n) < 0 \end{cases} \quad \ldots (14)$$

After evaluating all the five feature-components fc1 through fc5, shown in fig. 6, they are combined to yield the pre-final non-QRS feature signal Pre-F_{NQ}, by algebraically summing them all:

$$Pre\_F_{NQ}(n)=fc1(n)+fc2(n)+fc3(n)+fc4(n)+fc5(n) \quad \ldots (15)$$

Pre_F_{NQ}, in turn, is used to evaluate the final non-QRS feature signal F_{NQ} by truncating the values exceeding 1

and retaining all the other values of Pre-F_{NQ} lying between 0 and 1, including both these extreme values:

$$F_{NQ}(n) = \begin{cases} Pre\_F_{NQ}(n), & \text{if } 0 \le Pre\_F_{NQ}(n) \le 1 \\ 1, & \text{if } Pre\_F_{NQ}(n) > 1 \\ 0, & \text{if } Pre\_F_{NQ}(n) < 0 \end{cases} \quad \dots (16)$$

$Pre\_F_{NQ}(n)$ and $F_{NQ}(n)$ are shown in fig. 7(b) and (c).

It can be clearly seen that the P and T-waves regions have been enhanced substantially.

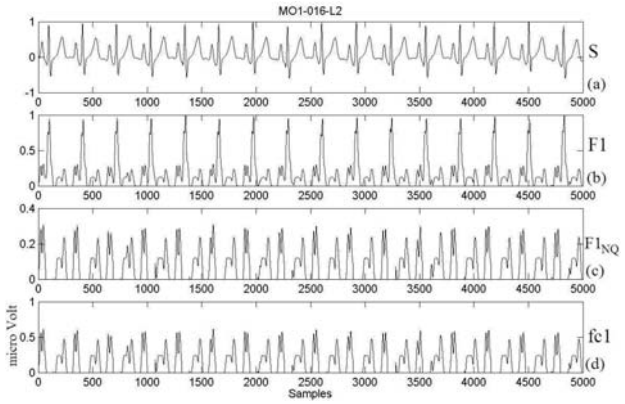

Fig. 1(a) ECG signal S (b) Filtered feature signal F1(c) $F1_{NQ}$ is F1 after eliminating F_Q (d) The first Feature-Component fc1

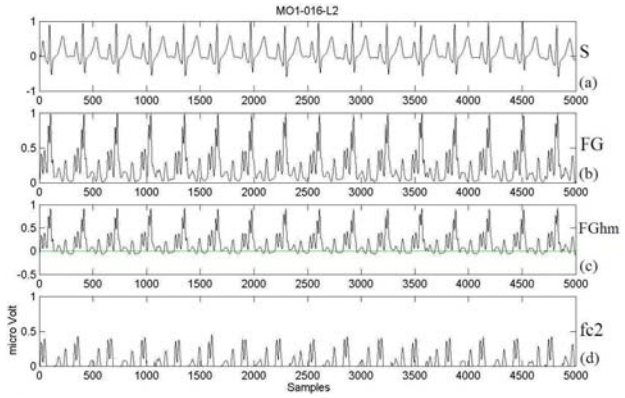

Fig. 2(a) ECG signal S (b) Filtered Gradient FG (c) FGhm is FG after treating with half the median value (d) Second feature-component fc2 after eliminating F_Q

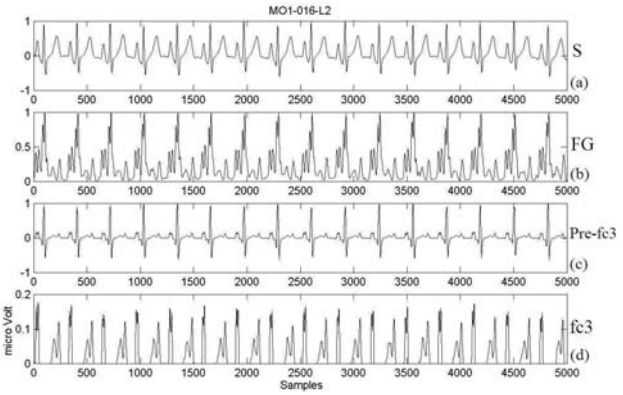

Fig. 3(a) ECG signal S (b) Filtered Gradient FG of ECG signal S (c) Pre-fc3 before eliminating F_Q (d) The third Feature-Component fc3 after eliminating F_Q

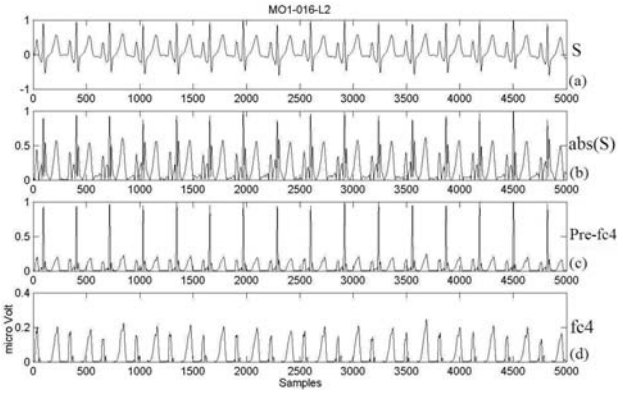

Fig. 4(a) ECG signal S (b) Absolute value of ECG signal S (c) Pre-fc4 before eliminating F_Q (d) The fourth Feature-Component fc4 after eliminating F_Q

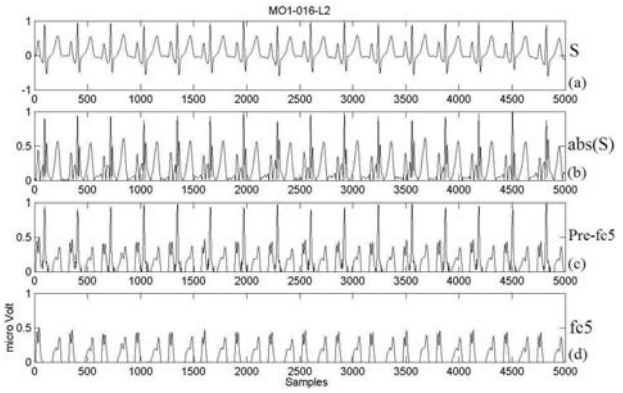

Fig. 5(a) ECG signal S (b) Absolute value of ECG signal S (c) Pre-fc5 before eliminating F_Q (d) The fifth Feature-Component fc5 after eliminating F_Q

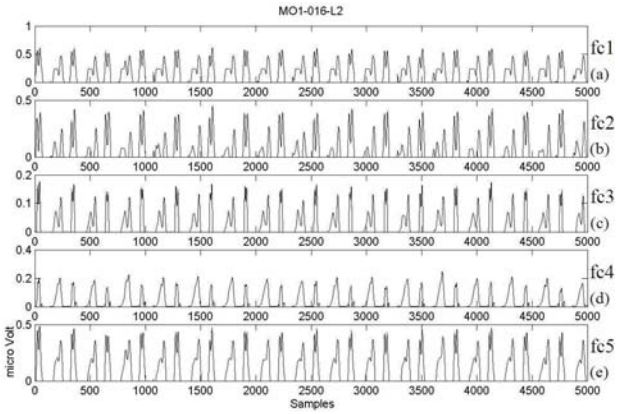

Fig. 6(a) The First Feature-Component fc1 (b) Second Feature-Component fc2 (c) Third Feature-Component fc3 (d) Fourth Feature-Component fc4 (e) Fifth Feature-Component fc5

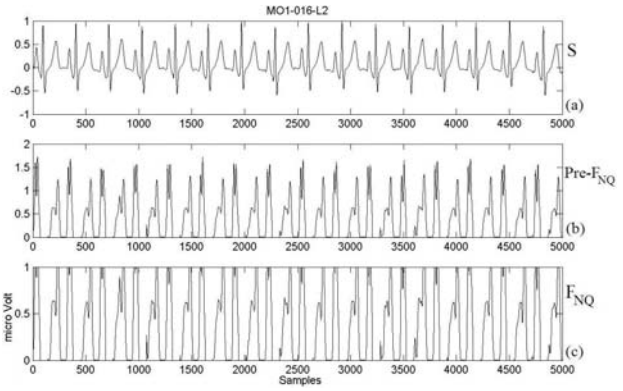

Fig. 7(a) ECG signal S (b) Pre-final non-QRS feature signal Pre_F_{NQ} (c) The final non-QRS feature signal F_{NQ}

4. Non-QRS Feature Extraction Algorithm

1. Acquire drift free ECG signal S(n);
   n=1, 2, …, 5000
2. Extract feature signal F1(n), using eqn. (1), (2) and (3)
3. Derive first feature-component fc1 using eqn. (4)
4. Derive transformed signal TS(n) by evaluating the sigmoid function using eqn. (5)
5. Evaluate gradient G(n) of transformed signal TS(n) by using eqn. (6) with a rectangular sliding window w_n:
   $G(n) = TS_{max}(w_n) - TS_{min}(w_n)$;
   Filter the gradient G(n) by moving averages method to evaluate filtered gradient FG(n) using eqn.(7)
6. Derive second feature component fc2(n) using eqn.(8)
7. Derive third feature component fc3(n) using eqn.(9) and (10)
8. Derive fourth feature component fc4(n) using eqn.(11) and (12)
9. Derive fifth feature component fc5(n) using eqn.(13) and (14)
10. Derive desired feature signal $F_{NQ}(n)$ corresponding to non-QRS regions of the ECG signal by eliminating those portions of Pre_$F_{NQ}(n)$ which represent the already detected QRS complexes, using eqn. (15) and (16). The final values of $F_{NQ}(n)$ lie between 0 and 1 on account of truncation done by eqn. (16) as shown in fig.7(c).

5. Algorithm for Detection of P and T-waves

1. Discard those portions of $F_{NQ}(n)$ whose magnitude is less than 2% of its maximum, so that small random variations in signal are dropped. Mark the portions of $F_{NQ}(n)$ greater than 2% of its maximum, with rectangular marking pulses $C_{NQ}(n)$ with fixed peak magnitude of 0.5 as non-QRS candidates and assigned a fixed peak magnitude of 0.5 to $C_{NQ}(n)$ and 0 where $F_{NQ}(n)$ is less than 2%. These demarcated rectangular pulses $C_{NQ}(n)$ are the candidate P and T waves (Fig. 8).

2. Identify and demarcate P-waves and T-wave out of candidates $C_{NQ}(n)$ with respect to each of the already detected QRS-complexes as reference.
Particularly here, when each single QRS is taken as reference, two types of search interval are sufficient for coverage of the entire range of 5000 sampling instants of a case:

– First search interval, from 1st sampling instant to the first QRS-onset, because this is the only interval where the algorithm searches for P- and T-waves occurring before the reference QRS, and
– Second search interval from the reference QRS-offset till the last sampling instant, as all the P- and T-waves occurring after the reference QRS are covered under this interval.

(a) Detection of P- and T-waves, out of candidate $C_{NQ}(n)$, occurring before the first QRS-complex (ref. Fig. 8):

```
if (Q_count = = 1)
    if (C_NQ = = 0.5) & (abs(C_NQ_end – QRS_end) >= 0.66*rr1_av) & (QRS_begin > C_NQ_end) & (F_NQ > 0.10)
        set T(i) = 0.6;                                   … (17)
    elseif (C_NQ= =0.5) & (abs(C_NQ_end–QRS_end) <=0.33*rr1_av) & (QRS_begin > C_NQ_end) & (F_NQ > 0.05)
        set P(i) = 0.3;                                   … (18)
    end
end
```

where, i = sampling instants from C_{NQ}_begin to C_{NQ}_end and Q_count = 1 refers to first QRS-complex

C_{NQ} are candidate P- and T-waves, F_{NQ} is non-QRS feature, abs(x) is absolute value of x, rr1_av is average value of RR1 (ref. Fig. 8), QRS_begin and QRS_end are the beginning and end of rectangular QRS marking pulses respectively,

C_{NQ}_begin and C_{NQ}_end are the beginning and end of rectangular C_{NQ} marking pulses respectively,

P(i) and T(i) are the detected P- and T-waves respectively.

(b) Detection of P- and T-waves, out of $C_{NQ}(n)$, occurring after each reference QRS-complex (ref. Fig. 8):

if (C_{NQ}= =0.5) & (abs(C_{NQ}_end – QRS_end)<= 0.66∗rr1_av) & (QRS_end < C_{NQ}_end) & (F_{NQ} > 0.10)

set T(i) = 0.6; … (19)

elseif (C_{NQ}= =0.5) & (abs(C_{NQ}_begin–QRS_end) >= 0.66∗rr1_av) & (QRS_end < C_{NQ}_end)

set P(i) = 0.3; … (20)

end

where, i = sampling instants from C_{NQ}_begin to C_{NQ}_end

3. Club deserving but split up P-waves or T-waves within each RR-interval. If they are not covered under the clubbing logic, then eliminate one with lower peak value of F_{NQ} – because multiple P-waves or T-waves cannot exist in one RR-interval.

Three search intervals are taken to cover entire range of 5000 sample points with reference to RR-intervals:

- First search interval from first sampling instant to the beginning of first QRS,
- Search intervals from first to last RR-interval, taking two adjacent QRS at a time iteratively, and
- Last search interval from end of the last QRS to the last sampling instant.

The logic for clubbing the deserving waves (separately for P-waves and T-waves), in all the three search intervals, is:

(a) The first search interval is identified by the condition:

if (Q_count = = 1)

When this condition is true, the first QRS is reached and the first search interval, from the 1st sampling instant to the beginning of the first QRS, is available.

If two P-waves are detected closely, such that, there lies a non-zero value of F_{NQ} or S in between then these P-waves should be clubbed to make them one by reducing the detection threshold (if the threshold is reduced for all cases the delineation of other cases is adversely affected):

if (w_{p1} > 0) & (w_{p2} > 0)

if (w_{p1} + w_{p2} + pp1 <= 100) & ((min(F_{NQ}(j)) >= 0.3) OR (min(abs(S(j))) >= 0.5))

set p(j) = 0.3; … (21)

end

end

Where, j = sampling instants from P1_end to P2_begin; w_{p1} & w_{p2} are widths of p-waves to be clubbed, pp1=pp-interval

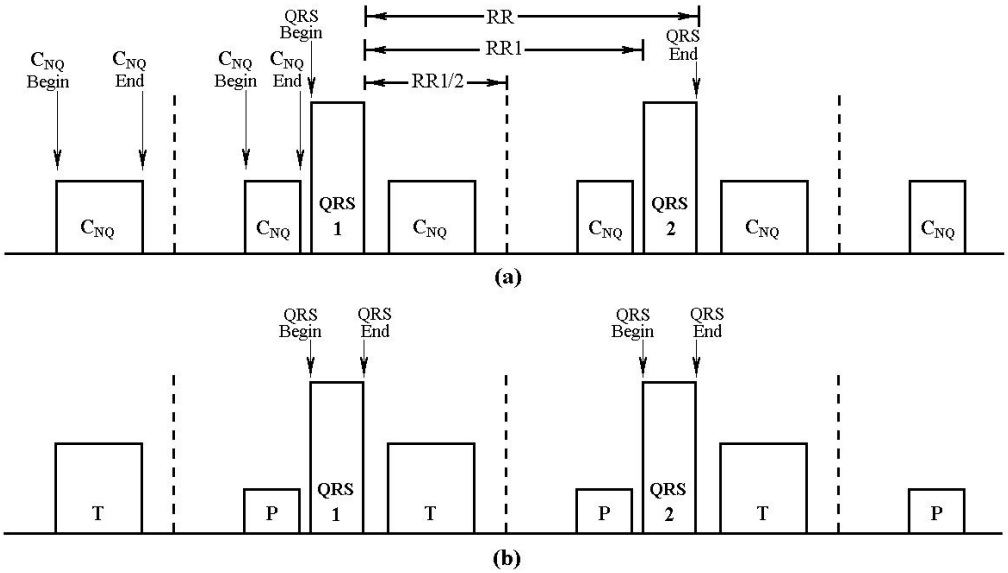

Fig. 8 (a) QRS 1 is first QRS-complex, C_{NQ} are demarcated candidate non-QRS
(b) P is C_{NQ} detected as P-wave, T is C_{NQ} detected as T-wave by the algorithm.

Note: (1) Peak magnitude of various rectangular marking pulses is kept different to make them easily distinguishable – it is assigned as 1 for QRS (fig. 8a & b), 0.5 for C_{NQ} (fig.8a), 0.6 for T-waves and 0.3 for P-waves (fig. 8b).
(2) RR is RR-interval, RR1 is interval from QRS_offset to next QRS_onset and RR1/2 is half of RR1.

Similarly, if two T-waves are detected closely, such that, there lies a non-zero value of F_{NQ} or S in between then these T-waves should be clubbed to make them one by reducing the detection threshold, with the following logic:

```
if w_t1 > 0 & w_t2 > 0
   if (w_t1 + w_t2 + tt1 <= 120) & ((min(F_NQ(k)) >= 0.5)
   OR (min(abs(S(k))) >= 0.7))
      T(k) = 0.6;                                   … (22)
   end
end
```

where, k=sampling instants from T1_end to T2_begin; w_{t1} & w_{t2} are widths of p-waves to be clubbed, tt1=tt-interval

(b) The second search interval is identified by the condition:

if (w_{q1} > 0) & (w_{q2} > 0)

Where w_{q1} and w_{q2} are the widths of two continuous QRS-complexes, their non-zero values are indicative of their existence and therefore the search interval RR1 between them is available. The logics for clubbing the split up P- or T-waves remain identical as in step 3(a) above.

(c) The third search interval is identified by the condition:

if (Q_count = = Q_No)

Where, Q_count is the QRS-to-QRS progressive count and Q_No is the total number of QRS-complexes detected in a case. When the two become equal, the last QRS is reached and the last search interval from QRS_offset to 5000th sampling instant is available. The logics for clubbing the split up P- or T-waves remain identical as in step 3(a) above.

6. Graphical Results of P and T-wave Detection

The graphical results of the P and T-wave detection are shown in figures from 9 to 12. It is clearly seen from these figures that all the varieties of slope, magnitude and polarity of the P and T-waves are successfully detected and delineated.

Fig. 9 illustrates the example of detection where both the P and T-wave are normal and erect, whereas Fig. 10 illustrates the detection of normal and inverted P and T-wave. Fig. 11 shows detection of feeble P-waves and T-waves, whereas the detection of tall and prominent T-waves is shown in fig. 12 as well as the detection of very feeble P -waves in the presence of these huge T-waves.

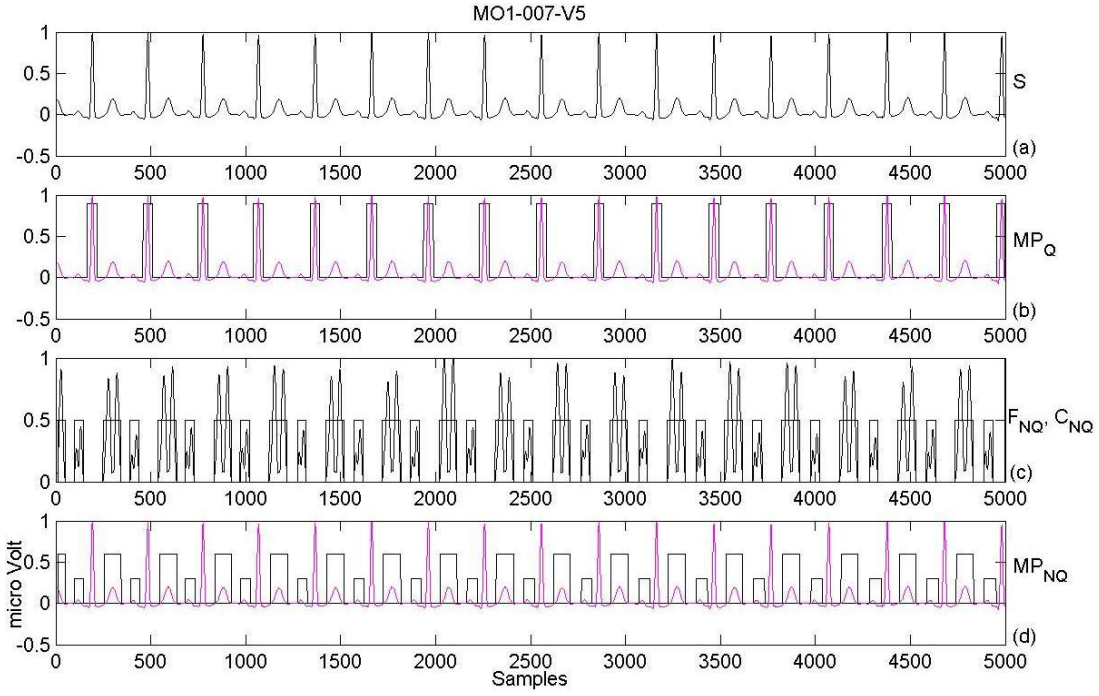

Fig. 9(a) ECG signal S (b) Already demarcated QRS marking pulses MP_Q superimposed over signal S (c) Final non-QRS feature signal F_{NQ} and non-QRS candidates C_{NQ} shown as rectangular pulses (d) Rectangular non-QRS marking pulses MP_{NQ}, delineating P and T waves, superimposed over signal S

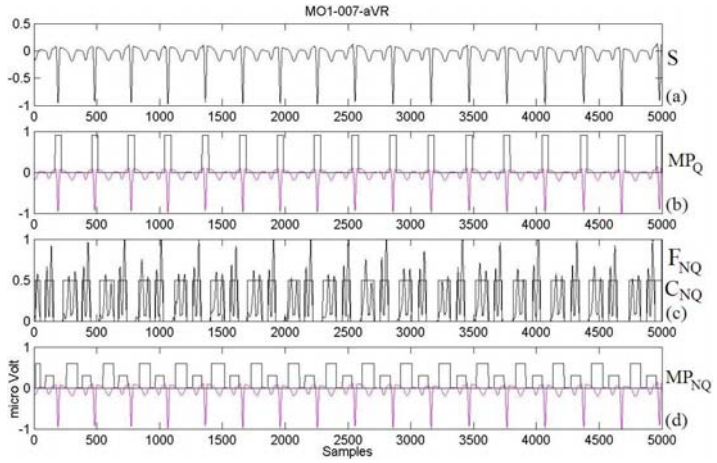

Fig. 10(a)) ECG signal S (b) Already demarcated QRS marking pulses MP_Q superimposed over signal S (c) Final non-QRS feature signal F_{NQ} and non-QRS candidates C_{NQ} shown as rectangular pulses (d) Non-QRS marking pulses MP_{NQ}, delineating P and T waves, superimposed over signal S

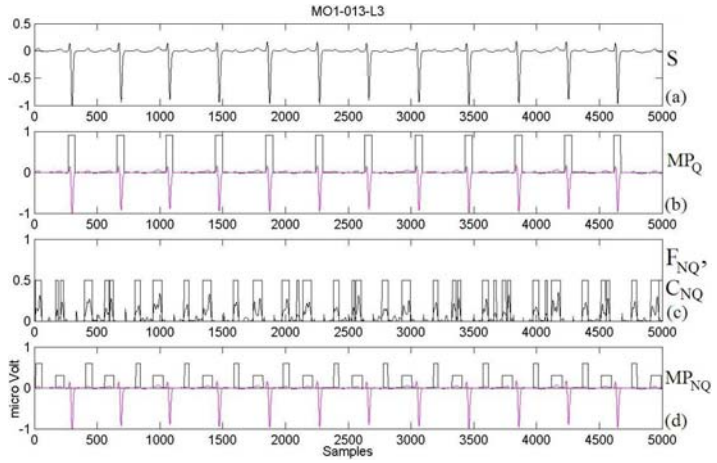

Fig. 11(a) ECG signal S (b) Already demarcated QRS marking pulses MP_Q superimposed over signal S (c) Final non-QRS feature signal F_{NQ} and non-QRS candidates C_{NQ} shown as rectangular pulses (d) Non-QRS marking pulses MP_{NQ}, delineating P and T waves, superimposed over signal S

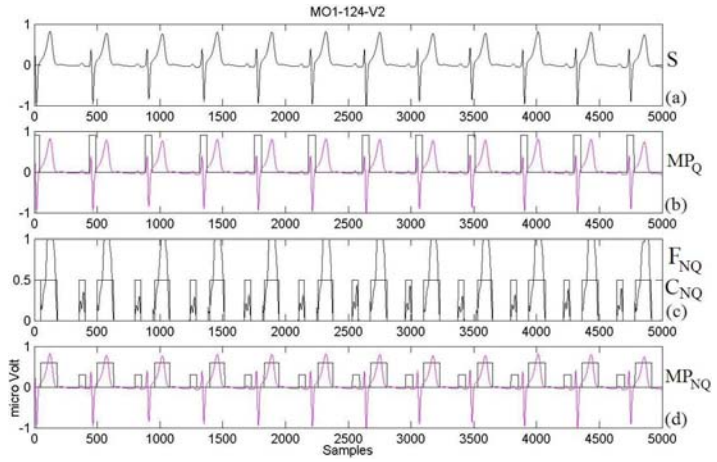

Fig. 12(a) ECG signal S (b) Already demarcated QRS marking pulses MP_Q superimposed over signal S (c) Final non-QRS feature signal F_{NQ} and non-QRS candidates C_{NQ} shown as rectangular pulses (d) Non-QRS marking pulses MP_{NQ}, delineating P and T waves, superimposed over signal S

7. Analytical Results of P and T-Wave Detection

The detection results of P and T-waves are summarized in Table 1 and 2 respectively:

7.1 Testing results of P-wave detection

Table 1 presents the number of actual P-waves, number of P-wave detections, true positive (TP), false negative (FN) and false positive (FP) detections for the entire CSE ECG library dataset-3. The standard parameters of the performance measurement of the P-wave detection results, the detection rate (DR) and positive predictivity (+P), are also shown in Table 1.

The table clearly shows that very good overall detection rate of 96.95% and positive predictivity of 97.35% is achieved for P-waves. A total of 3.01% FN and 2.62% FP detections are found for P-waves, which is considerably low indicating the performance of the algorithm.

7.2 Testing results of T-wave detection

Similarly, Table 2 presents the number of actual T-waves and number of T-wave detections, TP, FN and FP detections with a 98.01% overall DR and 96.98% overall +P for the entire CSE dataset-3.

A total of 1.93% FN and 3.08% FP detections are found in case of T-wave detections by the presented algorithm, which is considerably low indicating good performance of the algorithm.

Table 1. Combined overall results of P-wave detection for the entire CSE dataset-3

Actual No. Of P-waves	True Positive **TP**	False Negative **FN**	False Positive **FP**	Total Errors **TE**	%FN	%FP	Detection Rate ***DR***	Positive Predictivity ***+P***
16301	15810	491	427	918	3.01%	2.62%	96.95%	97.35%

Table 2. Combined overall results of T-wave detection for the entire CSE dataset-3

Actual No. Of T-waves	True Positive **TP**	False Negative **FN**	False Positive **FP**	Total Errors **TE**	%FN	%FP	Detection Rate ***DR***	Positive Predictivity ***+P***
17833	17479	354	549	903	1.93%	3.08%	98.01%	96.98%

8. Conclusion

Most of the work reported in the literature either deals with P-wave detection or T-wave detection. Both P and T-wave detection, if found in the literature, generally use different approaches to delineate them.

It is the effort of this work to detect and delineate both P and T-waves simultaneously using uniform strategy and with good detection rate as seen in Table 1 and 2.

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