P wave detector with PP rhythm tracking: Evaluation in different arrhythmia contexts

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P Wave Detector with PP Rhythm Tracking: Evaluation in Different Arrhythmia Contexts

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Abstract. Automatic detection of atrial activity (P waves) in electrocardiogram (ECG) is a crucial task to diagnose the presence of arrhythmias. P wave is difficult to detect and most of the approaches in the literature have been evaluated on normal sinus rhythms and rarely considered arrhythmia contexts other than atrial flutter and fibrillation. A novel knowledge-based P wave detector algorithm is presented. It is self adaptive to the patient and able to deal with certain arrhythmias by tracking the PP rhythm. The detector has been tested on 12 records of the MIT-BIH arrhythmia database containing several ventricular and supra-ventricular arrhythmias. On the overall records, the detector demonstrates Se=96.60% and Pr=95.46%; for the normal sinus rhythm, it reaches Se=97.76% and Pr=96.80% and, in the case of Mobitz type II, it demonstrates Se=72.79% and Pr=99.51%. It also shows good performance for trigeminy, and bigeminy and outperforms some more sophisticated techniques. Although the results emphasize the difficulty of P wave detection in difficult arrhythmias (supra and ventricular tachycardias), it shows that domain knowledge can support efficiently signal processing techniques.

Keywords. P-wave detection, ECG, knowledge based pattern recognition, cardiac monitoring

1 Introduction

Automatic electrocardiogram (ECG) analysis is a fundamental task in cardiac monitoring and Holter analysis to detect cardiac arrhythmias. The ECG reflects two main heart activities: the ventricular activity, represented by the QRS complexes and the T waves; and the atrial activity, represented by the P waves. The detection of the atrial activity is a crucial task to diagnose the presence of supra-ventricular arrhythmias as well as to confirm the presence of ventricular arrhythmias (Carrault *et al.*,2003). If the ventricular activity has been studied for many decades and several efficient solutions have been proposed (Kohler *et al.*,2002; Portet *et al.*,2005; de Chazal and Reilly,2006), the detection of the atrial activity is still an unsolved problem, especially in arrhythmic situations. P waves are difficult to detect particularly for four main reasons (Hernández *et al.*,2000):

1. P-waves have low signal-to-noise ratio (SNR), especially in clinical ECG and Holter;

2. P waveforms show high inter-patient variability, which makes a non adaptive approach inadequate;
3. P waves have no exclusive time and frequency characteristics, which makes a source separation approach difficult;
4. P waves may be invisible on the ECG signal, in case of atrioventricular (AV) dissociations. The AV dissociation leads to an ECG where QRS, T and P wave occurrences do not respect the normal time ordered sequence (P, QRS, T), and the P wave may be hidden by a bigger wave (QRS or T).

Due to the lack of annotated beat-to-beat P-wave databases, several P wave detection approaches have not been evaluated quantitatively. Moreover, some approaches, use a learning method that needs a pre-identification of the P waves, which might be too time consuming for the clinician in the stressful environment of Intensive Care Unit (ICU). Finally, some of the approaches are so complex that they are very hard to reproduce.

In this paper, we present a P wave detector algorithm that uses signal processing methods supported by knowledge about the cardiac domain. This algorithm is real-time implementable and tackles four main difficulties:

(1) The low SNR of the P wave is enhanced by an input filter that removes baseline wandering and high-frequency noise. Then, the algorithm localizes the area in which a P wave is most likely to appear and focuses the P wave detection solely in this area.

(2) The P wave variability is tackled by adapting the detection to the most recently detected P waves. Thus the algorithm adapts itself to the patient's P waves.

(3) The detection of P waves is based on generic heuristics that do not depend on pre-learning the patient characteristics, as is often required in the literature (Carrault *et al.*,2003; Madhukar *et al.*,1994; Pilla and Lopes,1999).

(4) Some of the AV dissociations are solved by tracking the PP rhythm (temporal distance between two successive P waves). We do not focus the detection on atrial flutter and fibrillation which are particular processes and for which promising studies have been undertaken (Dotsinsky,2007; Rieta and Hornero,2007; Stridh *et al.*,2004; Vayá *et al.*,2007).

We do not deal with invisible P waves (hidden by the QRS or T waves) in our method. Although hidden P waves can be crucial for identification of some cases of AV dissociations, the absence of P wave is informative in

many other rhythms. For example, the absence of a P wave before a QRS (either because the QRS hides the P wave or because no P wave exists) re-enforce the suspicion that the heart beat is abnormal.

We have compared our detector to another algorithm described in the literature (Laguna *et al.*,1994) and both have been evaluated on a large database (Moody and Mark,2001) that contains ventricular and supra-ventricular arrhythmias as well as normal sinus rhythms. To our knowledge, several studies are focused on P wave detection in normal sinus rhythm ECGs only. Except for AFL and AF (Dotsinsky,2007; Rieta and Hornero,2007), few studies have been undertaken also in presence of arrhythmias.

The following section gives a short review of the state of the art. Then, the implemented P wave detector is described in section III. The dataset used for evaluation is presented in section IV. The evaluation of the P wave detection, for which there are no standard procedures as yet, is explained in section V. Then, the results of our approach are compared to another detector from the literature in Section VI. These results are analyzed according to the context of the cardiac rhythm in order to assess the performance of the detectors in a more accurate way than common evaluations found in the literature. Finally, the approach and the results are discussed in section VII and conclusions are presented in section VIII.

2 Review of P wave detection algorithms

The algorithms found in the literature are mainly based on three approaches: a) localized search area methods, b) ventricular and atrial source separation methods, and c) Esophageal electrocardiogram (EECG) based methods.

2.1 Localized search area

The first method consists in searching for the P wave in a localized area outside the QRS-T (generally before the QRS) (Agilent Technologies,2000; Almeida *et al.*,2003; Goutas *et al.*,2005). Once the area is defined, the P wave can be detected directly by: heuristics (Agilent Technologies,2000); digital fractional differentiation (Goutas *et al.*,2005); differentiated low-pass filtering (Laguna *et al.*,1994); wavelet analysis (Almeida *et al.*,2003; Martinez *et al.*,2004; Sovilj *et al.*,2004); wavelet transform and neural network (Sternickel,2002); morphological transform (Sun *et al.*,2005); template matching (Dotsinsky,2007); or combination of Hidden Markov Model and wavelet (Graja and Boucher,2005). The localized search area approach presents satisfactory results for ECGs where the QRS is easy to identify. However, it relies only on ventricular activity (QRS) to estimate atrial activity

(P wave); thus, it is not able to deal with atrioventricular (AV) dissociations. Nevertheless, a recent approach (Dotsinsky,2007), that is close to the one presented in this paper, showed that, using adaptive threshold and templates similar to P-wave templates, a good detection of AFL and AF can be reached with the detection of visible F- or f-waves.

2.2 Ventricular and atrial source separation

The second approach consists in viewing P wave detection as a source separation problem. It first separates atrial activity from ventricular activity, either by direct separation or by QRS-T cancellation. This leads to a signal with an increased SNR in which the P waves are detected. This approach is expected to perform better in the presence of AV dissociations. The most common approach is the subtraction of a QRST template from the original signal (Gritzali *et al.*,1989; Hernández *et al.*,2000; Lemay *et al.*,2005 ; Thakor and Zhu,1991). To prevent poor performance in case of variation of the beat morphology, others methods, compared in (Rieta and Hornero,2007; Vayá *et al.*,2007) have been proposed consisting in neural networks (Vasquez *et al.*,2001), blind source separation or independent component analysis. After the cancellation, the atrial activity may be analyzed by a classification stage (Carrault *et al.*,2003; Hernández *et al.*,2000), or, more recently, by spectral profile analysis (Stridh *et al.*,2004).

Although these approaches separate ventricular activity from atrial activity, they remain sensitive to the presence of abnormal beats. Moreover, the QRS occurrence is not taken into account in detecting the P wave. Although the QRS is not useful in the presence of AV dissociations, it could be exploited in other situations to support P wave activity detection.

2.3 Esophageal electrocardiogram (EECG) based

The EECG is a semi-invasive technique used to obtain an amplified representation of the atrial activity (atria are close to the oesophagus). Despite its good SNR enhancement and the improvement of P wave detection (Hernández *et al.*,1999; Jeras *et al.*,2003), this technique is rarely used due to its semi-invasive aspect.

3 The P wave detector

The proposed P wave detector relies on a QRS detection stage coupled with a PP rhythm estimation to support P wave detection in case of AV dissociations. The proposed method is a knowledge-based approach coupled with

a signal processing one. All the parameters used in the study are derived from knowledge of cardiac physiology. Cardiac physiology is out with the scope of the paper, but all the parameter values have been chosen in accordance with ECG standards (Goldman,1973) and these choices are explained in this paper as much as possible. The whole processing chain, presented in Figure 1, is composed of 5 stages: (1) *filtering,* (2) *QRS detection,* (3) *P wave occurrence estimation,* (4) *area selection,* and finally (5) *P wave detection*. *Filtering* removes the main noise, and then *QRS detection* and *P wave occurrence estimation* trigger the *area selection* process. When triggered, *area selection* selects the ECG segment to be analyzed by the *P wave detection* stage. At the initialisation, the P wave buffer is empty so that the P detection relies only on the QRS detector. After a while there are sufficient P waves in the buffer to estimate the next P wave occurrence. Old P waves of the buffer are removed during the process so that the estimation relies only on the most recent previously detected P waves. All the stages are detailed in the following sections.

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3.1 Filtering

The filtering stage eliminates baseline wandering by using two consecutive median filters (de Chazal *et al.*,2004). The first median filter of width 200ms removes the QRS and P waves. The output feeds a second median filter of 600ms-width to remove the T waves. The resulting signal represents the baseline and is subtracted from the original ECG. The high frequency noise is then removed by a 5-order low pass Butterworth filter with a cutting frequency of 40Hz. After filtering in the forward direction, the filtered signal is then run back through the filter in the reverse order. This results in a filtered ECG with zero phase distortion, and magnitude modified by the square of the original magnitude response.

3.2 QRS detection

This study is focused on the P wave detection and does not investigate the QRS detection problem. The QRS occurrence times used in the study are taken from human annotations. However, any QRS detection algorithm or composition of QRS algorithms (Portet and Carrault,2005) can be used at this stage.

3.3 P wave occurrence estimation

This stage estimates the next P wave occurrence according to the previously detected P waves. This estimation

is then used by the *area selection* to define in which area of the ECG a P wave should be searched for. The estimation of the next P wave occurrence, called t_{Pestim}, is based on a time ordered buffer of Size *N* of the previously detected P waves. The PP intervals (temporal distance between two successive P waves) are first computed according to the following expression:

$$\forall i \in \{2,\mathrm{K}\ ,k,\mathrm{K}\ ,N\}, \quad PP(i) = t_P(i) - t_P(i-1) \qquad (\mathbf{1})$$

where $t_P(i)$ is the time occurrence of the i^{th} P wave in the buffer. The set of indexes $I_{PP} = \{i \in \{1,\mathrm{K}\ ,N-1\} : PP(i) \in [0.6,1]\mathrm{s}\}$ is then computed. I_{PP} represents the indexes of the PP values that belong to the interval [0.6, 1]s. This range corresponds to [60,100]bpm (beat-per-minute) which are the standard limits for bradycardia and tachycardia in adults (Goldman,1973). This can be justified by the fact that bradycardia is a slow rhythm for which P wave search can be based on the QRS, while tachycardia is a rapid rhythm in which the P wave is seldom visible. In the other cases, these values let the algorithm check whether a P wave is missing between two successive P waves, or two P waves are too close to each other. The estimates of the next P wave occurrence candidates are noted $\hat{t}_P(i)$ and are computed independently according to each acceptable P wave in the buffer by:

$$\forall i \in I_{PP}, n \in \mathbf{N}^*, \hat{t}_P(i) = t_P(i) + n \times PP(i), \textit{ where } t > t_P(i), n = 1 + \left\lfloor \frac{t - t_P(i)}{PP(i)} \right\rfloor \qquad (\mathbf{2})$$

where *t* is the current time (absolute time since last QRS detection or P wave detection). Thus, $\hat{t}_P(i)$ is computed by adding *n* times $PP(i)$ to $t_P(i)$ until $\hat{t}_P(i) > t$. From all the independent estimations $\hat{t}_P(i)$, the final estimated P wave occurrence t_{Pestim} is computed by:

$$t_{Pestim} = \begin{cases} \forall i \in I_{PP}, \textit{median}([\ldots,\hat{t}_P(i),\ldots]), & \textit{if } (|I_{PP}| \geq N/2) \\ \phi, & \textit{otherwise} \end{cases} \qquad (\mathbf{3})$$

If there are at least *N/2* candidates $\hat{t}_P(i)$, then the median of all the $\hat{t}_P(i)$ is taken to reduce the effect of outliers. As far as we are aware, the benefit of using PP rhythm tracking for the detection of P waves has rarely been investigated (Sovilj *et al.*,2004). An empirical study analyzing the detection sensitivity according to the

buffer length (on records independent from the ones used in the evaluation section with sampling frequency of 360Hz) concluded that an optimal value of the buffer length was 15s.

3.4 Area selection

The area selection extracts an ECG segment within which a P wave occurrence will be searched for. An average P wave width *W=100ms* (the average width of physiological and pathological P waves (Guray *et al.*,2003)), is defined to perform this operation. Area selection is activated if there is a QRS occurrence, or a P wave estimation not followed by a QRS occurrence during a defined period. The process is shown in Figure 2.

---INSERT FIGURE 2 ---

Two cases are considered:

1) If the area selection is triggered by the P wave estimation, then the area is estimated by the following expression:

$$AREA = \begin{cases} \left[t_{Pestim} - B_P^-, t_{Pestim} + B_P^+\right], & if\ next\, t_{QRS} > t_{Pestim} + B_P^+ \\ \phi, & otherwise \end{cases} \quad (\mathbf{4})$$

where t_{Pestim} is the estimated P wave occurrence and B^-_p and B^+_p are the backward and the forward P boundaries, respectively. The aim of the waiting condition is to sustain P wave detection with a QRS occurrence which is generally more reliable than P wave estimation. P wave estimation is thus used only when the PR interval is long, which can be the case in presence of an AV conduction anomaly. An empirical study performed on independent records (ECG records not used in the evaluation) resulted in the following optimal values: $B^-_p = 0.1s$ *and* $B^+_p = 0.4s$.

2) If the area selection is triggered by the QRS detection, then the area is estimated by equation (5)

$$AREA = \begin{cases} \left[t_{QRS} - C_{QRS}^- \times RR, t_{QRS} + C_{QRS}^+ \times RR\right], & if\ RR > RR_{Limit} \\ \phi, & otherwise \end{cases} \quad (\mathbf{5})$$

$$where \quad RR = t_{QRS} - t_{QRS-1}$$

where t_{QRS} is the current detected QRS occurrence, t_{QRS-1} is the previous QRS occurrence, and C_{QRS}^- and C_{QRS}^+ are the backward and the forward QRS coefficient boundaries, respectively. If the RR interval is larger than RR_{Limit} then the ECG segment is selected. RR_{Limit} is set to 450 ms; this represents the sum of the width of the P wave (100ms) plus the narrowest standard QT interval of 350ms (Goldman,1973). Indeed, a P wave is worth

searching for if there is enough time for the P-QRS-T waves to occur. The selection of an area before a QRS is related to the PR interval which varies with the RR interval: the higher the Heart Rate (HR), the shorter the PR interval. A standard PR interval is about 200ms for an 80bpm HR (Goldman,1973). Starting from this knowledge C_{QRS}^{-} and C_{QRS}^{+} have been set to *0.3s* and *0.1s*; this leads to an area between *[-0.3, -0.1]s* before the QRS for a *60bpm* HR, and *[-0.18, -0.06]s* before the QRS for a *100bpm* HR, which is in accordance with standard values (Goldman,1973). Thus, the system adapts itself to the patient's heart rate and avoids searching for a P wave when a very premature ventricular contraction occurs.

3.5 P wave detection

The P wave detection phase consists in searching for P wave candidates in the area defined by the area selection module. It detects local maxima above a baseline and selects which of the maxima is the most likely to be a P wave. The process is shown in figure 3.

---INSERT FIGURE 3 ---

The segment from the area selection is smoothed with a median filter of 36ms-width to reduce artifact. Then, a baseline is estimated by applying a *W*-width median filter to the absolute of the filtered ECG segment. Every interval of the absolute filtered ECG above the baseline is a possible candidate. The candidates are then eliminated using the tests below:

1- Every interval that starts or ends at the bounds of the area is removed (T end and QRS start)

2- Every interval whose maximum magnitude is outside the interval [MaxMed(P)/3, MaxMed(P)×3], is removed. MaxMed(P) is the median of the P wave maxima magnitudes of the buffer.

After this stage, the remaining intervals (if any) are supposed to contain a P wave. The probability of being a P wave is computed using the magnitude and the width according to formula 6. The most probable P wave is then retained and stored in the P wave buffer.

$$P(Pwave(i)) = \left(\frac{mag(P(i))}{\max(mag(P))} \times \frac{width(P(i))}{\max(width(P))} \right) \qquad (\mathbf{6})$$

4 Data

The data used for this evaluation consists of 12 two-lead records from the MIT-BIH arrhythmia database (Moody and Mark,2001) lasting about 30 minutes each with a sampling frequency of 360Hz. More precisely, records 100, 101, 103, 106, 117, 119, 122, 207, 214, 222, 223, and 231 were used. Only the upper signal (modified limb lead II), in which the P wave is visible, has been used in this study. These records present a representative variety of waveforms that an arrhythmia recognizer must deal with. Indeed, they include complex ventricular and supra-ventricular arrhythmias and conduction abnormalities that are difficult to process automatically. Globally, this dataset represents about 6 hours of ECG, 21354 beat-to-beat P wave expert annotations, which are the same as in (Carrault *et al.*,2003), and 12 arrhythmia types: Normal sinus rhythm (N), ventricular Bigeminy (B), ventricular Trigeminy (T), Ventricular FLutter (VFL), Ventricular Tachycardia (VT), IdioVentricular Rhythm (IVR), moBitz of type II (BII), NODal (AV junctional) rhythm (NOD), Atrial Bigeminy (AB), Atrial Fibrillation (AF), Atrial FLutter (AFL), Supra-ventricular TachyArrhythmia (SVTA). Thus, there is a good balance between normal sinus rhythms, ventricular and supra-ventricular arrhythmias.

5 P wave detector evaluation

The evaluation of the results of P wave detection is not straightforward. Indeed, sometimes a P wave occurrence is hidden by a QRS or a T wave on the ECG channel. Thus, some P wave detection methods that reconstruct the hidden P waves cannot estimate the detection results accurately (Almeida *et al.*,2003) as the hidden P waves have not been annotated by humans (because they are not visible on the ECG). In our case, we deal only with P waves that are visible. This approach makes sense since missing (hidden) P waves are also informative for diagnosing arrhythmia (the absence of P wave in a ventricular tachycardia confirms the diagnosis).

In this paper, the performance of P wave detection is assessed by computing the True Positive, TP (true detection), the False Negative, FN (missed detection) and the False Positive, FP (false detection). There is no standard for the evaluation of P wave detectors, but our approach mimics the ANSI/AAMI standard for ECG beat detector evaluation (ANSI/AAMI standard EC57:1998,1998). For each actual P wave annotation, a centred window of 170ms-size is defined (maximum length of a P wave). Every detected P wave that falls into one of

such windows is a TP. If several detected P waves fall into the same window, only one is counted as TP: the others are ignored. Every detected P wave that does not fall into a window is an FP. Finally, every window that does not contain a detected P wave is an FN. As atrial flutter and atrial fibrillation are particular processes, the episodes corresponding to these arrhythmias are excluded from the evaluation (likewise ventricular fibrillation periods for QRS detector assessment in the ANSI/AAMI standard(ANSI/AAMI standard EC57:1998,1998)).

TP, FP, and FN are used to compute three common criteria: Sensitivity (Se) = TP/(TP+FN), Precision (also called Positive Predictivity) (Pr) = TP/(TP+FP), Error Rate (ER) =(FP+FN)/(TP+FN+FP). We also compute the F-Measure (FM) (van Rijsbergen,1979) which combines Se and Pr in a single efficiency measure; FM = 2×Se×Pr/(Se+Pr).

6 Experiments

Two experiments have been undertaken to assess our P wave detector. Firstly, it has first been compared against the ECG beat segmentation algorithm called *ecgpuwave* of Laguna *et al.* (Laguna *et al.*,1994) which detects P, QRS and T waves. This algorithm has been validated on several databases and appears to perform heartbeat segmentation with accuracy comparable with inter-expert annotation variation. In our study, *ecgpuwave* has been fed with the manual QRS annotations to evaluate it in the same conditions as our detector. For a better analysis, the results are presented according to the records (classic presentation) and according to the arrhythmias (new presentation). Finally, to investigate the value of using other kinds of information provided by the QRS analysis, tests with QRS classification and on-line QRS detection have been made and are briefly described at the end of this section.

6.1 Global results

Detection results obtained on the selected records are presented in Table 1.

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They show that our method presents similar results as *ecgpuwave* for normal sinus rhythm records

(FM=99.70% against FM=99.76%). But our approach outperforms *ecgpuwave* on the entire dataset with Se=96.60% Pr=95.46% against Se=93.15% and Pr=92.91%. This suggests that our method performs better in the presence of rhythm disorders. However, Table 1 (classical presentation) is not informative enough to emphasize clearly the performance of the detectors in arrhythmic situations where a P wave detector is challenged. To analyze the results in a more informative way, we also present the results relatively to each arrhythmia.

6.2 Results according to arrhythmias

Table 2 presents the same information as in table 1, but rearranges the results according to the type of rhythm. In this table, each row is related to the normal sinus rhythm or to an arrhythmia. For each rhythm, the duration (in seconds) and the number of P wave annotations are given.

--- INSERT TABLE 2 ---

According to Table 2, and contrary to the results in table 1, our detector actually outperforms *ecgpuwave* in normal sinus rhythm episodes. This can be explained by the fact that normal sinus rhythm periods present in the arrhythmic records (106, 119, 207, 214, 222, 223, 231) are also taken into account. These specific periods are surrounded by arrhythmia periods, and also present some bundle branch block anomaly periods that perturb the detection. Thus, this better presentation of the results emphasizes that our detector is actually more robust for the detection of P waves in normal sinus rhythm than *ecgpuwave*. Figure 4 compares the outputs of *ecgpuwave* (part a) and the outputs of our method (part b) on an ECG excerpt containing LBBB QRS shapes and premature ventricular contractions.

The rest of the results show that our detector is the best for all the arrhythmias, except for NOD, VT and IVR. In theses cases both detectors perform quite bad. Satisfactory results are obtained for our detector for some ventricular arrhythmias: B (FM=91.08%), T (FM=93.98%); and some supra-ventricular arrhythmias: BII (FM=84.08%) and AB (FM=79.0.3%). The results obtained for Mobitz type II (BII) demonstrate the ability of our detector to deal with AV dissociation, whereas *ecgpuwave* missed one out of two, on average (Se=49.76%). Figure 4 (c and d) shows detection results in a Mobitz II context. *ecgpuwave* is perturbed, whereas our method detected all the P waves in this situation. Very poor results are obtained for NOD (FM=25.38%) VT (FM=6.89%),

IVR (FM=5.07%), and SVTA (FM=33.33%). Figure 4 e) and 4 f) show a SVTA followed by a NOD rhythm in which both methods failed. These rhythms are very difficult to analyze as the occurrences of the waves that compose them are difficult to predict. However, these results must be analyzed with caution as their duration is very short (except for NOD) and the low number of visible P waves leads to suspiciously high ER.

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The delay between the detected P waves (TP only) and their corresponding P wave annotations have also been computed and the results are presented in table III. This delay is useful in evaluating how much the detection is disturbed according to the arrhythmia. For example, in the IVR arrhythmia, the delay between the detection and the annotation is sensibly higher than for the rest of the arrhythmias (delay = 54±33ms). This suggests that, in the proposed method, the P waves that have been classified as TP are less reliable than for other arrhythmia periods. However, despite this isolated unreliability, the overall results deliver an accuracy comparable with inter-expert annotation variation (Jané *et al.*,1997).

--- INSERT TABLE 3 ---

6.3 Exploratory experiments for further extensions of the method

Other experiments have been conducted to study a possible enhancement of the algorithm by considering the QRS type (QRS classification) and the use of a QRS detector in the algorithm.

Table 4 shows the results obtained when the QRS type (human annotations) is used to prevent the search of the P wave in the case of premature ventricular contraction (PVC).

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As the recognition of PVC is improved, detection is enhanced in ventricular rhythms. The error is reduced for N, B and T rhythms. However, the detection is not improved in other rhythms.

QRS classification seems to be an interesting feature to exploit for P wave detection. However, while QRS detection has reached very high performance, QRS classification has not reached a sufficient accuracy to be used in practice.

Table 5 shows the results obtained when the QRS occurrences are detected using the inner QRS detector of

ecgpuwave which showed a Se=99.88% and a Pr=99.97% for the detection of the R wave in another ECG database (Jané *et al.*,1997).

--- INSERT TABLE 5 ---

Both of the detectors show an increase of errors. *ecgpuwave* seems to be less affected (ER=13.03% to 13.78%) than our method (ER= 7.64% to 9.13%). Periods of premature ventricular contraction (B and VT) lead to the highest increase of errors for both the detectors. However, the proposed method is still superior to *ecgpuwave*. Furthermore, the P wave detection of *ecgpuwave* is obviously adapted to its QRS detector. Regarding the overall delay, both the methods show similar performance (*ecgpuwave* = 6±7ms while our method has still 8±8ms overall delay). This shows that our method is able to work with on-line QRS detector.

7 Discussion

Results from the literature include those of Sternickel (Sternickel,2002) with a Se between 92.68% and 99.99%. However, the method was assessed on normal sinus rhythm ECGs only (with or without effort) and without any annotation of the true P wave occurrences (if a P wave is detected in a fixed window before QRSs then it is considered as a true positive). Almeida *et al.* (Almeida *et al.*,2003) reported an Se of 98.87% on 3194 annotations but without estimation of the precision. Hernández *et al.* (Hernández *et al.*,2000), compared their detector against several approaches and obtained a sensitivity of 80-90% for the records #100 of the MIT-BIH Arrhythmia Database. Their results were evaluated as being superior to those of Thakor and Yi-Sheng (Thakor and Zhu,1991) and Gritzali *et al.* (Gritzali *et al.*,1989). Carrault et al. (Carrault *et al.*,2003) reported a mean Se=99.3 and Pr=98.0 in different sinus rhythms, but the P waves of each patient were preliminary learnt. Other detectors in the literature have been evaluated on too few examples to be compared to the detector presented in this study.

Some reported methods need prior learning of patient characteristics (Carrault *et al.*,2003; Madhukar *et al.*,1994; Pilla and Lopes,1999). This bias the detection, as the intra-patient P wave morphology variability tends to be lower than the inter-patient P wave morphology variability, which is very high. This is why most of these studies were not compared to our approach. Moreover, these techniques require that a clinician initializes the program in order to learn the P wave features of the patient. In practice, that might be too time-consuming for the medical staff, and not free of human errors that can lead to inaccurate learning. Our approach adapts itself to the

patient. Indeed, the RR interval is taken into account and the PP rhythm tracking is, by definition, the PP related to the patient.

Despite the small number of available examples, the results show that the P wave detection fails in presence of certain arrhythmias. This shows that P wave detection is far from being solved in difficult ECG rhythms even if our approach can tackle some of them very well. To the best of our knowledge, a study that identifies which arrhythmias that penalise the most the P wave detection are, has never been undertaken. Along with our novel algorithm, this is one of our main contributions. In comparison, other studies generally report performance for the normal sinus rhythm case or use very little quantitative data. Presenting the results according to the context of the rhythm is also important to use the P wave detector in appropriate contexts as in the case of the cardiac monitoring system IP-Calicot (Portet *et al.*,2007).

Our method is not focused on the detection of the invisible P waves. This is mainly due to two reasons. Firstly, no database containing annotated invisible P waves is available. To construct such a database, EECG or pacemaker probes should be recorded with the standard ECG and such a study is hard to set up. Consequently the validation of invisible P wave detection is a bit fuzzy (Almeida *et al.*,2003; Martinez *et al.*,2004) or reduced to the studies that have access to such material (Jeras *et al.*,2003). Secondly, the detection of hidden P waves can also be important for identification of some cases of AV dissociations, but the absence (in the ECG trace) of P wave is also informative in the diagnosis of many heart rhythms.

The aim of the proposed detector was to build a real-time, knowledge based and generic algorithm. It was not expected to perform better than detectors using QRS-T cancellation techniques. But, it appears to have similar if not better performance in practice. This can be explained by the fact that even the QRS-T cancellation techniques rely on thresholds (e.g. thresholds used to select the frequency bands in multi-resolution analysis) and thus are subject to a lack of threshold adaptation to the patient. The reason for our good performance in case of AV dissociations is due to PP rhythm tracking that searches for P waves even when no QRS is present. This is the major limitation of the P wave detection based on the QRS. Moreover, the use of knowledge about cardiology supports efficiently the detection. Another example in which knowledge is used is the detector of Dotsinsky (Dotsinsky,2007) how uses a well-known QT formula to compute the search areas and decision rules for AFL/AF recognition.

Despite the good performance of our detector, it still needs to be improved and the combination of our approach with QRS-T cancellation applied inside the search area could improve its performance. Moreover, the parameter values of the detector are based directly on knowledge information. On-line parameter adjustment could lead to better performance.

8 Conclusion

In this paper, a novel approach for P wave detection is presented. The related detector uses a QRS detection based technique associated with PP rhythm tracking. This detector can run in real-time and is generic, self-adaptive to the patient's rhythm and P wave magnitude, and resistant to some atrioventricular (AV) dissociations other than atrial fibrillation and flutter.

The presented detection algorithm relies on heuristics and simple processing stages. This contrasts with current techniques which aim at using high level computing to enhance the P wave energy on the ECG and then use classification technique to detect P waves. However, despite its simplicity, our approach presents several advantages: 1) it is implementable in real-time (the whole signal is not needed before beginning the process), 2) it is human checkable (the parameter values are well known), 3) it is generic (there is no need to learn P wave features specific to the patient), 4) it adapts itself to the patient's rhythm and to the P waves magnitude, 5) it is resistant to some AV dissociations (like Mobitz type II), and 6) it has good performance.

The detector resulted in Se=97.76% and Pr=96.80% on normal sinus rhythm ECGs and Se=96.60% and Pr=95.46% on 12 ECG records of the MIT-BIH arrhythmia database containing several ventricular and supra-ventricular arrhythmias. The approach presented is particularly well adapted to the detection of P wave in some AV dissociations though it does not use any QRS-T cancellation technique. For example, in the case of Mobitz type II, it demonstrates Se=72.79% and Pr=99.51%. The results are presented according to each arrhythmia for an estimation of the most perturbing heart rhythms. The method has been evaluated on normal and arrhythmic ECG records and demonstrated a good ability to deal with some arrhythmias (trigeminy, bigeminy, Mobitz II). To be fair, poorer results were obtained with other arrhythmias, but this was also the case for other comparable detectors.

Fig. 1. Overall process of the P wave detector.

Fig. 2. Area selection process.

Fig. 3. P wave detection process.

Fig. 4. Excerpts of P wave detection results: (a) ecgpuwave detection on normal ECG with LBBB; (b) our method on normal ECG with LBBB; (c) ecgpuwave with mobitz II; (d) our method with mobitz II; (e) ecgpuwave with SVTA followed by NOD; (f) our method with SVTA followed by NOD.

Table 1. Global results.

Records	nb P	ecgpuwave				Proposed method			
		ER(%)	Se(%)	Pr(%)	FM(%)	ER(%)	Se(%)	Pr(%)	FM(%)
Normal sinus rhythm records[a]	10210	0.60	99.68	99.84	**99.76**	0.60	99.57	99.83	**99.70**
Entire dataset	21354	13.03	93.15	92.91	**93.03**	7.64	96.60	95.46	**96.03**

[a]Records: 100, 101, 103, 117, 122

Table 2. Contextual results.

Rhythm	Duration (s)	nb P	ecgpuwave				Proposed method			
			ER(%)	Se(%)	Pr(%)	FM(%)	ER(%)	Se(%)	Sp(%)	FM(%)
N	18421	19540	8.33	95.12	96.19	**95.65**	5.29	97.76	96.80	**97.28**
B	1087	610	35.81	90.82	68.65	**78.19**	16.37	98.85	84.45	**91.08**
BII	700	838	50.30	49.76	99.76	**66.40**	27.47	72.79	99.51	**84.08**
NOD	583	40	79.04	87.50	21.60	**34.65**	85.47	42.50	18.09	**25.38**
T	333	247	16.43	94.74	87.64	**91.05**	11.36	97.98	90.30	**93.98**
VT	115	2	96.15	100.00	3.85	**7.41**	96.43	100.00	3.57	**6.89**
IVR	109	14	90.16	42.86	11.32	**17.91**	97.40	14.29	3.08	**5.07**
AB	109	60	43.16	90.00	60.67	**72.48**	34.67	81.67	76.56	**79.03**
SVTA	59	3	88.89	100.00	11.11	**20.00**	80.00	33.33	33.33	**33.33**
Total	21516	21354	13.03	93.15	92.91	**93.03**	7.64	96.60	95.46	**96.03**

Table 3. Median delay and standard deviation for the correctly detected P waves (TP).

Rhythm	Duration (s)	nb P	ecgpuwave Delay (ms)	Proposed method Delay (ms)
N	18421	19540	6±6	8±8
B	1087	610	6±7	6±5
BII	700	838	3±3	6±4
NOD	583	40	8±18	8±15
T	333	247	6±7	6±5
VT	115	2	8±0	13±2
IVR	109	14	14±27	54±33
AB	109	60	8±18	8±7
SVTA	59	3	8±43	6±0
Total	21516	21354	6±6	8±8

Table 4. Comparison of the P wave detection performance without and with the QRS type.

Rhythm	Duration (s)	nb P	Without QRS type ER(%)	With QRS type ER(%)
N	18421	19540	5.29	4.92
B	1087	610	16.37	5.49
BII	700	838	27.47	27.47
NOD	583	40	85.47	85.47
T	333	247	11.36	5.18
VT	115	2	96.43	100.00
IVR	109	14	97.40	100.00
AB	109	60	34.67	34.67
SVTA	59	3	80.00	80.00
Total	21516	21354	7.64	6.41

Table 5. Contextual results using the QRS detector of ecgpuwave.

Rhythm	Duration(s)	nb P	ecgpuwave				Proposed method			
			ER(%)	Se(%)	Pr(%)	**FM(%)**	ER(%)	Se(%)	Pr(%)	**FM(%)**
N	18421	19540	9.28	94.51	95.77	**95.14**	6.47	96.37	96.94	**96.65**
B	1087	610	36.56	90.16	68.15	**77.62**	23.06	95.74	79.67	**86.97**
BII	700	838	50.36	49.64	100.00	**66.35**	29.50	71.00	99.00	**82.69**
NOD	583	40	80.24	82.50	20.63	**33.01**	81.13	50.00	23.26	**31.75**
T	333	247	17.44	93.93	87.22	**90.45**	12.32	97.98	89.30	**93.44**
VT	115	2	98.11	50.00	1.92	**3.70**	97.53	100.00	2.47	**4.82**
IVR	109	14	90.32	42.86	11.11	**17.65**	97.44	14.29	3.03	**5.00**
AB	109	60	49.49	83.33	56.18	**67.11**	35.53	81.67	75.38	**78.40**
SVTA	59	3	93.62	100.00	6.38	**11.99**	80.00	33.33	33.33	**33.33**
Total	21516	21354	13.78	92.53	92.67	**92.60**	9.13	95.19	95.25	**95.22**

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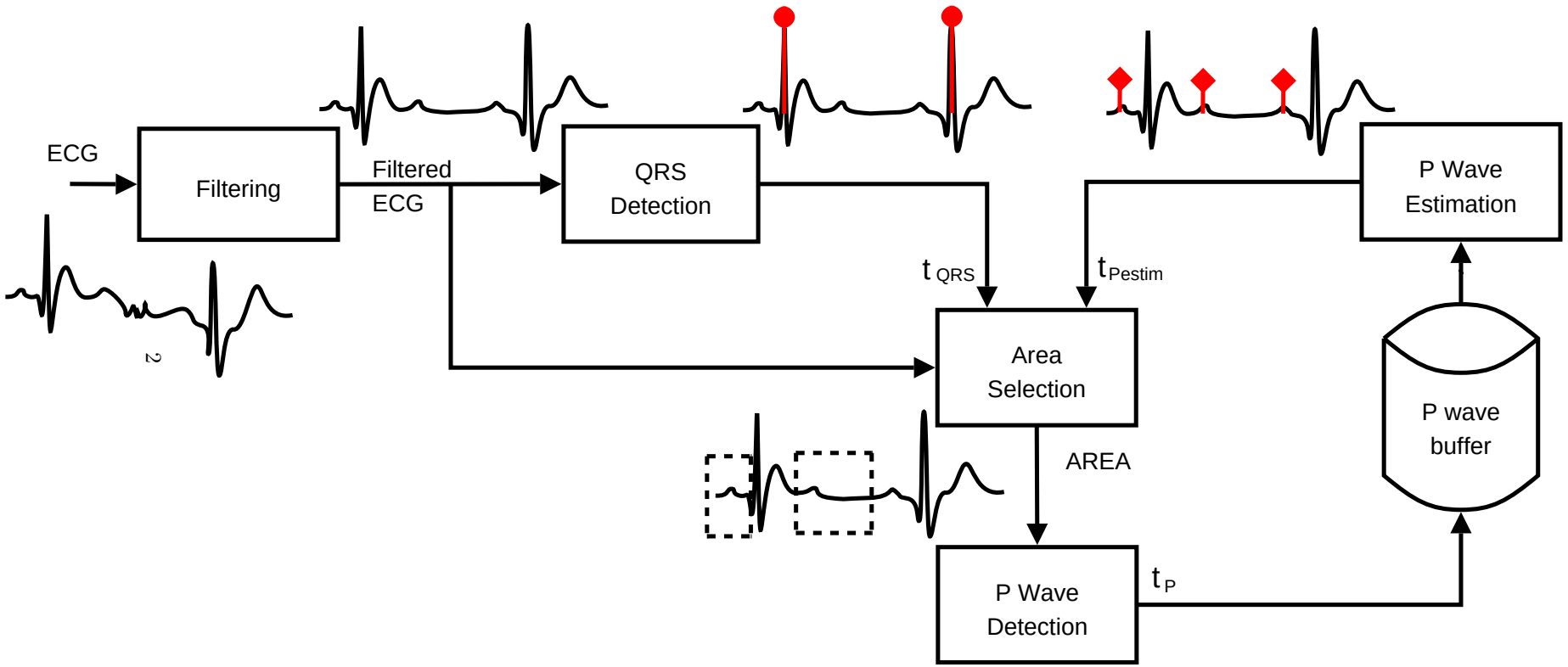
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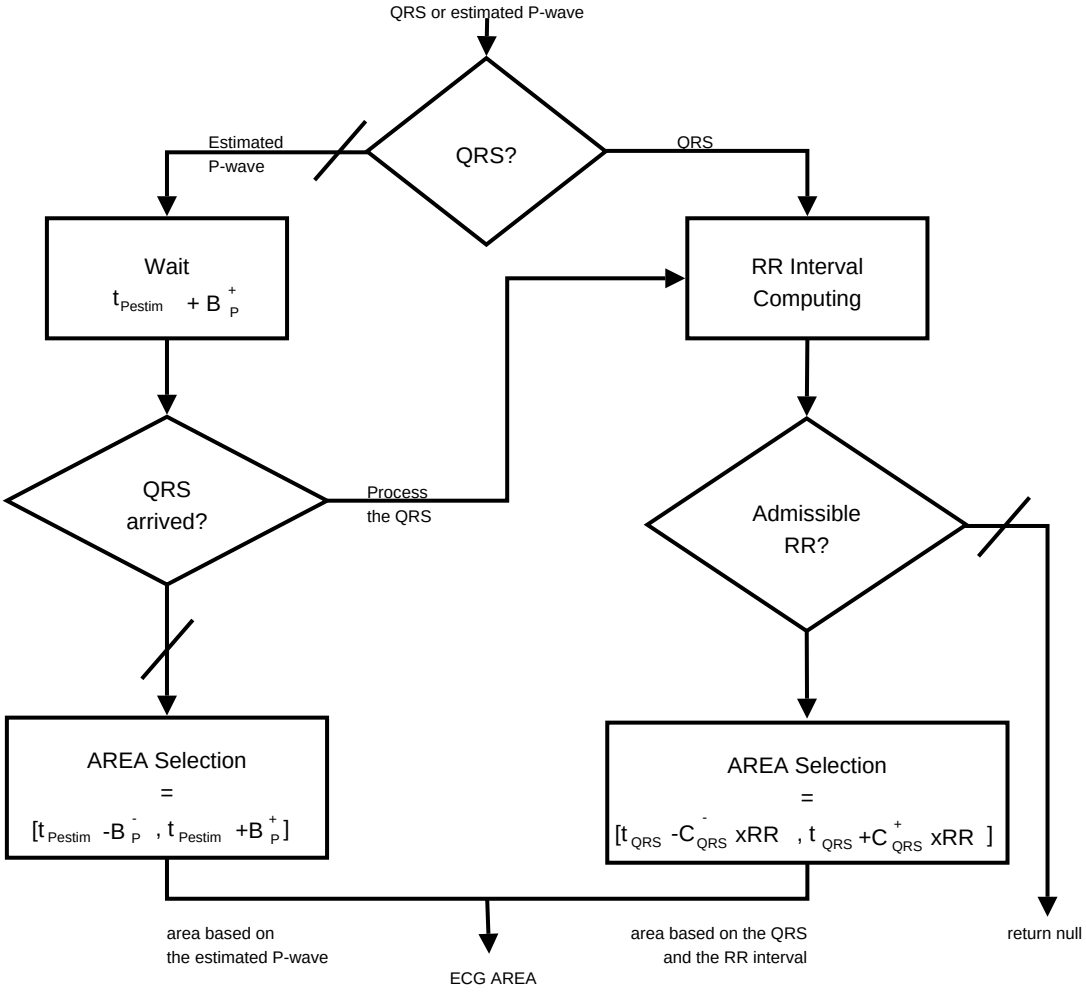
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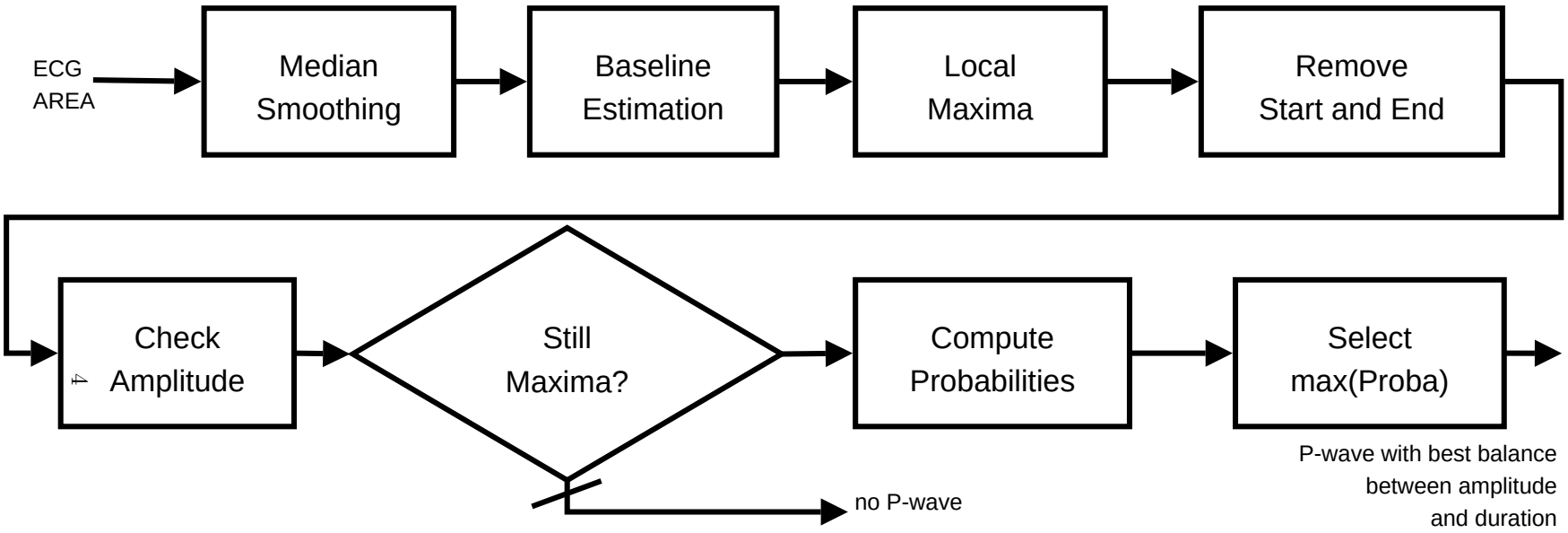
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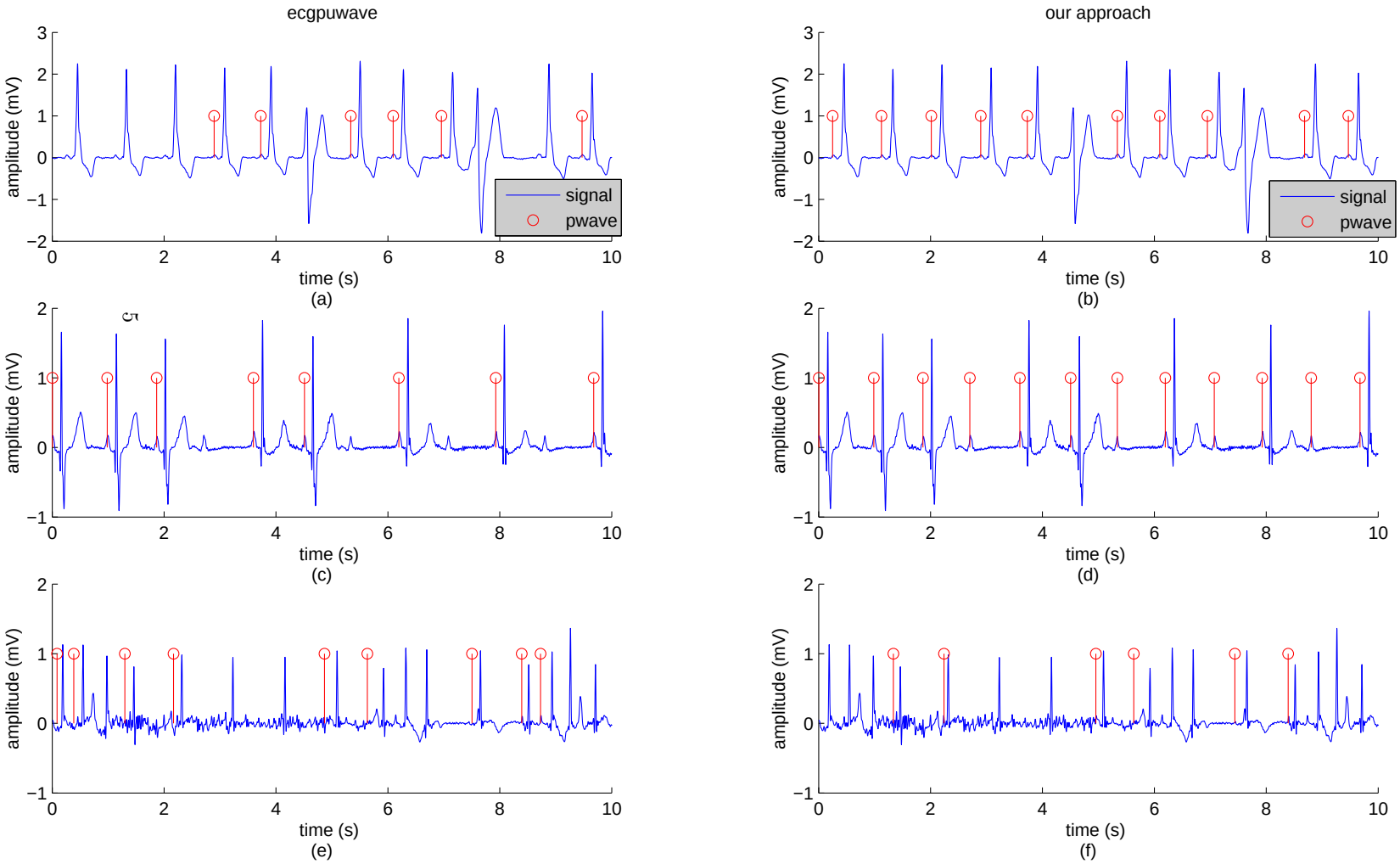
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