

# An Automated Algorithm for Fast Pulse Wave Detection

Bistra Nenova, Ivo Iliev\*

Technical University – Sofia  
8 Kliment Ohridski Blvd., 1000 Sofia, Bulgaria  
E-mail: [izi@tu-sofia.bg](mailto:izi@tu-sofia.bg)

\*Corresponding author

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**Abstract:** This study presents an automated algorithm for fast pulse wave detection, directed to establishing the presence of cardiac activity in an emergency. The method relies on real-time estimation of similarity of closely positioned rising edges of the waveform and decision logic. The algorithm was tested on a set of pressure pulse waves from the MGH/MF waveform database from PhysioNet. Our approach to assessing the algorithm performance was based on location and classification of suspicious 10 s signal epochs by means of detection of dissimilar peak-to-peak intervals. The detected epochs were visually inspected and compared to the corresponding ECG-based expert beat annotations. The main epoch and error types were summarized. The performance of the algorithm and the visual interpretation of the results were illustrated by means of examples. The review of the recordings showed that the proposed algorithm correctly identifies cardiac pulsations even under considerable artefacts. Our conclusion is that the algorithm reliably detects critical periods in cardiac activity and is applicable to fast pulse wave detection in real-time applications and ambulatory measurement setups.

**Keywords:** Pulse wave detection, Beat detection, Real-time algorithm, Pulse wave contour.

## Introduction

In a series of resuscitation guidelines produced by International Liaison Committee on Resuscitation (ILCOR), European Resuscitation Council (ERC) and American Heart Association (AHA) is emphasized that checking the carotid pulse by palpation is an inaccurate method of confirming the presence or absence of circulation [7]. The time for a single pulse check is limited to no more than 10 s for healthcare providers. In relation to this, the design and usage of a specialized pulse wave detector in an emergency would be of great diagnostic significance.

In the course of blood circulation through the arteries three coherent phenomena can be observed: blood flow (flow pulse), the increase of blood pressure (pressure pulse wave) and extension of transverse profile (volume pulse wave) [8]. There are several non-invasive methods for peripheral pulse measurement based on different principles and depending on the type of measured pulse wave. The most widespread method for volume pulse wave detection is photoplethysmography (PPG) [1]. The blood volume pulse has similarities with the blood pressure pulse, with similar changes occurring in vascular disease, such as damping and a loss of pulsatility. The typical pulse wave morphology has two phases: the anacrotic phase being the rising edge of the pulse, and the catacrotic phase being the falling edge of the pulse. The first phase is primarily concerned with systole, and the second phase with diastole and wave reflections from the periphery. A dicrotic notch, followed by a dicrotic peak, is usually seen in catacrotic phase of subjects with healthy compliant arteries [1]. The pulse wave contour is

influenced by physiological conditions and diseases and varies in different parts of the circulation [13].

Beat detection algorithms with different level of complexity are published, including computer-based filtering, feature extraction, adaptive thresholding, derivative calculation etc [2-4, 9, 10, 16]. Automatic beat detection in presence of severe movement artifacts and low signal-to-noise ratio is a non-trivial task in computer signal processing. Ambulatory pulse wave measurements are very sensitive to noise and artifacts. In addition, the waveform morphology can be highly variable, even over short periods of time, in response to altered pathologic or physiologic stresses. Most pulse and pulse-component detection algorithms identify the peak of the pulse as the fiducial mark of the waveform. Traditionally, the pulse contour analysis extracts evaluation parameters through identification of characteristic points of the pulse. From the literature, many features have been investigated, including beat-to-beat pulse rise time, foot-to-peak amplitude, dicrotic wave amplitude, dicrotic wave time, total pulse duration, pulse transit time, etc [1, 8]. Morphological analysis of pulsatile signals is a popular technique for assessing vascular disease.

This study presents an automated algorithm for fast pulse wave detection. It is directed to establishing the presence of cardiac activity in an emergency and is applicable in an ambulatory measurement setup, such as a photoplethysmograph. The method relies on real-time estimation of similarity of closely positioned rising edges of the waveform and decision logic. The algorithm was developed in the signal processing environment Matlab and was tested on pulse signals from a subset of the publicly available MGH/MF waveform database from PhysioNet [5].

## Method

The presented pulse wave detection algorithm was originally developed using non-invasive PPG waveforms recorded from the region of the neck by an especially designed pulse wave detector [11]. A pulse wave detector must be able to recognize cardiac pulsations with a heart rate from 0.5 Hz (30 bpm (beats per minute)) to 4-5 Hz (240-300 bpm). In an emergency, the monitoring devices operate under unfavorable environment and intensive movement artifacts. Moreover, the identification of presence of pulsations, not the shape of the waveform is important. We recommend the use of first order hardware filters with a relatively narrow pass-band – between 0.5 and about 12 Hz. A sampling frequency of 250 Hz and a small amplitude resolution of 8 bits were adopted in our implementation. The signal processing was performed in the signal processing environment Matlab 7.0 (The MathWorks, Inc.).

### *Preprocessing filtration*

A real-time digital filtering of the registered pulse wave is necessary to reject the baseline drift, as well as other low-frequency signal components, and to smooth the pulse waveform. This facilitates the subsequent waveform interpretation. A particular benefit of the proposed digital filters is the simple implementation using minimal computing resources. Short description of the filters follows.

#### A. High-pass filter for real-time baseline drift reduction

The filtering procedure is similar to the ECG baseline drift reduction found in [6, 15], but adapted to pulse wave signals [12]. The proposed filter implements moving average of a number of signal samples,  $N$ , at a predefined distance between them,  $D$  (as a number of samples):

$$y[i] = x[i] - \frac{1}{N} \sum_{j=-(N-1)/2}^{(N-1)/2} x[i + jD], \quad (1)$$

where  $x[i]$  is the input signal and  $y[i]$  is the output signal. For the predefined sampling frequency, we applied averaging over 25 samples distanced by 15 samples, thus realizing a comb filter with a high-pass cut-off frequency of 0.5 Hz (corresponding to the lowest heart rate of 30 bpm) and a zero at 50 Hz – Fig. 1. The filter has time-interval for averaging of about 1.5 s, which defines the operational time-delay of the filter's output. A disadvantage is the ripples in the pass-band.

### B. Smoothing filter

The moving average low-pass filter [12, 14] operates by averaging a number of consecutive points,  $N$ , from the input signal:

$$y[i] = \frac{1}{N} \sum_{j=-N/2}^{N/2} x[i + j], \quad (2)$$

In the our implementation (sampling frequency of 250 Hz) we applied averaging over 20 consecutive samples to achieve a comb filter with a low-pass cut-off frequency of 5.5 Hz (to accommodate the highest heart rate of 240-300 bpm) and a zero at 50 Hz – Fig. 1.

### Pulse wave detection algorithm

The pulse wave detection algorithm includes the following steps.

#### 1. Identification of extrema – possible peaks and foots of individual pulsations

##### 1.1. Maximum (MAX) identification

- The waveform is divided into consecutive 200 ms time intervals and the absolute maximum is determined for every segment. Some of these maximums are rejected according to the following criteria.
- The maximums lying below a predetermined amplitude threshold near the middle line of the waveform are rejected. The threshold was set to 3 bits above the middle line to ignore a very low-amplitude noise.
- If the distance between two maximums is less than or equal to 200 ms, the lower-amplitude maximum is rejected. This will also remove the false maximums which appear along the slopes of the waveform, at the boundaries of the 200 ms intervals.

##### 1.2. Minimum (MIN) identification

The absolute minimums between every two adjacent maximums are determined. If a minimum is above a predetermined amplitude threshold near the middle line of the waveform the minimum is rejected. The threshold was set to 3 bits below the middle line to ignore a very low-amplitude noise. The lower-amplitude maximum of the two maximums adjacent to a rejected minimum is discarded too.

The characteristic points along a pulse wave are illustrated in Fig. 2.

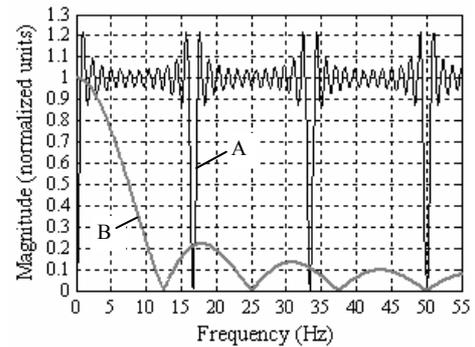


Fig. 1 Frequency responses of the digital filters, calculated for 250 Hz sampling frequency: A – high-pass filter; B – smoothing filter.

2. Examination and verification of the rising edges of the waveform

Two threshold points are defined along a rising edge (Fig. 2), based on the values of its maximum,  $MAX$ , and its amplitude  $AMPL = MAX - MIN$ :

- $HAT$  – the first point of the waveform to the left of the maximum that is lower than or equal to a high amplitude threshold of  $(MAX - 0.1AMPL)$ ;
- $LAT$  – the first point of the waveform to the left of the maximum that is lower than or equal to a low amplitude threshold of  $(MAX - 0.7AMPL)$ .

2.1. Validation criteria concerning the characteristics of a single rising edge

If the following criteria are not fulfilled the rising edge is discarded (its minimum and maximum are rejected).

- Minimum amplitude ( $AMPL$ ) of the rising edge. An amplitude threshold of 20 bits is set on the assumption of an 8-bit resolution and normalized amplitude of the input signal (automatic gain control).
- Minimum duration of the rising edge between the two threshold points  $LAT$  and  $HAT$ :  $S_{HAT} - S_{LAT} \geq 10$  (or 40 ms for the 250 Hz sampling frequency), where  $S_{HAT}$ ,  $S_{LAT}$  are the sample indexes of the threshold points.
- A requirement for a smooth rising edge between the two threshold points  $LAT$  and  $HAT$ :  $PW_i - PW_{i-1} \geq 0$ , where  $PW_i$  is the amplitude of the  $i$ -th signal sample in the interval,  $i = (S_{LAT} + 1), \dots, S_{HAT}$ .

2.2. Estimation of the similarity of a rising edge to accepted as valid preceding rising edges and to following rising edges

2.2.1. Criteria for similarity of two rising edges

Two rising edges are considered similar if the following criteria are fulfilled.

- Amplitude similarity  
The amplitude of the lower-amplitude rising edge must be greater than 50% of the amplitude of the higher-amplitude rising edge.
- Position similarity
  - The maximum of the lower-amplitude rising edge must be in the interval defined by the maximum of the higher-amplitude rising edge  $\pm 60\%$  of the amplitude of the higher-amplitude rising edge.
  - The minimum of the lower-amplitude rising edge must be in the interval defined by the minimum of the higher-amplitude rising edge  $\pm 60\%$  of the amplitude of the higher-amplitude rising edge.
- Duration similarity of the upslope segments between the threshold points  $LAT$  and  $HAT$   
The duration ( $S_{HAT} - S_{LAT}$ ) of the shorter upslope segment must be greater than 33% of the duration of the longer upslope segment.

2.2.2. Estimation of the similarity of the current rising edge to the accepted as valid preceding rising edges whose maximums are within 2 s before the maximum of the current rising edge

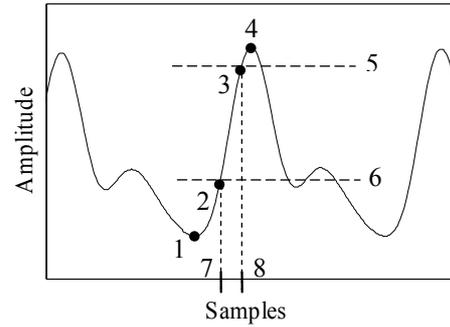


Fig. 2 Characteristic points along a pulse wave: 1 –  $MIN$ ; 2 –  $LAT$ ; 3 –  $HAT$ ; 4 –  $MAX$ ; 5, 6 – the amplitude thresholds  $(MAX - 0.1AMPL)$  and  $(MAX - 0.7AMPL)$ ; 7, 8 – the sample indexes  $S_{LAT}$ ,  $S_{HAT}$ .

The following data are obtained, applying the criteria for similarity of two rising edges:

- SIM\_BEf – the number of the accepted as valid rising edges having a maximum within 2 s before the maximum of the current rising edge and which are similar to the current rising edge.
- NOTSIM\_BEf – the number of the accepted as valid rising edges having a maximum within 2 s before the maximum of the current rising edge and which are not similar to the current rising edge.

### 2.2.3. Estimation of the similarity of the current rising edge to the following rising edges whose maximums are within 2 s after the maximum of the current rising edge

The following data are obtained applying the criteria for similarity of two rising edges:

- SIM\_AFT – the number of the rising edges having a maximum within 2 s after the maximum of the current rising edge and which are similar to the current rising edge.
- HIGH\_AFT – the number of the rising edges having a maximum within 2 s after the maximum of the current rising edge which are not similar to the current rising edge and are higher in amplitude than the current rising edge.

### 2.3 Verification of the current rising edge

The decision logic uses the quantities obtained above from the estimation of similarity of closely positioned rising edges. The decision rules are specified on separate lines in Table 1. The current rising edge is considered a valid edge of a pulse wave if one of the decision rules is fulfilled. For example, the decision rule 2, stated in words, reads as follows: “In comparison to the current rising edge:

- 1) There are 2 or more similar and 1 or more not similar accepted for valid rising edges within 2 s before the maximum of the current rising edge.
- 2) Within 2 s after the maximum of the current rising edge there are 1 or more similar rising edges, and the number of the higher-amplitude not similar rising edges is at least lesser by 1 than the number of the similar rising edges (in the same time-interval)“.

The last means that, if there is 1 similar edge within 2 s after the maximum of the current edge, no higher-amplitude not similar edges are allowed in the same interval; if the similar edges are 2, 1 higher-amplitude not similar edge is allowed and so on.

Table 1

Decision rule №	SIM_BEf	NOTSIM_BEf	SIM_AFT	HIGH_AFT
1	$\geq 2$	0		
2	$\geq 2$	$\geq 1$	$k, k \geq 1$	$\leq k - 1$
3	1	0	$k, k \geq 1$	$\leq k - 1$
4	1	$\geq 1$	$k, k \geq 2$	$\leq k - 2$
5	0	$\geq 1$	$k, k \geq 3$	$\leq k - 3$
6	0	0	1*	0
7	0	0	$k, k \geq 2$	$\leq k - 2$

\* The maximum of this rising edge must be more than 0.9 s after the maximum of the current rising edge.

## *Performance assessment of the pulse wave detection algorithm*

### 1. Test signals

There is an abundance of publicly available digital recordings containing expert-annotated electrocardiographic (ECG) signals, such as those accessible from PhysioNet (<http://www.physionet.org>) [5] – a large database collection of a variety of physiologic signals. Generally, however, there is a lack of benchmark databases with approved beat annotations for the evaluation of pulse wave detection algorithms. The small CSL database (<http://bsp.pdx.edu>) [3] containing six 60 minutes manually annotated recordings from six patients, may be mentioned as an exception (two arterial blood pressure, two pulse oximetry and two intracranial pressure recordings).

To test the performance of the proposed algorithm a set of signals from an internationally recognized database was selected – The Massachusetts General Hospital/Marquette Foundation (MGH/MF) Waveform Database from PhysioNet. This is a collection of recordings from 250 patients in critical care units and represents a broad spectrum of physiologic and pathophysiologic states. The typical recording contains as a subset an arterial pressure pulse wave as well as synchronously-sampled ECG waveforms with approved beat annotations. The database is classified as Class 1 (completed reference databases) which means that these data have been carefully scrutinized and have been thoroughly annotated. Although there are no reference beat annotations for the pulse wave signals, the ECG based beat annotations can indirectly help the assessment of the algorithm performance. Obviously, a direct comparison between the number of the detected by this algorithm pulses and the number of the ECG based beat annotations is not appropriate.

The algorithm performance was tested on the first 12 recordings (mgh001, ..., mgh012) from the MGH/MF Waveform Database discussed above. These signals are digitized by a 12 bit resolution ADC and are relatively low-amplitude which does not comply with the assumption of an 8-bit resolution and normalized amplitude of the input signal (automatic gain control). Reducing the resolution to the 8 most significant bits in order to simulate an 8 bit analog-to-digital conversion would produce a very low-amplitude signal. We chose to test the algorithm on the original 12 bit resolution signal and to adapt the threshold for the minimum amplitude (*AMPL*) of the rising edge from 20 to 160 bits (point 2.1. of the pulse wave detection algorithm). Since the sampling frequency of the recordings is 360 Hz, the signals were downsampled to 250 Hz prior to the test.

### 2. Test procedure

We adopted an approach to assessing the algorithm performance based on detection and visual inspection of suspicious signal epochs featuring abrupt peak to peak interval shortenings or prolongations (like arrhythmia or other major disturbances of heart rate periodicity). The aim is to check if the algorithm correctly recognizes the absence of valid pulsations. The test procedure uses the maximums (peaks) of the detected by the algorithm pulse wave rising edges.

#### 2.1. Detection of dissimilar peak to peak (*PP*) intervals

Every peak to peak interval,  $PP_i$ , is compared to a current average value of eight peak to peak intervals,  $PPmean_j$ .  $PP_i = P_i - P_{i-1}$ , where  $P_i$  denotes the sample index of the maximum of the  $i$ -th accepted for valid rising edge from the beginning of the recording.  $PPmean_j$  is initialized with the average value of the first eight *PP* intervals having duration between 50 and 500 samples (or 0.2 s to 2 s). Then  $PPmean_j$  is updated with every detected similar peak to

peak interval. This could be written as  $PPmean_j = \sum_{n=1}^8 PP_{m-n} / 8$ , where  $PP_{m-1}$  is the last element of an array starting with the first eight  $PP$  intervals with a duration between 50 and 500 samples and continuing consecutively with the detected similar peak to peak intervals.

The  $i$ -th peak to peak interval,  $PP_i$ , is considered dissimilar to the current average value,  $PPmean_j$ , if  $PP_i < 0.5PPmean_j$  or  $PP_i > 1.5PPmean_j$ . The intervals from the beginning of the recording to the first maximum and from the last maximum to the end of the recording are also considered as dissimilar, if they exceed 1.5 times the corresponding  $PPmean_j$  (the first interval is compared to the initial average  $PP$  interval  $PPmean_1$ ).

## 2.2. Location of suspicious 10 s signal epochs and classification of the epochs

Based on the detected dissimilar peak to peak intervals, suspicious signal epochs are located and classified. The duration of each epoch is 10 s (2500 samples). The location of the epochs is as follows.

- If the interval from the beginning of the recording to the first maximum is dissimilar the beginning of the recording is a beginning of a 10 s epoch.
- If a signal segment that is not a part of an epoch and is free from dissimilar intervals is followed by a dissimilar  $PP$  interval the beginning of the dissimilar  $PP$  interval (the first peak) is a beginning of a 10 s epoch.
- If the end of a suspicious 10 s epoch intersects a dissimilar  $PP$  interval the epoch is immediately followed by a new epoch.
- If the end of the recording occurs before the end of a 10 s epoch the epoch is discarded.

For every epoch the total duration and number of dissimilar  $PP$  intervals are calculated. An interval portion at an epoch boundary is also added to the total duration and number of dissimilar intervals for that epoch. The suspicious 10 s epochs are classified as follows.

- Epochs with presence of pulse – epochs with detected maximums and in which the dissimilar intervals add up to less than or equal to 40% of the epoch duration AND there are less than 5 dissimilar intervals.
- Bad epochs – epochs with at least one detected maximum after the beginning of the epoch and in which the dissimilar intervals add up to more than 40% of the epoch duration OR there are more than or equal to 5 dissimilar intervals.
- Empty epochs – epochs without detected maximums after the beginning of the epoch.

## 2.3. Visual inspection of the detected epochs in the pulse wave signal

The detected epochs (especially the bad and empty ones) are subjected to careful visual inspection with the help of ECG based beat annotations as a means of verification.

## Results and discussion

The total duration of the examined recordings was 13 h 59 min. The pulse wave detection algorithm identified 62363 heart beats. The test procedure located 1495 suspicious 10 s epochs. They were classified as follows: 976 empty epochs, 113 bad epochs and 406 epochs with presence of pulse. The recordings were visually reviewed and the detected epochs were checked for errors with the aid of ECG based beat annotations. All of the quantities cited below should be taken as approximate only, because of the lack of pulse wave based expert annotations.

## 1. Visual inspection of the empty epochs

In 964 of all 976 empty epochs no errors were found.

### 1.1. Empty epochs with undetected beats

Undetected beats were found in 12 empty epochs. (In 9 of these epochs there was only one undetected beat, in the rest three epochs there were 2, 3 and 5 undetected beats respectively). The main types of errors could be summarized as follows.

#### a) Undetected last beat before an empty segment at low heart rates

In 7 epochs (all from recording mgh001) there was a single undetected beat lying between a series of similar valid pulses and an empty segment. An example is shown in Fig.3a). Such type of undetected beats would be common at the lowest heart rates from about 30 to 60 bpm because of the decision rules. At these low heart rates the adopted 2 s window for analysis around a rising edge could only accommodate one pulse upslope. We chose the decision rules to be tight in order to reduce false detections.

#### b) Undetected beats distorted by the digital filtration

In 3 epochs there were undetected beats distorted by the digital filtration. The worst case epoch with 5 undetected pulses is shown in Fig. 3b). Such waveform distortions could be expected at abrupt signal transitions because of the settling time of the filters. It should be noted that in many cases of signal transitions (e.g. at a boundary with an empty segment) the filters does not produce any problem.

## 2. Visual inspection of the bad epochs

### 2.1. Bad epochs without errors

In 75 of all 113 bad epochs no errors were found – no falsely detected beats or undetected beats. The main types of free from errors bad epochs could be summarized as follows.

#### a) Epochs with an empty segment within them

In 29 epochs there were empty segments (without detected pulses) within them. In most of these epochs the empty segment continued from the previous epoch and the pulses started with a delay after the beginning of the epoch.

#### b) Epochs with low amplitude and/or missing pulses corresponding to abnormal ECG beats

In 45 epochs there were low amplitude and/or missing pulses corresponding to abnormal beats in the ECG – Fig. 3c), Fig. 3d). The number of such pulses was between 3 and 4 in each epoch. The low amplitude pulses predominated. We considered that these undetected pulses were not errors of the algorithm since they were visually much lower in amplitude than the annotated as normal pulses.

The amplitude range of the annotated as abnormal pulses is very wide – from a completely missing pulse to a pulse similar to the annotated as normal pulses. According to the criterion for amplitude similarity of two rising edges (step 2.2.1. of the algorithm), pulses with an amplitude below about 50% of that of the neighbouring ones would be undetected by the algorithm. This threshold was chosen to reduce false detections (e.g. mistaking of high amplitude dicrotic notches for valid pulses). An expert opinion is needed about the amplitude threshold above which a pulse resulting from abnormal ECG beat should be considered valid.

### 2.2. Bad epochs with falsely detected beats

Falsely detected beats were found in 16 bad epochs. (In 14 of these epochs there was only one false beat, in 1 epoch – two and in 1 epoch – multiple (10) false beats.) The main types of errors could be summarized as follows.

#### a) False detection of a series of calibration pulses

In 5 epochs a pulse waveform was not present and there was a series of falsely detected calibration pulses, probably related to some of the other parallel measurements from the

database. They were rectangular pulses smoothed by the digital filtration. Such calibration pulses are not expected to be present in real pulse wave measurements but they bring up some discussion. The smoothing of steep rising edges (including steep artifacts) by the filtering procedure is accompanied with an increase in the number of points forming a rising edge. That makes the validation criterion concerning the minimum duration of the rising edge between two amplitude thresholds (step 2.1. of the algorithm) ineffective in some cases. The benefit of applying this same criterion to a corresponding section of the original (unfiltered) signal could be considered against the corresponding software complication.

b) False detection of the first of two adjacent false peaks with similar rising edges  
In 4 epochs there was a false detection of the first of two adjacent false peaks with similar rising edges. This error was caused by decision rule 6 which allows the current rising edge to be considered valid if there is one similar rising edge with a maximum between 0.9 s and 2 s after the maximum of the current rising edge. This decision rule is needed to “catch” the first pulse after an empty segment at the lowest heart rates (30-60 bpm). In two of the epochs the two adjacent peaks in the filtered signal resembled in shape their corresponding peaks in the original signal, Fig. 3e) (the first false detection from left to right). In the other two epochs the two adjacent peaks were formed as a result of smoothing of steep artefacts, Fig. 3f).

c) False detection of a peak adjacent to a valid pulse  
In 7 epochs there was a false detection of a peak adjacent to a valid pulse. In 3 of all 7 epochs there was an obvious discrepancy between the ECG annotations and the position of the falsely detected rising edge, Fig. 3e) (the second false detection from left to right). In the rest 4 epochs our opinion was based on a visual inspection of the rising edge in the original recording. In 2 of all 7 epochs the falsely detected rising edge was a smoothed steep artifact.

d) Multiple false detections  
In one epoch a series of 10 falsely detected pulses were found – Fig. 3g). The origin of these pulses was unknown. They resembled a pulse wave in shape and frequency but it was evident from the ECG annotations that they were not cardiac pulsations. Moreover, the test procedure assessed only about a half of the *PP* intervals within this false series as dissimilar (4 dissimilar against 5 similar intervals). This was the worst epoch with respect to false detections and the most serious error of the algorithm.

### 2.3. Bad epochs with undetected beats

Undetected beats were found in 26 bad epochs. (In 14 epochs there was only one undetected beat and in 4, 2, 4 and 2 epochs there were 2, 3, 4 and 5 undetected beats respectively.) The main types of errors could be summarized as follows.

a) Undetected beats distorted by the digital filtration  
In 9 epochs there were undetected beats distorted by the digital filtration.

b) Undetected beats distorted by artifacts, noise or interference  
In 5 epochs there were undetected beats distorted by artifacts, noise or interference. One of the worst case epochs is shown in Fig. 3h) (3 undetected beats). Expert annotations are particularly necessary when the waveform is distorted.

(The discussed in subsections a) and b) above distortions caused in rare cases a valid pulse next to a distorted pulse to be undetected in addition to or instead of the distorted one.)

c) Undetected lower amplitude pulses corresponding to abnormal beats in the ECG

In 5 epochs there were undetected lower amplitude pulses corresponding to abnormal beats in the ECG. These pulses were of the type shown in Fig.3c), but visually higher in amplitude.

d) Undetected low amplitude beats  
In 4 epochs there were undetected low amplitude beats. The amplitudes of their rising edges were below the adopted minimum amplitude threshold of 160 bits.

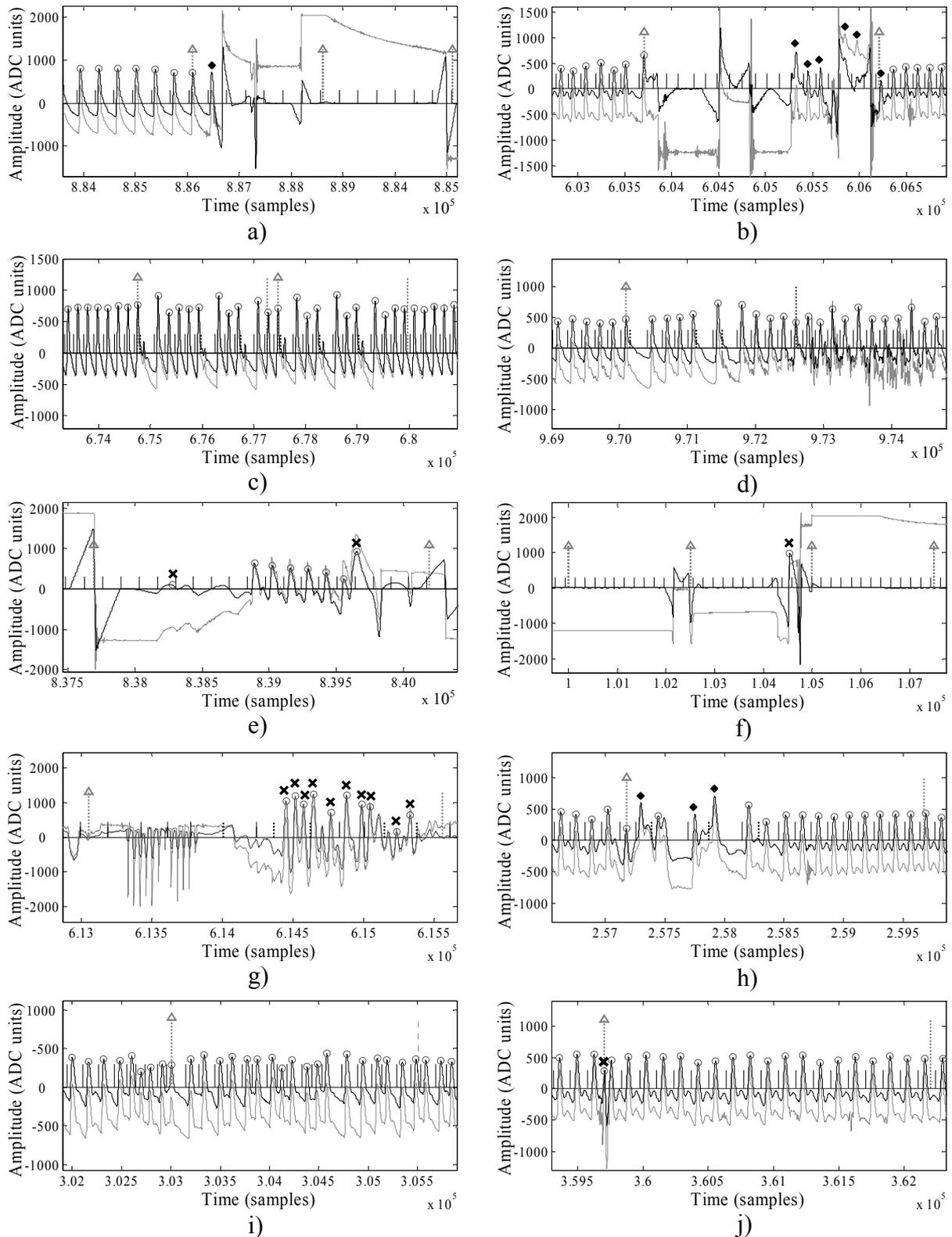


Fig. 3 Examples illustrating the performance of the algorithm and the visual interpretation of the results: a), b) – empty epochs with undetected beats; c), d) – bad epochs without errors; e), f), g) – bad epochs with falsely detected beats; h) – a bad epoch with undetected beats; i) – an epoch with presence of pulse without errors; j) – an epoch with presence of pulse with a falsely detected beat; — – filtered signal, - - original signal; ○ – detected beats; ◆ – undetected beats; ✕ – falsely detected beats; ▲ – start of an epoch; ▮ – end of an epoch; | – normal beat; |· – abnormal beat (ECG annotations).

#### e) Undetected isolated pulses

In a few epochs there were undetected isolated pulses (a single beat or the second of two adjacent beats). Omission of such beats would be common because of lack of enough similar pulses within the 2 s time windows around a rising edge covered by the decision rules.

### 3. Visual inspection of the epochs with presence of pulse

The large number of epochs with presence of pulse (406) is because of the fact that an epoch is classified as suspicious even if it contains only a part of a dissimilar *PP* interval.

#### 3.1. Epochs with presence of pulse and without errors

In 325 (of all 406) epochs with presence of pulse no errors were found. The main types of free from errors epochs with presence of pulse could be summarized as follows.

##### a) Epochs with an empty segment within them

In most of these epochs the pulses started with a delay after the beginning of the epoch. Short empty segments with artifacts occurred in a few epochs.

##### b) Epochs with low amplitude and/or missing pulses corresponding to abnormal ECG beats

Between 0 and 2 low amplitude and/or missing pulses corresponding to abnormal beats in the ECG occurred in each epoch. (0 means that only a part of the dissimilar *PP* interval that contains the annotated as abnormal beat is within the epoch (not the beat itself).)

##### c) Epochs with irregular *PP* intervals (arrhythmia)

The test procedure located epochs with irregularities in the rhythm of the heartbeat. It takes into account only the detected dissimilar *PP* intervals, i.e. the abrupt *PP* interval irregularities – shortenings or prolongations. (A *PP* interval is considered dissimilar if it is not within  $\pm 50\%$  of a current average *PP* value.) Dissimilar *PP* intervals were observed between two annotated as normal beats, Fig. 3i), as well as between a normal and an abnormal beats.

#### 3.2. Epochs with presence of pulse and with falsely detected beats

##### a) False detection of a peak adjacent to a valid pulse

In 9 epochs there was a false detection of a peak adjacent to a valid pulse. An example is shown in Fig. 3j).

##### b) Multiple false detections

In one epoch multiple (3) falsely detected peaks were found.

#### 3.3. Epochs with presence of pulse and with undetected beats

##### a) Undetected beats distorted by artifacts, noise or interference

##### b) Undetected lower amplitude pulses corresponding to normal ECG beats

The test procedure located epochs with undetected lower amplitude pulses corresponding to normal ECG beats. The algorithm (step 2.2.1.) rejects pulses with amplitude below about 50% of that of the neighbouring ones – a threshold chosen to reduce false detections. Expert-annotated pulse waveform databases would be very valuable for adjustment of such algorithm parameters.

##### c) Undetected lower amplitude pulses corresponding to abnormal ECG beats

##### d) Undetected beats distorted by the digital filtration

(The examples in Fig. 3 were extracted from the following recordings from the MGH/MF database: a) – recording mgh001; d), g) – mgh002; e) – mgh007; b), h), j) – mgh010; c), f) – mgh011; i) – mgh012.)

### 4. Visual inspection of the segments of the recordings that were not classified as suspicious

A pulse wave was present in all segments of the recordings that were not classified as suspicious. Some very rare cases of undetected or falsely detected beats were noticed that

would not prevent the correct recognition of presence of pulse. On the whole, the test procedure correctly located the various epoch types.

## Conclusion

In this study we presented an automated algorithm for fast pulse wave detection, directed to establishing the presence of cardiac activity in an emergency. The method relies on real-time estimation of similarity of closely positioned rising edges of the waveform and decision logic. The algorithm was tested on a set of arterial pressure pulse waves from the internationally recognized MGH/MF waveform database from PhysioNet. We adopted an approach to assessing the algorithm performance based on location and classification of suspicious 10 s signal epochs by means of detection of dissimilar peak-to-peak intervals. The detected epochs (especially the bad and empty ones) were subjected to careful visual inspection with the help of the available ECG-based expert beat annotations. The main epoch and error types were summarized.

The review of the recordings showed that the proposed algorithm correctly identifies cardiac pulsations even under considerable artefacts. The algorithm performed very well with respect to falsely detected pulses with a single exception – a short burst of pulse wave – like artefacts. Our conclusion is that the algorithm reliably detects critical periods in cardiac activity and is applicable to fast pulse wave detection in real-time applications and ambulatory measurement setups.

On the whole, the testing method correctly located and classified suspicious epochs in the pulse wave signal. The total time limitation of 10 s for pulse detection makes difficult and/or inappropriate the usage of criteria involving comparison of peak-to-peak intervals. If the situation, however, allows longer measurement time after the initial estimation of the patient's condition, a similar test procedure could be incorporated into the signal analysis.

We found difficulties in the interpretation of some peaks because of the lack of reference beat annotations for the pulse wave signals. The unavailability of benchmark databases of expert-annotated pulse waveforms makes difficult the development, evaluation and tuning of pulse wave detection algorithms, as well as the comparison of results achieved by different authors.

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**Bistra Nenova, Ph.D. Student**

E-mail: [bistranenova@hotmail.com](mailto:bistranenova@hotmail.com)



Bistra Nenova graduated Technical University – Sofia, Faculty of Electronic Engineering and Technology, specialty Electronic Medical Equipment in 1996. She is a Ph.D. student with the Department of Electronics and Electronics Technologies, Faculty of Electronic Engineering and Technologies, Technical University – Sofia. Her professional interests are in the field of embedded control, digital signal processing and electronic circuits.

**Assoc. Prof. Ivo Iliev, Ph.D.**

E-mail: [izi@tu-sofia.bg](mailto:izi@tu-sofia.bg)



Assoc. Prof. Ivo Iliev graduated from the Technical University – Sofia, Faculty of Electronic Engineering and Technology, division of Biomedical Engineering in 1989. He is presently with the Department of Electronics of the Technical University – Sofia, working on methods and instrumentation for bio-signal registration and analysis, telemetry and wireless monitoring of high-risk patients.