Performance Comparison of Automatic Peak Detection for Signal Analyser

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ABSTRACT

The aim of this paper is to propose a new peak detection method for a portable device, which know as modified automatic threshold peak detection (M-ATPD). M-ATPD evolves out of ATPD with a focus on reducing computational time. The proposed method replaces the clustering threshold calculation in ATPD with a standard deviation threshold calculation. M-ATPD reduces computational time by 2 times faster compared to ATPD for control signal and 8.65 times faster compared to ATPD for raw biosignals. Modified ATPD also shows a slight improvement in terms of detection error, with a decrease of about 6.66% to 13.33% in peak detection of noise signals. Modified ATPD successfully fixes the error of peak detection on pulse control signals associated with ATPD. For raw biosignals, in total M-ATPD achieved 19.41% lower detection error compare to ATPD.

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1. INTRODUCTION

Amplitude response is most common in electronic application. Peak detection plays the most important role in analysing amplitude response signals. However, noise will cause false peak detection or report a missing peak. This will decrease the accuracy of peak detection. Hence, intelligent peak detection methods are required to increase the accuracy of analysis. From time to time, peak detection methods are design for general or specific signal, such as automatic multiscale peak detection (AMPD) [1], the automatic chromatographic peak detection (ACPD) [2], the adaptive threshold method (ATM) [3], the peak of Shannon energy envelope (PSEE) [4] and ATPD [5], [6].

AMPD and ATPD are designed for general signal peak detection. ACPD is specifically designed for chromatographic signals. The PSEE is specifically designed for electrocardiogram (ECG) signals, while the ATM is specifically designed for photoplethysmorgraphy signals. Although some peal detection algorithms are designed for specific signals, certain criteria in the algorithm might be applicable to each other due to the similarity of signals.

Besides accuracy, computational complexity is the main concern when designing an algorithm[7]. Computational complexity relates to the direct effect of the efficiency of time and power[8], [9]. Our aim is to design a peak detection algorithm for a portable nano-biosensor device, which will require lower power consumption such that the size of the battery and the portable device overall can be reduced. According to the literature, ATPD methods show the lowest detection error with moderate computational timing. Hence, ATPD is proposed to improve computational timing.

The rest of the paper is organized as follows. Section II reviews the existing ATPD algorithm. Section III elaborates on the evolution of the ATPD algorithm. The results of our experiment are presented in Section IV, while Section V concludes this paper.

2. LITERATURE REVIEW

Figure 1 is a flow chart for the threshold calculation method in ATPD. At the threshold calculation stage, clustering methods are applied. Initially, the algorithm will load the signal data (x[n]). Then, the first signal data (x[1]) and the second signal data (x[2]) will be set as a cluster value 1 (C1) and cluster value 2 (C2), respectively. The algorithms will continuously load the next data on a loop in order to compare C1 and C2, such that the data will grouped into the nearest cluster class and a new cluster value will be calculated from the mean of the cluster class. After a new cluster value is calculated, this will be compared to the last cluster value. The loop will repeat until the differences between the new cluster value and the last cluster value are smaller than those for the termination condition (Ɛ). Then, the smallest cluster value will be selected as the threshold value.

The selected threshold value will be used to determine the peak. The peak is defined when the difference between the trough and the peak is greater than threshold value; otherwise, it will not counted as the peak. By using the threshold value, much of the false peak created by noise will be eliminated.

Then, the simulation of ATPD algorithm is conducted using MATLAB. Figure 2 shows the results of peak detection using ATPD. The triangular mark represents the detected peak. The purpose of simulation is to identify the computational time for each stage. Figure 3 shows the profile summary from MATLAB simulation. From the study, the most time-consuming stage is the threshold calculation stage. The time taken to carry out the cluster threshold calculation is 0.334s out of a total time of 0.556s. This shows that more than half of the total time is used for the threshold calculation. Hence, improvements at the threshold calculation stage are required in order to reduce the overall computational time. A new threshold calculation algorithm using standard deviation is proposed. The next section will discuss the new threshold calculation.

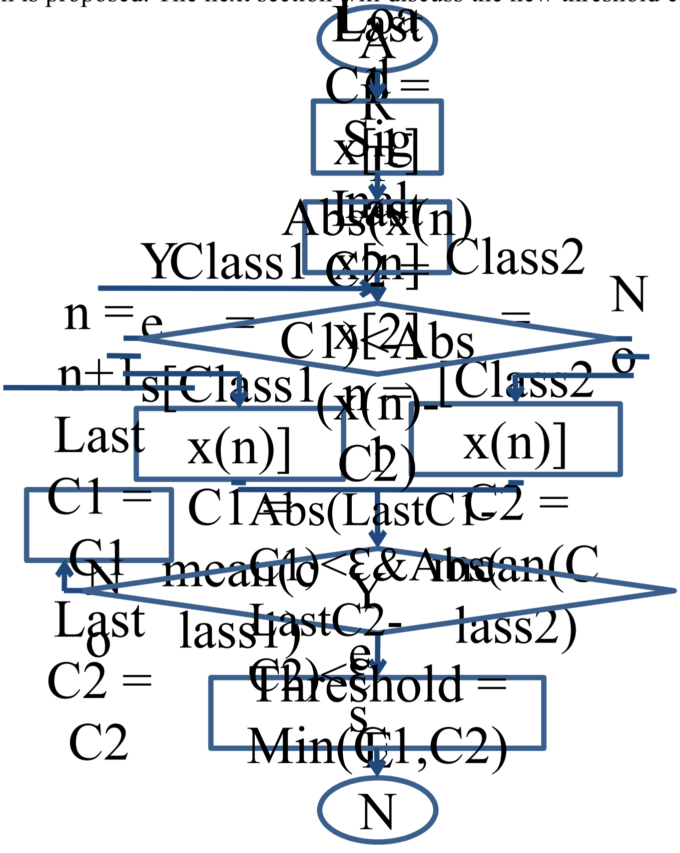

Figure 1. Flow chart for the cluster threshold calculation method

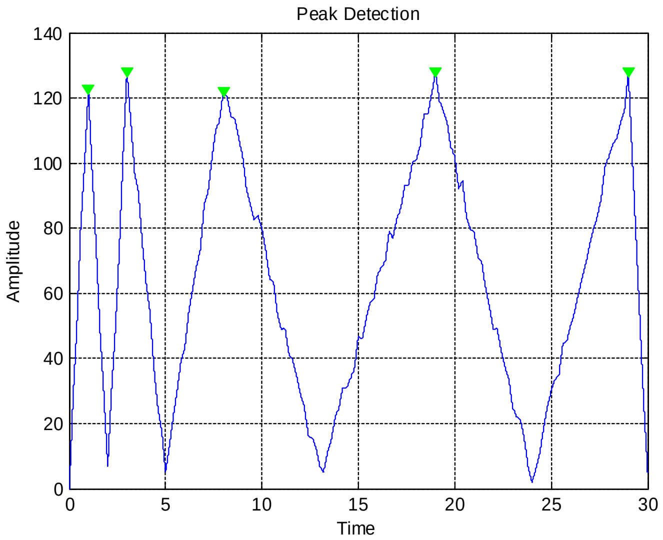

Figure 2. Peak detection using ATPD

Profile Summary

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Function Name	Calls	Total Time	Self Time*	Total Time Plot (dark band = self time)
ATPD	1	0.555 s	0.070 s	
twoclass	1	0.334 s	0.334 s	
newplot	1	0.087 s	0.002 s	
cla	1	0.085 s	0.003 s	
newplot>ObserveAxesNextPlot	1	0.085 s	0.000 s	
graphics\private\clo	1	0.082 s	0.012 s	
setdiff	2	0.064 s	0.011 s	
setdiff>setdifflegacy	2	0.053 s	0.034 s	
PTDetect	1	0.036 s	0.036 s	
ismember	1	0.019 s	0.004 s	
ismember>ismemberlegacy	1	0.015 s	0.015 s	
xlabel	2	0.010 s	0.004 s	

Figure 3. Profile summary of ATPD created by MATLAB simulation

3. METHODOLOGY

In Section II, the details of the ATPD algorithm was discussed. In this section, the details of the proposed threshold calculation method will be considered. According to the literature, standard deviation is widely use to estimate the noise level[10], [11]. Hence, the proposed method is referred to as the standard deviation threshold calculation. The purpose of the proposed new method is to solve the problem of heavy computational complexity at the threshold calculation stage in ATPD. In the proposed method, standard deviation is used to estimate the noise level, which is then adopted as the threshold to eliminate the false peak. The usual purpose of standard deviation is to calculate abnormal data or explain why the data are too different from other data. Figure 4 illustrates the concept of standard deviation. Abnormal data will be outside the range of standard deviation. In real signals, noise peak will occur more frequently than true peaks. Hence, noise peaks will be in the majority, while true peaks be in the minority. As such, the peak within the standard deviation range will be the noise peak, whereas the true peak will be outside the standard deviation range.

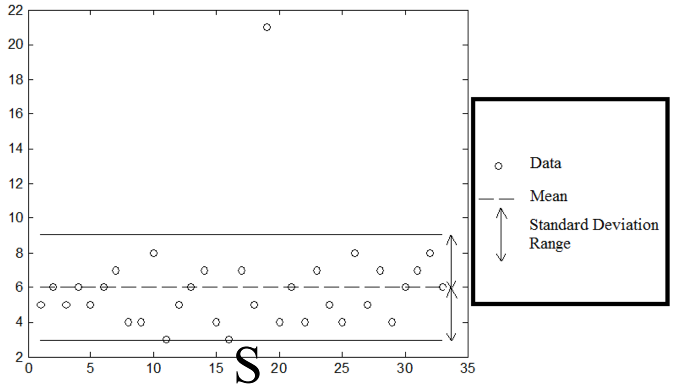

Figure 4. Concept of standard deviation

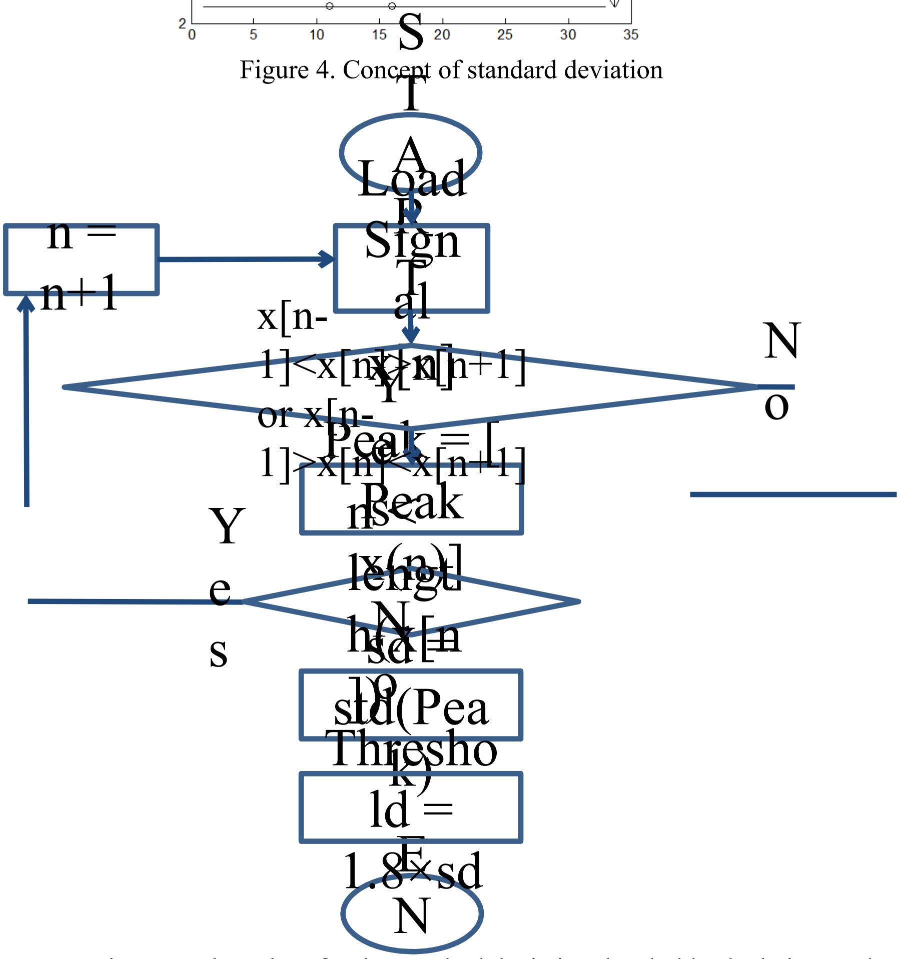

Figure 5. Flow chart for the standard deviation threshold calculation method

Figure 5 is a flow chart for the standard deviation threshold calculation method. In the standard deviation threshold calculation, the signal data (x[n]) will initially be loaded. Then, all the turning points of the loaded signal will be detected, which are shown in Figure 6 as triangular marks. After that, the detected turning points are used to calculate standard deviation for the purpose of estimating the noise level. Lastly, the threshold value will be defined by α×sd, where α is the coefficient calibrate based on the signal and sd is standard deviation.

Firstly, control signal are used to evaluate the M-ATPD. Eighteen control signals are generated consisting of three types of peak: pulse, sinusoidal, and triangular. Each type of peak signal has a best, typical, and worst case. The same control signals are then combined with noise to test the performance of the algorithms. All control signals are generated using Matlab and have a signal length of 30 seconds and a sampling frequency of 640Hz.

Next, several biosignals were chosen: electrocardiogram (ECG), blood pulse (BP), electroencephologram (EEG) and sum of respiration (Resp(sum)) to further evaluation. The raw signals of ECG, BP, EEG and Resp(sum)were applied in the experiment to determine the ability of M-ATPD to analyse various types of signal. The length of each signal is 900 000 data in 3600 seconds. M-ATPD required adjustment of the coefficient when applied to different signals. This adjustment of the coefficient was done manually. The coefficients for ECG/BP, EEG, and sum of respiration were set to 4.0, 2.5 and 1.0 respectively.

The same signal was then applied using ATPD. The raw signal required a level-shifting process to ensure that ATPD worked correctly with each signal, and this level-shifting process was done manually. Level shifts for ECG, BP, EEG and Resp(sum) were +250, +300, +100 and +600 respectively. A comparison was then made to assess the improvements from M-ATPD in comparison with ATPD. The results will be discuss in next section.

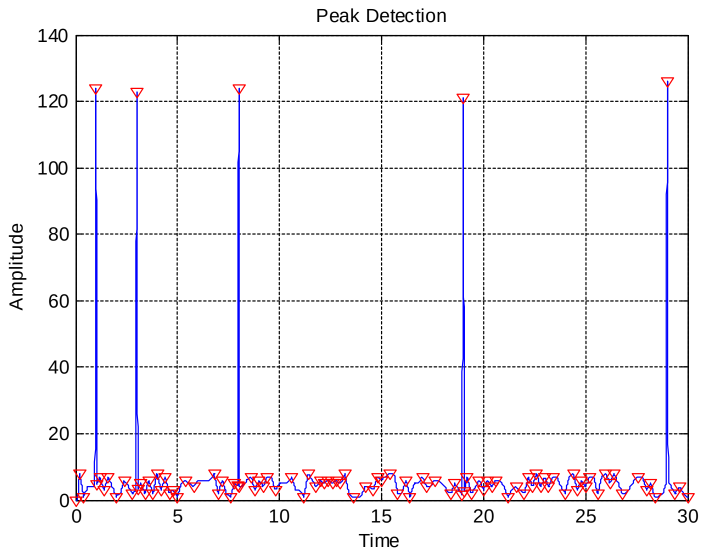

Figure 6. All determined turning point using the standard deviation threshold calculation method

4. RESULTS AND DISCUSSIONS

In Section III, the details of the standard deviation threshold calculation method were discussed. This method replaces the original clustering threshold calculation in ATPD. Hence, we have a new peak detection method called M-ATPD. Figure 7 shown peak detection using M-ATPD. Figure 8 shows the profile summary for M-ATPD using MATLAB simulation. Results show that the standard deviation threshold calculation time reduces from 0.334s to 0.042s. In other words, more than 80% of the time taken for threshold calculation is saved when the standard deviation threshold calculation replaces the cluster threshold calculation. Table 1 summarizes the computational time for M-ATPD and another five studied algorithms using MATLAB simulation. The results show that M-ATPD reduces computational time by 50% compared to ATPD. M-ATPD also has the lowest computational time, along with the ATM. Computational time is direct proportional to power consumption, which means that M-ATPD may able to reduce power consumption by 50%. In turn, great improvements have been achieved in term of reducing computational complexity.

Table 2 summarizes the accuracy of peak detection using M-ATPD when compared with another five studied algorithms using MATLAB simulation. To evaluate the performance of the peak detection algorithm, we use three benchmark parameters, which are positive prediction (+P), sensitivity (SE) and detection error (DER). To calculate +P, SE and DER, we use rates such as false negative (FN), which represents the failure to detect a true peak (a peak that is not detected as a peak), and false positive (FP), which refers to false peak detection (a non-peak detected as a peak). By using FN and FP,+P, SE and DER can be calculated as shown in Eqs. (1), (2) and (3), respectively, as suggested by [12]–[15].

$$+P=\frac{TP}{TP+FP} \quad (1)$$

$$SE=\frac{TP}{TP+FN} \quad (1)$$

$$DER=\frac{FP+FN}{TPN} \quad (1)$$

TP represents the number of true positive detections (peaks detected as peaks), while TPN represents the total number of peaks in a signal. +P reports the percentage of peak detections that can be regarded as true peaks. SE reports the percentage of true peaks that were correctly detected by the algorithm. DER reports the percentage of peak detection errors by the algorithm.

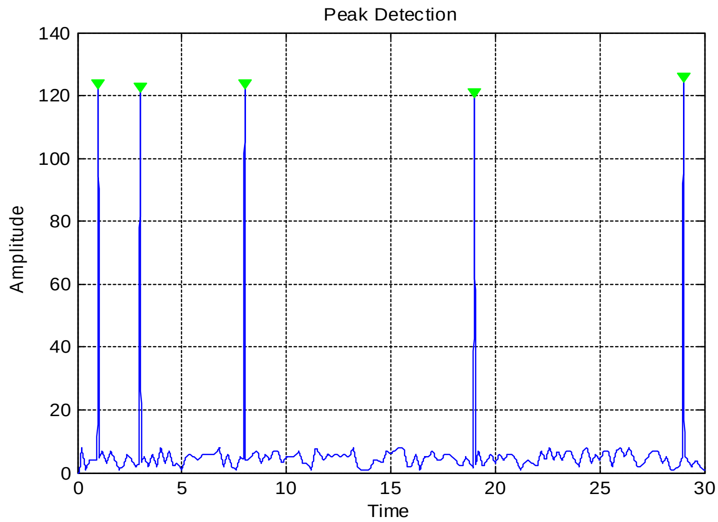

Figure 7. All determined turning point using the standard deviation threshold calculation method

Profile Summary

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Function Name	Calls	Total Time	Self Time*	Total Time Plot (dark band = self time)
ATPD_evo1	1	0.278 s	0.084 s	
newplot	1	0.088 s	0.000 s	
newplot>ObserveAxesNextPlot	1	0.087 s	0.001 s	
cla	1	0.086 s	0.003 s	
graphics\private\clo	1	0.083 s	0.014 s	
setdiff	2	0.064 s	0.012 s	
setdiff>setdifflegacy	2	0.052 s	0.032 s	
SDTC	1	0.042 s	0.037 s	
PTDetect	1	0.037 s	0.037 s	
ismember	1	0.020 s	0.005 s	
ismember>ismemberlegacy	1	0.015 s	0.015 s	
xlabel	2	0.011 s	0.004 s	

Figure 8. Profile summary of M-ATPD created by MATLAB simulation

Table 1. Computational time of M-ATPD compared to other methods

		ATPD (s)	M-ATPD (s)
Non-Noise Signal	Pulse	NA	0.29
	Sinusoidal	0.56	0.28
	Triangular	0.58	0.29
Noise Signal	Pulse	NA	0.29
	Sinusoidal	0.56	0.28
	Triangular	0.56	0.28
	Average	0.57	0.29
	Normalize of average to ATPD	2.0	1.00

*NA is refer to non-stop simulation.

From the results, M-ATPD fixed the error in the non-stop simulation of ATPD for detecting pulse signals. The peak detection error of non-noise sinusoidal signals increases from 26.67% to 33.33%. The peak detection error of non-noise triangular signals increases from 13.33% to 33.33%. This shows a slight degradation in the accuracy of peak detection of non-noise signals when comparing M-ATPD to ATPD. The peak detection error of noise sinusoidal signals decreases from 26.67% to 13.33%. The peak detection error on noise triangular signals increases from 13.33% to 6.67%. This shows a slight improvement in the accuracy of peak detection of noise signals when comparing M-ATPD to ATPD.

Although M-ATPD shows as degradation in the accuracy of detecting non-noise signals, there is improvement in relation to noise signals. This is due to the standard deviation threshold calculation method, which is purposely proposed for noise signals, because standard deviation is used to estimate the noise level. Hence, the standard deviation threshold is used to eliminate the noise peak. When the method is applied to non-noise signals, the accuracy will be lower. However, noise will always exist in real signals. Hence, this method can be applied in real applications.

Next, the experiment results of M-ATPD to biosensor signal will be discuss. Table 3 shows the performance results of M-ATPD using simulation in MATLAB. M-ATPD obtained 100% for SE and +P when applied to the ECG, BP, and EEG signals. It therefore achieved a zero percentage DER for these signals. For the Resp(sum) signal, M-ATPD reached 99.13% SE and 99.27% +P. It therefore achieved 1.59% DER for the Resp(sum) signal. The results for ATPD, on the other hand, show better performance for BP, followed by ECG, EEG and Resp(sum). This is because M-ATPD can perform better peak detection on the signal, giving a higher contrast between noise level and peak level. On average, M-ATPD reached99.95% SE and 99.96% +P, and therefore achieved 0.10% DER.

Figures. 9, 10, 11 and 12 show the results of the experiment for ECG, BP, EEG and Resp(sum) signals respectively. Each figure shows only a 30s signal from the full signal 3600s signal, due to the limited space for presentation. The mark "*" represents the peak detection by the ATPD algorithm, and the mark "▼" represents the peak detection by M-ATPD. Table 4 presents the computational time results of M-ATPD. These results for computational time are based on a simulation in MATLAB of the computational time of the algorithms. M-ATPD required the shortest time for EMG, followed by BP, ECG and Resp(sum), and these times were 4.80s, 4.96s, 5.32s and 5.32s respectively. M-ATPD used an average computational time of 5.10s. The results show that the times required for each signal were approximately equal.

Table 2. Detection error of M-ATPD compared to other methods

		ATPD (%)	M-ATPD (%)
Non-Noise Signal	Pulse	NA	33.33
	Sinusoidal	26.67	33.33
	Triangular	13.33	33.33
Noise Signal	Pulse	NA	0.00
	Sinusoidal	26.67	13.33
	Triangular	13.33	6.67

*NA is refer to non-stop simulation.

Next, the results of ATPD are presented. Table 5 shows the performance results from ATPD using simulation in MATLAB. ATPD obtained 99.43% SE and 100% +P for ECG, hence achieving 0.57% DER; it reached 99.61% Se and 100% +P for BP, hence achieving 0.39% DER; it achieved 100% SE and 57.60% +P for EEG, hence achieving 73.61% DER; and reached 82.73% SE and 100% +P for Resp(sum),hence achieving 16.52% DER. The results show that ATPD gives best performance for BP, followed by ECG, Resp(sum) and EEG. This is due to the noise level and the signal shape. On average, ATPD achieved 98.64% SE and 84.44% +P, thus achieving 19.51%DER.

Table 6 shows the computational time results for ATPD. ATPD required the shortest time for Resp(sum), followed by BP, EMG and ECG, and the times for these were 14.75s, 35.87s, 43.73s and 82.15s respectively, giving an average computational time of 44.13s. The results show that the time required to process each signal varied widely. This is due to the threshold calculation process requiring a different period of time for each type of signal.

Lastly, the results of M-ATPD and ATPD are compared shown in Table 7. In terms of DER, M-ATPD has lower DER% overall, in comparison with ATPD; M-ATPD has only 0.10% DER, while ATPD has 19.51% DER. In terms of computational time, M-ATPD required 5.10s on average, while ATPD requires 44.13s. These results show that M-ATPD can perform peak detection on average 8.65times faster than ATPD for the same signal.

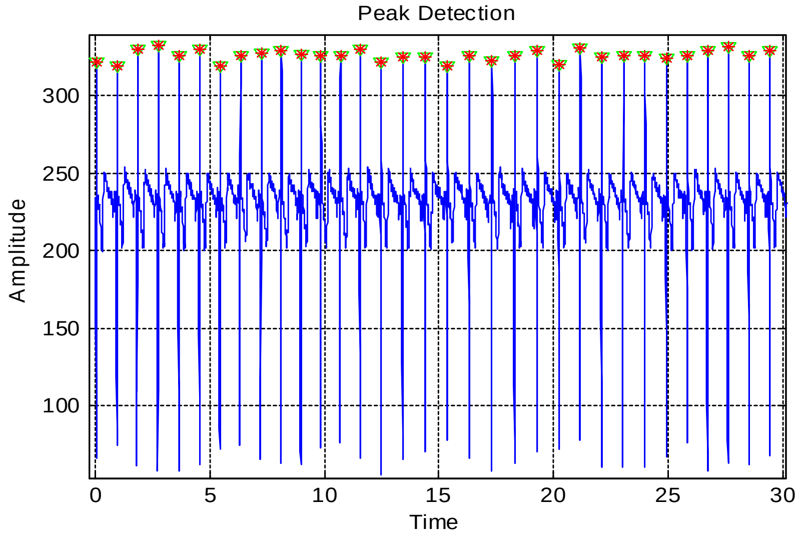

Figure 9. Results of ECG signal

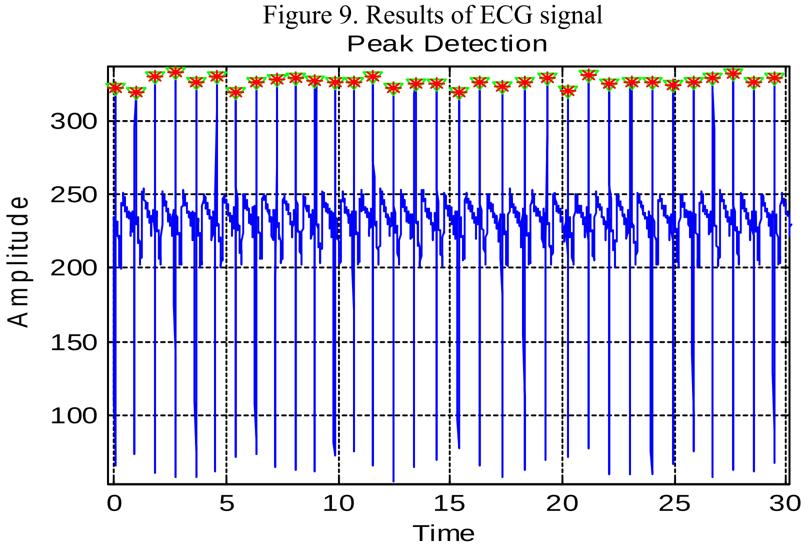

Figure 10. Results of BP signal

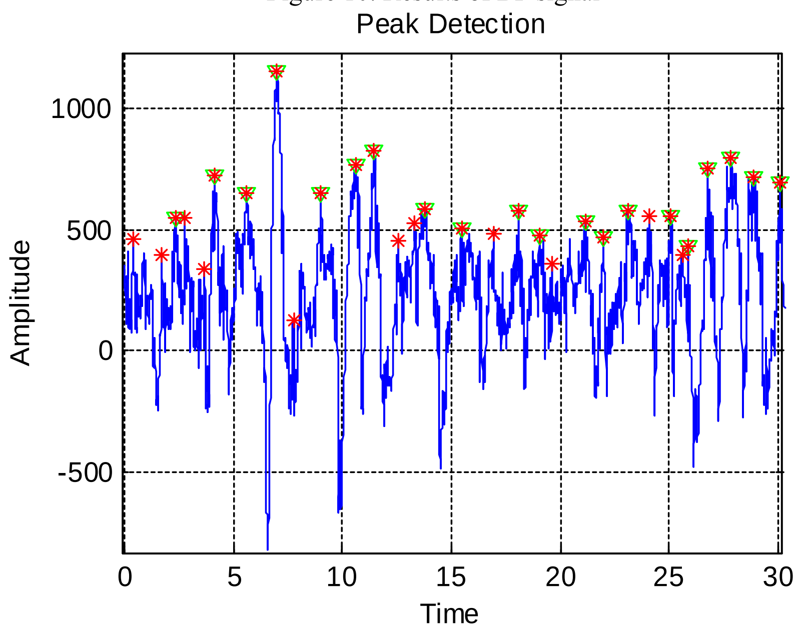

Figure11. Results of EEG signal

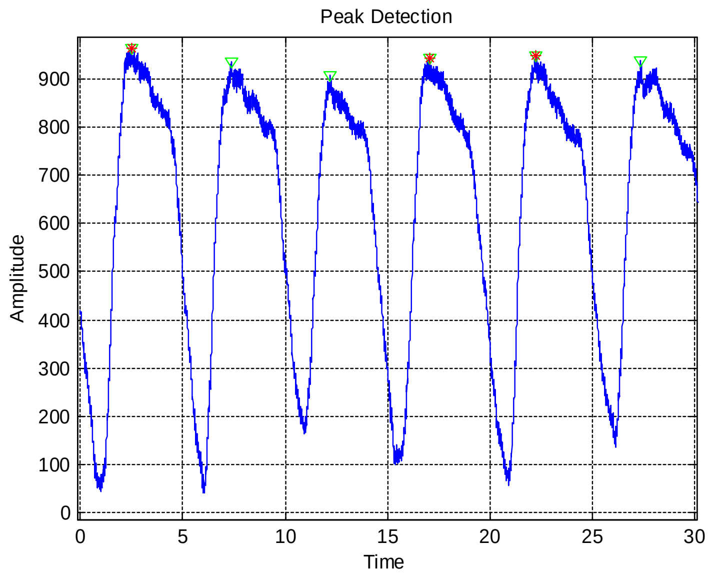

Figure 12. Results of Resp(sum) signal

Table 3. Results of M-ATPD

Signal	TPN	TP	FP	FN	Se%	+P%	DER%
ECG	3846	3846	0	0	100.00%	100.00%	0.00%
BP	3846	3846	0	0	100.00%	100.00%	0.00%
EEG	2743	2743	0	0	100.00%	100.00%	0.00%
Resp(sum)	690	684	5	6	99.13%	99.27%	1.59%
Total	11125	11119	5	6	99.95%	99.96%	0.10%

Table 4. Computational time results of M-ATPD

Signal	1	2	3	4	5	Average
ECG	5.30	5.34	5.31	5.35	5.32	5.32
BP	4.92	4.88	4.89	4.96	5.14	4.96
EEG	4.77	4.73	4.99	4.72	4.80	4.80
Resp(sum)	5.30	5.33	5.27	5.31	5.37	5.32
		Average				5.10

Table 5. Results of ATPD

Signal	TPN	TP	FP	FN	Se%	+P%	DER%
ECG	3846	3824	0	22	99.43%	100.00%	0.57%
BP	3846	3846	0	15	99.61%	100.00%	0.39%
EEG	2743	2743	2019	0	100.00%	57.60%	73.61%
Resp(sum)	690	546	0	114	82.73%	100.00%	16.52%
Total	11125	10959	2019	151	98.64%	84.44%	19.51%

Table 6. Computational time results of ATPD

Signal	1	2	3	4	5	Average
ECG	82.18	82.12	82.14	82.17	82.16	82.15
BP	35.90	35.84	35.84	35.87	35.88	35.87
EEG	43.72	43.74	43.73	43.75	43.72	43.73
Resp(sum)	14.70	14.82	14.76	14.76	14.73	14.75
		Average				44.13

Table 7. Comparison results of M-ATPD and ATPD

Signal	M-ATPD	ATPD
ECG	0.00%	0.57%
BP	0.00%	0.39%
EEG	0.00%	73.61%
Resp(sum)	1.59%	16.52%
Total	0.10%	19.51%

5. CONCLUSION

In this paper, a new algorithm was proposed, which is modification of ATPD. In previous work, ATPD have the better performance among the method mention in Section I. This work continuous to further improve the performance of ATPD by modification. ATPD is modified in order to improve the significant level of time consumption at the threshold calculation stage, while ensuring the accuracy of the algorithm is maintained. To overcome the problem, a new threshold calculation method is proposed, namely, a standard deviation threshold calculation. The results show that the standard deviation threshold calculation reduces time consumption by more than 80% compared to a cluster threshold calculation.

For control signal experiment, when the standard deviation threshold calculation is applied using a peak detection known as M-ATPD, time consumption is reduced by about 2 times faster compared to ATPD. The detection error of M-ATPD in relation to noise signals decreases by 6.67% compared to ATPD. In other words, M-ATPD is a more accurate method for conducting peak detection on noise signals compare to ATPD.

For raw signal, four types of biosignal (ECG, BP, EEG and Resp(sum)) were selected in order to investigate the performance of M-ATPD. The results show that the M-ATPD algorithm can achieve 19.41% lower DER compared with ATPD, and in terms of computational time, M-ATPD can perform 8.65times faster than ATPD. Overall, the results demonstrate that the proposed M-ATPD algorithm gives better performance than ATPD.

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	Prof. Dr. Uda Hashim is a Professor at Institute of Nano Electronic Engineering (INEE), Universiti Malaysia Perlis (UniMAP), and was a Director for the INEE, UniMAP since October 2008 . He has more than 25 years experience in Semiconductor Devices, CMOS Based Sensor, Nanoelectronic and Nano Biochip in both the industry and academic sectors.