Performance Comparison of Automatic Peak Detection for Portable Signal Analyser

Teh Yi Jun[1], Asral Bahari Jambek[2] and Uda Hashim[3]
[1,2]*School of Microelectronic Engineering, Universiti Malaysia Perlis, Perlis, Malaysia*
[3]*Insituite of Nano Electronic Engineering, Universiti Malaysia Perlis, Perlis, Malaysia*
Email: [1]kelvinteh90@gmail.com, [2]asral@unimap.edu.my, [3]uda@unimap.edu.my

***Abstract*—The aim of this paper is to discuss the automatic threshold peak detection method. An automatic threshold peak detection algorithm is simulated with a control signal in MATLAB to determine ability to detect different signal types. A comparison is made between automatic chromatographic peak detection, adaptive threshold detection, peak of Shannon energy envelop detection, and automatic multiscale peak detection. Based on the experiment results, automatic threshold peak detection can perform peak detection for sinusoidal or triangular signal but not pulse signal. Other algorithms can perform peak detection for pulse signal but not sinusoidal or triangular signal. Automatic threshold peak detection is about 4.47 times faster than peak of Shannon energy envelop and 3980 times faster than automatic multiscale peak detection; however, automatic threshold peak detection is about twice as slow as the adaptive threshold method and automatic chromatographic peak detection.**

***Index Terms*—Nano-biosensor, Biosensor signal anlysis.**

I. INTRODUCTION

Nowadays, nano-biosensors are growing rapidly in importance, mainly in healthcare contexts. The most common biosensors are the glucose biosensor, sensor, cell-based biosensor, cardiomyocyte-based impedance sensor, and electrochemical impedance biosensor[1]–[5]. An efficiency algorithm is required to extract signal from biosensors to create a readable signal for users. Algorithms that have been studied include automatic threshold peak detection (ATPD), automatic chromatographic peak detection (ACPD), adaptive threshold detection (ATM), peak of Shannon energy envelop (PSEE), and automatic multiscale peak detection (AMPD)[6]–[11]. In our previous study, we proposed automatic threshold peak detection for portable nano-biosensor analysers due to its high accuracy and optimal computational speed. In the present work, the proposed method will be compared with other methods by simulation with a control signal.

The rest of the paper is organized as follows. Section II elaborates the detail of the experiment set-up and the method of evaluating the performance of the algorithms. The results of our experiment are presented in Section III. Section IV will make a comparison between the proposed method and other existing methods. Finally, Section V provides conclusions.

II. METHODOLOGY

In this section, first we explained the experiment. Control signals are used to test the ability and accuracy of the algorithms under review. Eighteen control signals had generated, which consisting of three types of peak: pulse, sinusoidal, and triangular, as shown in Fig.1, Fig. 2, and Fig. 3, respectively. Each type of peak signal has a best, typical, and worst case. Fig. 1 shows the best case of the non-noise pulse peak signal; Fig. 4 shows the typical case, Fig. 5 the worst case, and Fig. 6 the best 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.

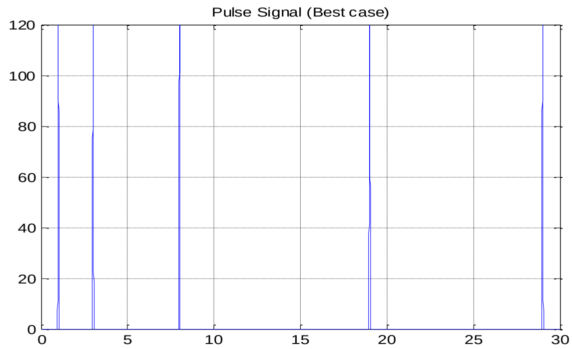

Fig. 1. Best case of non-noise pulse peak signal

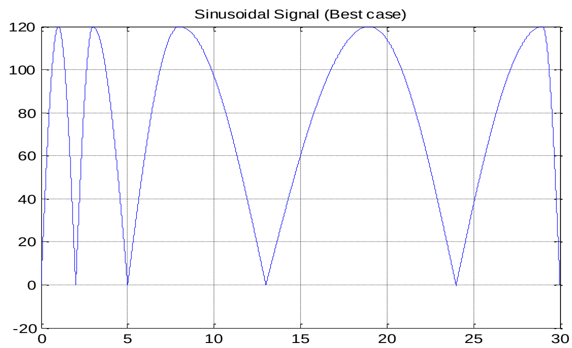

Fig. 2. Best case of non-noise sinusoidal peak signal

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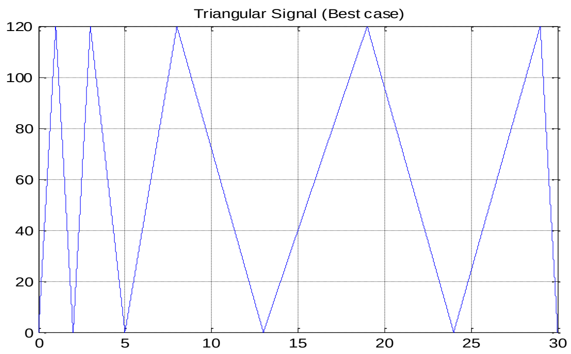

Fig. 3. Best case of non-noise triangular peak signal

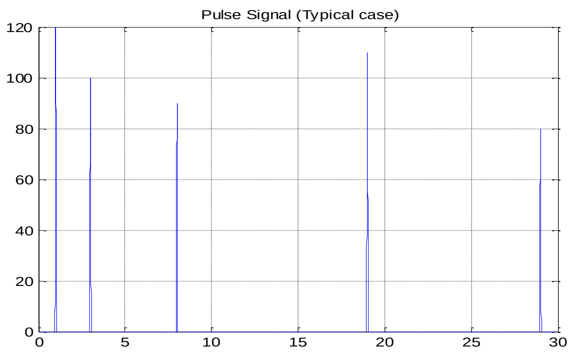

Fig. 4. Typical case of non-noise pulse peak signal

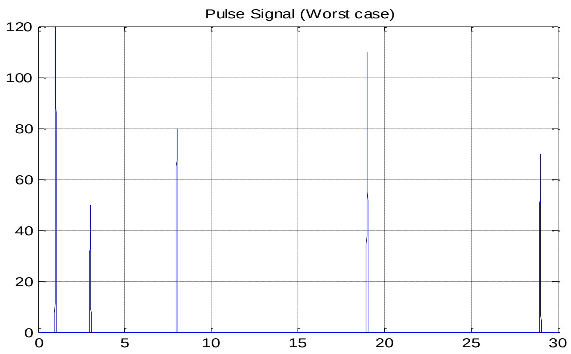

Fig. 5. Worst case of non-noise pulse peak signal

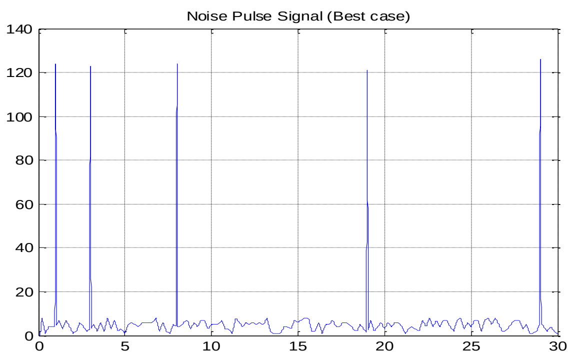

Fig. 6. Best case of noise pulse peak signal.

Next, we explained the simulation set-up. The performance and accuracy of the algorithm are simulated in a MATLAB environment (MathWorks, USA) using a computer with Win8 (64-bit) Intel®Core™i7 CPU (2.4 GHz, 8 G RAM). The simulation is carried out for 18control signals. The speed of each algorithm is obtained from the profiler feature in MATLAB.

Lastly, we explained the method to evaluate algorithm performance. To evaluate the performance of each peak detection algorithm, we use three benchmark parameters: positive prediction (+P), sensitivity (SE), and detection error (DER). To calculate +P, SE, and DER, we include false negative (FN), which represents failure to detect a true peak (peak not detected as a peak), and false positive (FP), which means false peak detection (non-peak detected as a peak). 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].

$$+P = \frac{TP}{TP+FP} \tag{1}$$

$$SE = \frac{TP}{TP+FN} \tag{2}$$

$$DER = \frac{FP+FN}{TPN} \tag{3}$$

TP is the number of true positive detections (peak detected as a peak), and TPN is the total number of peaks in a signal. +P reports the percentage of peak detections that are true peaks. SE reports the percentage of true peaks that are correctly detected by the algorithm. DER reports the percentage of peak detection error.

III. Result and Discussions

In this section, we will discuss the experimental results. First, we will explain the results of the non-noise signal. The three types of peak control signal are used as the input of the simulation to test the performance of the ATPD algorithm. The results show that ATPD is not able to perform peak detection for pulse peak control signal in the non-stop simulation. Fig. 7 shows the results of peak detection for best-case non-noise sinusoidal peak signal with ATPD. ATPD can achieve 100% positive prediction for all signals. ATPD achieves 100% error sensitivity for sinusoidal peak control signals in the best case, but for the typical case and worst case the sensitivity is 80% and 40%, respectively. ATPD achieved 100% sensitivity for triangular peak control signal in the best and typical case; however, for the worst case, the sensitivity was 60%.The total detection error for all non-noise signals was20%, with 100% positive prediction and 80% sensitivity.

Next, we will explain the results for noise signal. The three types of peak control signal with noise are used as the simulation input to test the performance of ATPD. The results show ATPD is not able to perform peak detection on pulse peak control signal with non-stop simulation. Fig. 8 shows the results of peak detection for best-case noise sinusoidal peak signal using ATPD.ATPD achieved 100% positive prediction

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for all signals. ATPD can achieve 100% sensitivity for sinusoidal peak control signal in the best case; however, the sensitivity for the typical case and worst case is 80% and 40%, respectively. ATPD achieved 100% sensitivity for triangular peak control signal in the best and typical case; however, the worst-case sensitivity was 60%.The total detection error for all noise signals was20%, with 100% positive prediction and 80% sensitivity.

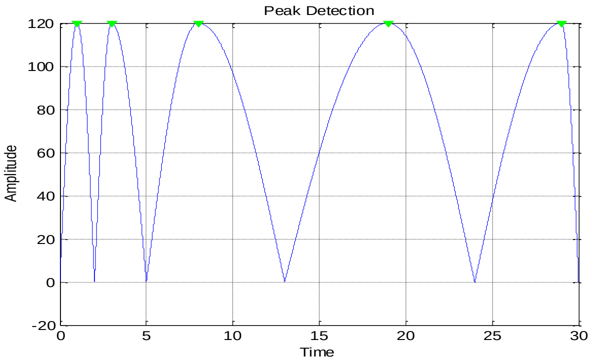

Fig. 7. Peak detection of best case non-noise sinusoidal peak signal using ATPD.

Table 1. Performance table of ATPD for non-noise control signal.

	Signal	TPN	TP	FP	FN	Se%	+P%	DER%
Pulse	Best	NA	NA	NA	NA	NA	NA	NA
	Typical	NA	NA	NA	NA	NA	NA	NA
	Worst	NA	NA	NA	NA	NA	NA	NA
Sinusoidal	Best	5	5	0	0	100.00%	100.00%	0.00%
	Typical	5	4	0	1	80.00%	100.00%	20.00%
	Worst	5	2	0	3	40.00%	100.00%	60.00%
Triangular	Best	5	5	0	0	100.00%	100.00%	0.00%
	Typical	5	5	0	0	100.00%	100.00%	0.00%
	Worst	5	3	0	2	60.00%	100.00%	40.00%
	Total	30	24	0	6	80.00%	100.00%	20.00%

*NA refer to non-stop simulation.

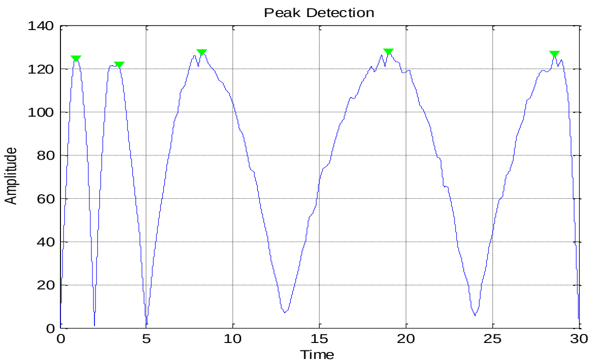

Fig. 8. Peak detection of best case noise sinusoidal peak signal using ATPD.

Table 2. Performance of ATPD for noise control signal.

	Signal	TPN	TP	FP	FN	Se%	+P%	DER%
Pulse	Best	NA	NA	NA	NA	NA	NA	NA
	Typical	NA	NA	NA	NA	NA	NA	NA
	Worst	NA	NA	NA	NA	NA	NA	NA
Sinusoidal	Best	5	5	0	0	100.00%	100.00%	0.00%
	Typical	5	4	0	1	80.00%	100.00%	20.00%
	Worst	5	2	0	3	40.00%	100.00%	60.00%
Triangular	Best	5	5	0	0	100.00%	100.00%	0.00%
	Typical	5	5	0	0	100.00%	100.00%	0.00%
	Worst	5	3	0	2	60.00%	100.00%	40.00%
	Total	30	24	0	6	80.00%	100.00%	20.00%

*NA refer to non-stop simulation.

The results for the non-noise and noise control signal show that ATPD can achieve the same accuracy with both. In neither case is ATPD able to detect peaks in the pulse peak control signal. In the simulation, the algorithm was still repeating the threshold calculation steps after five hours.

Next, we will discuss the comparison between the ATPD algorithm and the other existing algorithms described in Section II, in terms of accuracy and speed. The results show that ATPD is able to perform peak detection for sinusoidal and triangular peak control signal, but not pulse peak control signal in non-stop simulation. PSEE, ATM, ACPD and AMPD are able to perform peak detection for all types of signal, but give very high detection error for sinusoidal and triangular signals–more than 50%. PSEE and ACPD use the gradient of the signal to detect the peak. In these two algorithms, a peak is defined when the positive and negative gradients are much greater than otherwise. For sinusoidal and triangular peaks, the gradient is always constant, so the peaks cannot be detected. With ATM, a peak is detected when there is a negative gradient greater than the slope of the algorithm. In sinusoidal and triangular peak control signal, the peak negative gradient is always smaller than the slope of the algorithm; therefore, peak detection cannot take place. AMPD uses window size to perform peak detection. Thus, in the noise pulse peak control signal, some noise is detected as peaks. For the sinusoidal and triangular peak control signal, the peaks occur at different times, and hence have different window sizes; peak detection therefore cannot take place. Table 3 summarizes the detection error for each method. Fig. 9, Fig. 10, Fig. 11, and Fig. 12 show the peak detection of best-case non-noise pulse peak signals using PSEE, ATM, ACPD, and AMPD, respectively.

Table 3. Comparison of detection error.

		ATPD (%)	PSEE (%)	ATM (%)	ACPD (%)	AMPD (%)
Non-Noise Signal	Pulse	NA	40.00%	0.00%	40.00%	0.00%
	Sinusoidal	26.67%	140.00%	166.67%	100.00%	73.33%
	Triangular	13.33%	193.33%	73.33%	100.00%	66.67%
Noise Signal	Pulse	NA	0.00%	0.00%	0.00%	140.00%
	Sinusoidal	26.67%	293.33%	206.67%	100.00%	66.67%
	Triangular	13.33%	333.33%	86.67%	100.00%	73.33%

*NA refer to non-stop simulation.

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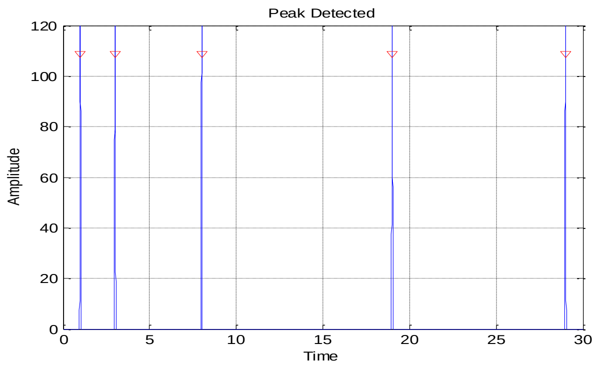

Fig. 9. Peak detection for best case non-noise pulse peak signal using PSEE.

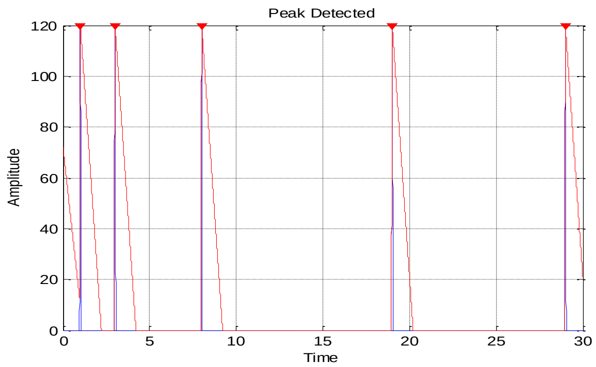

Fig. 10. Peak detection for best case non-noise pulse peak signal using ATM.

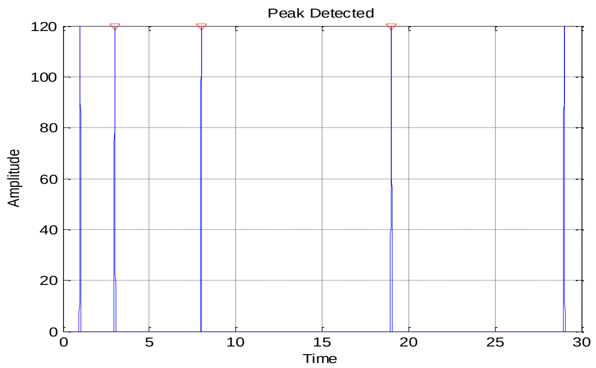

Fig. 11. Peak detection for best case non-noise pulse peak signal using ACPD.

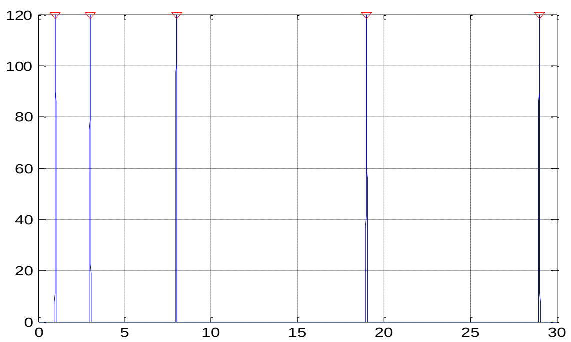

Fig. 12. Peak detection for best case non-noise pulse peak signal using AMPD.

Table 4. Comparison of speed.

		ATPD (s)	PSEE (s)	ATM (s)	ACPD (s)	AMPD (s)
Non-Noise Signal	Pulse	NA	2.604	0.279	0.326	2397.588
	Sinusoidal	0.561	2.582	0.291	0.327	2359.904
	Triangular	0.581	2.476	0.294	0.328	2095.117
Noise Signal	Pulse	NA	2.587	0.281	0.328	2368.870
	Sinusoidal	0.563	2.516	0.287	0.326	2077.474
	Triangular	0.562	2.450	0.287	0.335	2239.899
	average	0.567	2.536	0.287	0.328	2256.475
	Normalize of average to ATPD	1.00	4.47	0.51	0.58	3979.67

*NA refer to non-stop simulation.

Table 4 summaries the computational speed of ATPD, PSEE, ATM, ACPD and AMPD. The average results show that ATM is the fastest algorithm and AMPD the slowest. ATM can perform detection in 0.287s;meanwhile, AMPD requires 2256.475s. The second fastest algorithm is ACPD, followed by ATPD and PSEE, which need 0.328s, 0.567s, and 2.536 s, respectively. The comparison shows that ATPD is in the middle among the five algorithms in terms of speed. ATPD is about 4.47 times faster than PSEE and 3980 times faster than AMPD; however, ATPD is about twice as slow as ATM and ACPD.

IV. Conclusions

In this paper, the performance of a proposed ATPD algorithm has been discussed in detail. The performance has been evaluated using a benchmark method proposed by other researchers. The performance of the ATPD algorithm was compared to that of the PSEE, ATM, ACPD and AMPD algorithms. From the experimental results, ATPD can perform peak detection for sinusoidal and triangular types of signal, but not pulse signals. Meanwhile, other algorithms can perform peak detection for pulse but not sinusoidal or triangular signal. In terms of computational time, ATPD was 4.47 times faster than PSEE and 3980 times faster than AMPD, but twice as slow as ATM and ACPD.

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