Proceedings Paper:

Yang, D., Bhargava, E., Elphick, H. et al. (1 more author) (2023) An adaptive CUSUM approach for automating sleep apnoea analysis based on pulse and oximetry data. In: 2023 IEEE International Conference on Mechatronics and Automation (ICMA) Proceedings. 2023 IEEE International Conference on Mechatronics and Automation (ICMA), 06-09 Aug 2023, Harbin, Heilongjiang, China. Institute of Electrical and Electronics Engineers (IEEE) , pp. 557-562. ISBN 9798350320855

https://doi.org/10.1109/ICMA57826.2023.10215850

An Adaptive CUSUM Approach for Automating Sleep Apnoea Analysis Based on Pulse and Oximetry Data

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***Abstract*—Sleep apnoea is a common sleep disorder during human sleep. It is usually diagnosed by a doctor after recording one nights' sleep signals. Patients have to go to the hospital to record sleep signals, which is time-consuming and resource-intensive. The study focused on two signals, pulse data and oximetry data, with the aim of detecting apnoea using a single signal. This paper introduced an anomaly detection approach using the adaptive cumulative sum (ACUSUM) change point detection algorithm to monitor outliers in the signal. In addition, the test results of ACUSUM will be compared with the test results of classical CUSUM. Besides, the threshold selection has been changed from an unchanging constant to a value related to the standard deviation of the selected signal based on a rational subgroup process. The results of the comparison confirm that ACUSUM is better than classical CUSUM in the accuracy of automatic detection.**

***Index Terms*—Adaptive CUSUM, Sleep Apnoea.**

I. Introduction

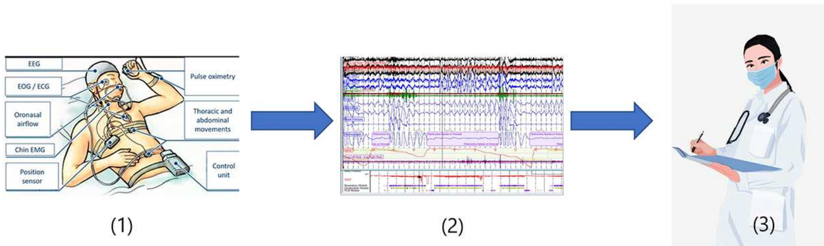
A. Background

Humans spend about a third of their lives sleeping. Sleep disorders, such as insomnia and obstructive sleep apnoea, severely impact the quality of life of patients. Without restrictive criteria, the prevalence of insomnia is approximately 33% in the general population [1]. Patients with sleep apnoea experience periods of no or shallow breathing while sleeping. The former situation, in which breathing temporarily stops, is referred to as apnoea, whereas the latter, in which breathing is shallow or airflow is restricted, is referred to as hypopnoea. Both diseases can result in clinical comorbidities and are thus harmful to human health [2]. Snoring, gasping during sleep, dry mouth upon awakening, and overall poor sleep quality are all physiological indicators of sleep apnoea, which can lead to poor focus, insomnia, cognitive decline, accidents, memory loss, and depression. Sleep apnoea can cause serious problems such as diabetes, cardiovascular problems, high blood pressure, neurological problems, and liver problems, in addition to a reduced quality of life caused by lack of sleep and fatigue. Because of its high global prevalence and long-term effects on sleep, detection and treatment of sleep apnoea are critical. [3].

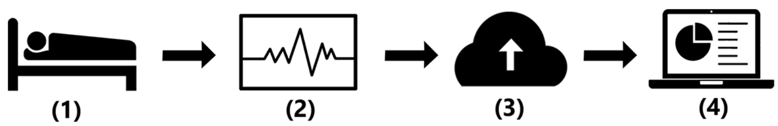
There are three types of sleep apnoea [4]:

1) Obstructive sleep apnoea (OSA) is the more frequent pattern, characterized by the presence of thoracic effort for continuing breathing while air flow completely stops. When the hard palate muscles at the back of the throat that support the soft palate relax, the soft palate blocks air from entering the respiratory system. This causes short-term cessation of breathing.
2) Central sleep apnoea (CSA) occurs when the brain fails to generate or transmit the signals that control the muscles of breathing. It is characterized by a complete cessation of respiratory movement and airflow for at least 10 seconds.
3) Mixed sleep apnoea (MSA): Complex sleep apnoea syndrome is characterized by persistent central apnoea even after obstructive events have resolved after Positive Airway Pressure (PAP) therapy. This pattern is a combination of the first two patterns, defined as central apnoea followed by obstructive ventilatory efforts in relatively short time intervals.

Polysomnography (PSG) is a gold standard diagnostic test used to study sleep and diagnose various sleep disorders. Some people refer to PSG as a sleep study. Sleep technologists perform tests that are usually performed in hospitals, independent facilities, or specialized sleep clinics [5]. Sleep monitoring is a complex process and requires a unique set of skills, including detailed knowledge of Electroencephalography (EEG), respiration monitoring, and Electrocardiography (ECG) [6]. Sleep monitoring [6] was traditionally accomplished by recording polygraphs using ink pens that produced tracings on paper. A common paper speed for sleep recording is 10 mm/s, with a 30 cm page corresponding to 30 seconds. Each period represented by a page is called an epoch. Most sleep recordings are digital these days, but the convention of scoring sleep in 30-second epochs or windows is still the standard. PSG is a recognized technique for sleep analysis of patients. However, it requires patients to go to hospitals or special wards, because patients need to wear relevant sensors to record signals, which will increase medical expenses. After the data is obtained, the clinician must manually diagnose it, which consumes a lot of time for the doctor (see Figure 1a). To address this issue, researchers have focused their efforts on automated



(a) Polysomnography based sleep apnoea analysis framework. (1) Patient wearing full sensors while sleeping. (2) PSG recording. (3) Clinician diagnosis.



(b) Automated Sleep Apnoea Analysis Framework. (1) Patient sleep at home with simple instrument. (2) Data (Pulse, SPO2) recording. (3) Upload to cloud. (4) Automatic analysis

Fig. 1 sleep apnoea analysis framework

sleep disordered breathing (SDB) detection. Mendonça [7] presents an analysis of a series of existing algorithms and evaluates the performance of different signals (pulse oximetry, ECG, respiration, sound and combined methods) to detect apnoea. Nocturnal pulse oximetry [8] is suggested to replace polysomnography because it can easily measure heart rate (Pulse data) and oxygen saturation (SPO2 data). In addition, there are more advanced technologies (such as the Apple Band) to monitor the heartbeat. This means that patients can perform data collection at home and the collection method is more convenient. After the data is collected, it will be directly uploaded to the cloud network for automatic analysis, as shown in Figure 1b. For sleep apnoea detection, most detection rules are based on the American Academy of Sleep Medicine (AASM) manual [9]. In this manual, it gives several ways to evaluate the sleep signal, especially sleep stage classification and sleep apnoea analysis. Most sleep research revolves around the detection of a single signal.

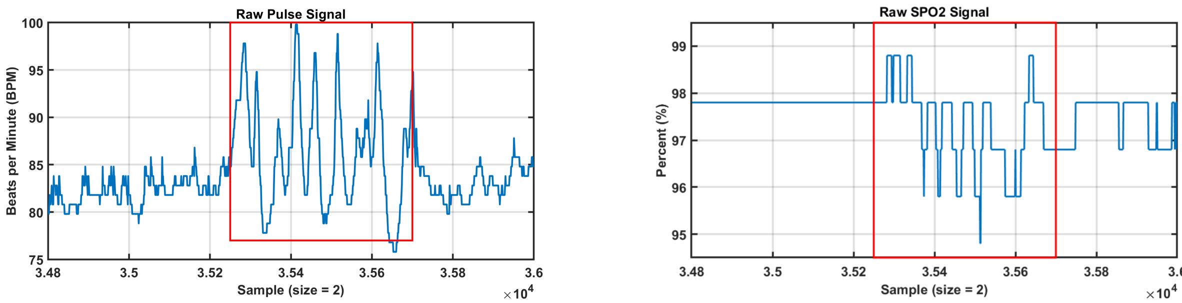
This research mainly focuses on oxygen saturation data and pulse data. Through data visualization and comparison with normal sleep signals, it could be found some difference between normal and abnormal. Figure 2 shows the differences on oxygen and pulse data when sleep apnoea happened. From Figure 2, the red box circles the moment when the apnoea occurs. It can be seen that both the pulse and oxygen data fluctuate violently, which shows that the variance of the signal is constantly changing. This is also the main signal feature, mean and variance, extracted in this experiment.

B. Related Work

In the long history, people's research on sleep signals and the detection of sleep apnoea disease have not stopped. Fabio Mendonca and his colleague publish an article on sleep apnoea disease detection [7]. This article evaluates the performance of different algorithms and methods for apnoea detection by using different sensors (pulse oximeter, ECG, respiration, sound, and combined methods). In addition to this, existing algorithms that have not yet been implemented in hardware but whose performance has been validated by at least one experiment designed to detect obstructive sleep apnoea to predict trends are also analysed. The author provides valuable information for those researchers who want to carry out a hardware implementation of potential signal processing algorithms. This article also mentioned the use of sound to determine the appearance of apnoea and provides a better understanding of the software implementation. However, the fly in the ointment is that the article mainly introduces single signal detection and methods, and now people have gradually beginning to combine signals for detection, and achieved good results.

In 2017, Gokhan Memis and Mustafa Sert present a multimodal approach for the OSA classification task [10]. They extracted features from ECG and SpO_2 signals, combined these features with appropriate fusion methods, and fed them to learners. The researchers use Support Vector Machine (SVM), and K-nearest neighbors (kNN) classifiers to demonstrate the effectiveness of their proposed method by considering different test scenarios. Moreover, in all scenarios, the average accuracy of the SVM method is 96.64%, which is the best classification method among the proposed multimodal methods with feature-level fusion. Although the author provides good training ideas, he does not describe the details of the selected features.

Different from the article introduced above, the classification of EEG signals which published in 2019 [11] is to use different frequencies as a means of classification. Using frequency to study the signal can extract features more intuitively, which is very helpful for the classification of sleep stages. This work employs features such as energy, entropy, and variance,



(a) Raw pulse signal which has apnoea (b) Raw oxygen signal which has apnoea

Fig. 2 Examples of apnoea and normal signal

which are computed for each frequency band obtained from the decomposed EEG signal. Similar to this author, Wu Huang [12] proposed to use frequency as a method to do classification. However, the difference is that he used frequency as pre-processing. He uses multi-channel signal superposition, and finally obtains 12 effective features. Then, using SVM classifier, the classification accuracy can reach up to 98.28%.

Change point detection (CPD) is useful in time series modelling and forecasting [13], as well as in applications such as medical condition monitoring, climatic change detection, voice and image analysis, and human activity analysis. Many of the proposed approaches for identifying change points in time series are enumerated, classified, and compared by Samaneh. According to this survey, the window size influences practically all techniques of change detection. Combining various window widths can be an effective way to use the best window length for each subsequence. The sleep signal is an instantaneously observed signal, online change detection can be a future development trend. Thomas [14] proposed a method seems more suitable for change detection which is Cumulative Sum (CUSUM) and kernel-based methods for online detection. Although this algorithm has proven to be widely used in, there still one thing needs to be considered is that most present algorithms compare detection change scores with a threshold to evaluate whether a change has happened. Choosing the optimal threshold is difficult. Moreover, these methods are mostly used to deal with stationary sequences, while sleep signals are mostly non-stationary sequences. An ongoing challenge for CPD is dealing with non-stationary time series. In 2011, Varun Chandola published an article that introduced a Gaussian Process Based Online Change Detection Algorithm [15]. He gave a detailed algorithm of Gaussian processing (GP) and added further calculation of Gaussian parameters on this basis. The new algorithm, called ToeplitzSolveInc, is more efficient, computationally faster, and able to have more cloud memory than the old one. To prove that his algorithm is more efficient, he also gave a table [15] (table I) to show other time series algorithms performance, such as Seasonal Autoregressive and Integrated Moving Average (SARIMA), Recursive Merging (RM), CUSUM, Log-likelihood Ratio Test (LRT) and Bayesian Online Change Detection (BOCD).

Table I gives references on which method is suitable for ECG signal. Compared with the automatic calculation of parameters above, the article [16] published in 2016 gives

TABLE I

RELATIVE PERFORMANCE OF DIFFERENT CHANGE DETECTION ALGORITHMS.

	GPC	SARM	RM	CSUM	LRT	BOCD
SYNC1	√	√	√	×	√	×
SYNC2	√	×	√	×	√	×
SYNC3	√	√	√	×	×	×
ECG1	√	N A	√	√	×	√
ECG2	√	N A	√	√	×	√
NVDI1	√	×	×	×	×	×
NVDI2	√	√	√	×	√	×
NVDI3	√	√	√	×	×	×
NVDI4	√	√	√	√	√	×

a new application idea of Gaussian parameters. This paper presents the recently proposed modelling of normal inverse Gaussian (NIG) probability density function (pdf) modeling in the adjustable tunable-Q factor wavelet transform (TQWT) domain for computer-aided sleep apnoea diagnosis from single-lead ECG signals. The researchers calculated the corresponding NIG parameters based on the subbands of each ECG signal segment decomposed by TQWT, which are used as features in the proposed apnoea detection algorithm. The advantage of this algorithm is that the characteristic parameters are intuitively given. However, as Varun said, the calculation and parameter selection increase the workload. In spite of this, the performance of this algorithm is also superior, after all the parameters are explicit.

The main contributions of this paper are as follows: First, the Adaptive CUSUM (ACUSUM) algorithm is used to detect abnormalities in Pulse and Oximetry data, and automatically identify whether there is sleep apnoea in a epoch. Second, a rational subgroup process is proposed to improve the detection results by changing the threshold. Next, the two detection results are combined for automatic analysis. Finally, compare with the detection results of the traditional CUSUM algorithm. The traditional CUSUM algorithm as well as the modified CUSUM algorithm, which is ACUSUM, including parameter configuration are discussed in Section II. Section III presents a comparison of the accuracy and computational complexity of CUSUM and adaptive CUSUM. In addition, the preparation process before automatic detection is also provided. Furthermore, single data detection and combined data detection are also compared.

II. METHODOLOGY

A. The Cumulative Sum Algorithm

The cumulative sum (CUSUM) is a sequential analysis algorithm developed by E. S. Page of the University of Cambridge [17]. It is often used to monitor change detection [18].CUSUM has different methods to determine if process is out of control. Rather than finding non-constant control limits for the CUSUM, it is easier to transform the CUSUM to a score for which the control limits is constant. This separate score is called the Mean Adjust CUSUM [19], which is mainly introduced here.

Instead of examining the mean of each subgroup independently, the CUSUM plot displays information accumulating current and previous samples. Therefore, a CUSUM chart is generally better at detecting small changes in the process mean than an X-bar chart. CUSUM plots rely on the specification of the target value and the standard known or reliable estimated deviation. Therefore, after establishing process control, it is best to use the CUSUM chart. [20] CUSUM plots typically represent runaway process summations by accumulating upward or downward drift until it crosses a boundary. Following the CUSUM procedure presented by Koshti [21], the steps for creating a CUSUM control chart can be summarized as follows:

1) Cumulative Sum: Let us collect m samples, each of size n, and compute the mean μ_i of each sample. A Gaussian (normal) distribution $\mathcal{N}(.)$ is considered in the analysis:

$$x_i \sim \mathcal{N}(\mu_i, {\sigma_i}^2), \tag{1}$$

where μ_i is the mean and σ_i is the standard deviation of the samples. Then the CUSUM control chart is formed by plotting one of the following quantities [22]:

$$C_m = \sum_{i=1}^{m}(x_i - \hat{\mu}_i), \tag{2}$$

against the sample number m, where $\hat{\mu}_i$ is the estimate of the in-control mean.

2) The Tabular CUSUM for Monitoring the Process Mean: In the last part of the introduction, when the process is under control, x_i has a normal distribution with mean μ_i and standard deviation σ_i (known or estimable). The tabular CUSUM works by accumulating deviations from μ_i which displayed as C^+ and C^-. C^+ means one sided upper and C^- means one sided lower. With the starting value $C_i^+ = C_i^- = 0$, they are calculated as [17]

$$\begin{aligned} C_i^+ &= max[0, x_i - (\mu_i + k) + C_{i-1}^+], \\ C_i^- &= max[0, (\mu_i - k) - x_i + C_{i-1}^+], \end{aligned} \tag{3}$$

where k is the "slack" allowed in the process, and it is chosen halfway between the target μ_0 and the mean shift of interest μ_1 to detect

$$k = \frac{1}{2} \cdot |\mu_1 - \mu_0|. \tag{4}$$

The CUSUM values C^+ and C^- accumulate the deviation from the target value μ_0 that are greater than k. In this experiment, mean shift is choose 1, so K=0.5. If H is the decision interval and if either C^+ and C^- exceeds H, the process is said to be out of control [23]. The H interval is determined as follows

$$H = h \times \sigma, \tag{5}$$

where h is a commonly used constant whose values are between 2 and 4 and $\times$ denotes the multiplication operation. In the adaptive CUSUM algorithm presented in the next section the value of σ varies according to a decision making rule.

B. Adaptive CUSUM Based on log-likelihood Ratio

As the introduction of CUSUM in Section II-A, the parameter k which known as mean shift is set to be 1 as usual. However, it should be change every time depend on the window. To overcome the problem of unknown parameters changing over time, an adaptive cumulative sum is presented. The combination of detecting changing processes and estimating parameters is thought to improve performance. [24] The concept is to guess the parameters in a continuous form, with the CUSUM test beginning immediately regardless of the precision of the prediction. Because more sample estimation may result in more accurate estimation, the estimation procedure proceeds while detection is performed. [25] This section mainly introduced what ACUSUM is and how it improve the classical CUSUM algorithm.

Let $X = \{x_1, x_2, ..., x_m\}$ be a random collection of data received consecutively. For the sleep apnoea analysis, these are typically polysomnography, oxymetry and pulse data. We suppose that each value x_i belongs to a known pdf $p(x_i, \theta)$, in this case to a Gaussian distribution. These samples have a known mean μ_i and variance σ^2. Assume a change happened at time t_c, so there are two possible hypotheses: $\mathcal{H}_0$ for pre-change (with a parameters $\theta = \theta_0$) and $\mathcal{H}_1$ for post-change (with other parameters $\theta = \theta_1$). The parameter θ is in the form: $\{\mu, \sigma\}$.

The instantaneous log-likelihood ratio test is used to decide between the two hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$:

$$S_i = ln\left(\frac{p(X, \theta_1)}{p(X, \theta_0)}\right) \tag{6}$$

and the cumulative sum of S_i from 0 to m is

$$S_m = \sum_{i=0}^{m} S_i \tag{7}$$

When the difference gt between the value of the cumulative sum S_m and its present minimum value m_n at time m is greater than a specified threshold value h, CUSUM detects a change in X [26]:

$$G_m = S_m - m_{S_m} \geq h, m_n = \min_{1 \leq i \leq n} S_m. \tag{8}$$

For normal distribution function, equation (6) could be simplified [25] to

$$S_i = \frac{\mu_{x_1} - \mu_{x_0}}{\sigma_X^2}(x_i - \frac{\mu_{x_1} + \mu_{x_0}}{2}). \tag{9}$$

C. Threshold Selection Based on Rational Subgroup

The expression of the decision interval H from equation (5) is used in the change detection process. However, different sample sizes affect the variance, which means that the thresholds for each window are not defined under the same conditions [27].

To solve this, the standard deviation σ should replaced by sampled deviation in rational subgroup [28] (of sizes $n > 1$):

$$\sigma_{sample} = \frac{\sigma}{\sqrt{n}}. \tag{10}$$

In classical CUSUM algorithm, σ for threshold calculation is deviation of signal data value. Usually the threshold of ACUSUM is a self-defined constant within a certain range. In this test, according to the same threshold calculation idea (using variance), ACUSUM uses decision function Gm to calculate σ and adds overlap to achieve adaptive threshold.

III. Experimental Validation

A. Data Analysis and Pre-processing and Initialization

The data is from public organization National Sleep Research Resource (NSRR). There are 387 edf data sets and each of them has different data inside such as Pulse data, Oxygen data, which are used in this research. First, the data should be extracted one by one and transfer from edf format to mat format. Considering the erroneous data caused by the movement of the device on the wearer during sleep, those data with more than half of the erroneous values need to be discarded. For instance, one of the Pulse data has more than half of the value 300. Because this research wants to compare the separately detection results and combined detection results, if any one of the oxygen data and pulse data has an excessive error, the patient's data will be discarded. In addition to this, those selected data will also have wrong values, and these values will be replaced by the correct values behind it. Finally, recording the sampling frequency will be helpful to judge threshold of each window (equation (10)).

Based on AASM, the window size of this experiment is 30 seconds. In order to make the experiment more accurate, overlap is set when moving the window, so that each epoch can be compared before and after.

B. Detection Results

In this detection, the window size (WL) for calculation is one epoch (30 seconds) which means $WL = 30 \times fs(sample\ size)$. In order to get higher accuracy of detection, an overlap was added in this algorithm, which is set to 10. In addition to this, mean shift is set to default 1. Furthermore, as Subsection III-A mentioned, after data processing, there are 367 data sets used in test.

Figure 3 and Figure 4 give a results of the sleep signals change detection and comparison between the ACUSUM and classical CUSUM algorithm. First two of each figure are the results of two algorithm. The blue line in ACUSUM is the decision function (G_m) from equation 8 and the blue line in CUSUM is upper sum (C^+) from equation 3. The red line is the threshold in the different algorithms above which the signal is out of control, which is considered sleep apnoea. The black vertical line is the actual sleep apnoea occurrence time, which is used to compare with the detection results. The third figure of each is original sleep signal. By comparing with the original signal, it can be seen that both algorithms can detect signal changes to varying degrees. However, compared with the actual time of apnoea occurrence time, CUSUM algorithm can detect the moment of signal change, while ACUSUM algorithm can more effectively distinguish whether the apnoea occurs in an epoch.

Table II gives statistical results - the average accuracy of detection. It can be seen that the accuracy of ACUSUM is naturally higher than that of classical CUSUM. Combined detection is the intersection of the results of individual detection, and its accuracy is much higher than that of individual detection, which is the same as the expected. However, the time of

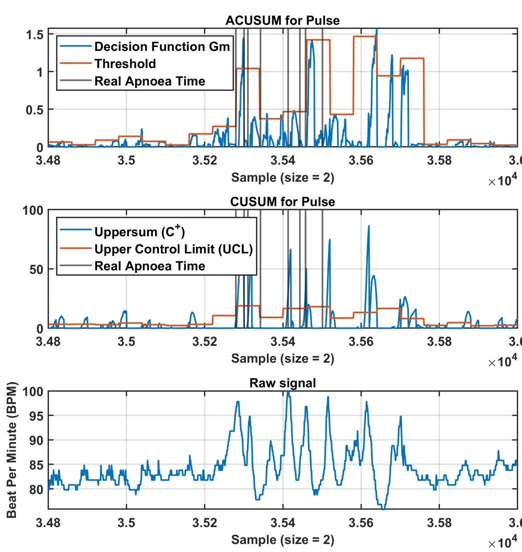


Fig. 3 Comparison between Adaptive CUSUM Algorithm and classical CUSUM on Pulse Signal.

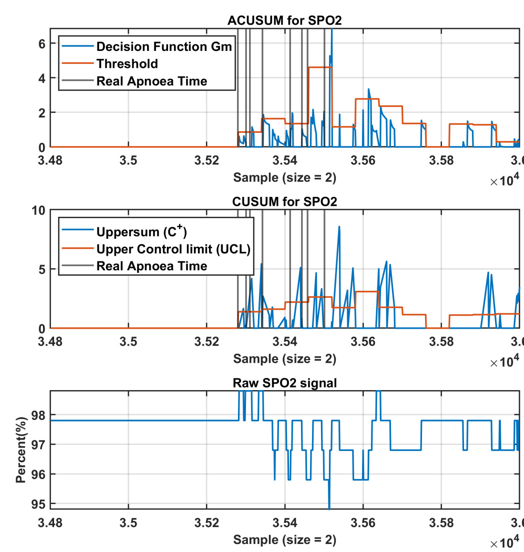


Fig. 4 Comparison between Adaptive CUSUM Algorithm and classical CUSUM on Oxygen Signal.

TABLE II
AVERAGE ACCURACY OF DETECTION OBTAINED AFTER AVERAGING OVER 367 DATA SETS.

	ACUSUM	CUSUM
Detection of combination	91.78	88.97
Detection of Pulse	79.57	73.68
Detection of SPO2	85.74	74.85

ACUSUM Algorithm is much longer than classical CUSUM. Classic CUSUM takes about 1 second on average for one dataset, while ACUSUM takes about 10 minutes on average because it takes more time if the sample values are large.

IV. CONCLUSION AND FUTURE WORK

This paper proposes automating the sleep apnoea via an adaptive CUSUM algorithm. The algorithm is compared with the classical CUSUM algorithm. In addition, this experiment used two kinds of data, pulse signal and blood oxygen signal. The experiments tested them separately and finally combined the results. Analytical results proved that adaptive CUSUM is generally better than the classical CUSUM algorithm. One problem of this test is this program can only do offline detection since it concerned different sample value of the signal. If the data is huge, it will cost long time to get results. One possible solution is to introduce a related method of Gaussian processing to fit the data to obtain a simple signal for detection. In addition to improve data processing, more functions can be added in the detection. The data selected in this research contained a combination of obstructive, central and mixed apnoeas, as described in Section I. Future research could explore distinguishing features of the individual types of apnoea.

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