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Research Article

Automatic Threshold Determination for a Local Approach of Change Detection in Long-Term Signal Recordings

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CUSUM (cumulative sum) is a well-known method that can be used to detect changes in a signal when the parameters of this signal are known. This paper presents an adaptation of the CUSUM-based change detection algorithms to long-term signal recordings where the various hypotheses contained in the signal are unknown. The starting point of the work was the dynamic cumulative sum (DCS) algorithm, previously developed for application to long-term electromyography (EMG) recordings. DCS has been improved in two ways. The first was a new procedure to estimate the distribution parameters to ensure the respect of the detectability property. The second was the definition of two separate, automatically determined thresholds. One of them (lower threshold) acted to stop the estimation process, the other one (upper threshold) was applied to the detection function. The automatic determination of the thresholds was based on the Kullback-Leibler distance which gives information about the distance between the detected segments (events). Tests on simulated data demonstrated the efficiency of these improvements of the DCS algorithm.

1. INTRODUCTION

Change detection and segmentation are the first steps of many signal processing applications (see, e.g., speech processing [1–4], video tracking [5], ergonomics [6], biomedical applications [7–9], seismic applications [10]). Most detection and segmentation algorithms are based on the theory of statistical detection and hypothesis testing [10–12].

In such an approach, a change occurs when the statistical properties of the signal are modified. Roughly speaking, this can be expressed either by a different distribution function before and after the change time, or by a modification of the parameter value of the same distribution. For the latter case, when the parameter values are a priori known, an efficient algorithm to solve the detection problem is the CUSUM (cumulative sum) algorithm based on the log-likelihood ratio [10, 13]. CUSUM algorithm is optimal in the sense that it optimizes the worst detection delay when the mean time between false alarms goes to infinity [10].

In many applications, modifications can affect energy, frequency, or both [14, 15]. Detection of a change in the frequency content can be performed using the CUSUM algorithm applied on the innovation of an AR (auto regressive) or ARMA (auto regressive moving average) modeling [4, 10], the AR (or ARMA) coefficients carrying information about the frequency content of the signal [14].

In usual applications, the parameters corresponding to the segments to be detected are often unknown and other algorithms have to be applied for change detection. Such algorithms can be found in [9, 16], based on the computation of a dynamic cumulative sum (DCS) of the likelihood ratio between two locally estimated distributions. These distributions are estimated at each time t using two sliding windows before and after the current time t.

In this paper, we propose a modified method of DCS that can be adapted to long duration signals. This modification is achieved on windows length and thresholding. The main application of our study is to detect fatigue of in postural muscles during driving. For that purpose, electromyography (EMG) signals are acquired continuously during a long-term driving task and the first step of the analysis is to detect segments of the signal that contains EMG with a reasonable signal to noise ratio.

The first part of this paper provides an overview of the CUSUM algorithm, focusing on the dynamic cumulative sum to describe its main properties and limits. Then a modified detection algorithm is proposed to go beyond these

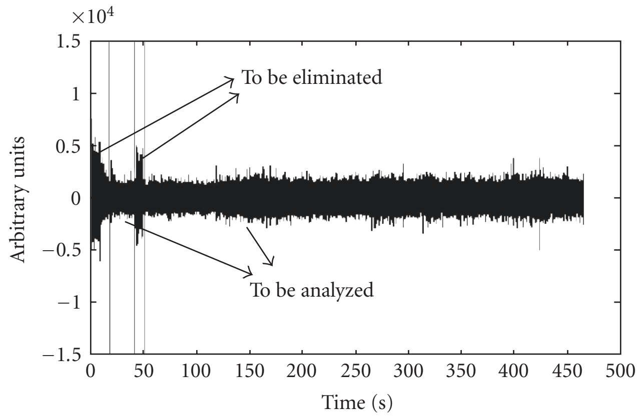

Figure 1: EMG signal and its contents. Contractions have to be detected (segmented) and eliminated. x-axis: time in secondS. y-axis: arbitrary unit.

limits. An automatic determination of the thresholds is presented in the third part of the paper.

2. PROBLEM STATEMENT

The fatigue that can be produced during driving can be detected by studying the EMG signal of the active muscles. In our work, this signal is acquired on the muscles during 2.5 hours of driving, the global aim being to detect the level of the fatigue during driving.

These signals contain a background (low-level) activity corresponding to the postural maintaining (what is the part of interest for the study) as well as high level epochs corresponding to muscle contractions related to voluntary motions. These events have to be eliminated from the signal in order to keep the only muscle activity corresponding to the "resting" state (postural activity: Figure 1).

To eliminate the voluntary contractions from the signal, we developed a new method of detection (MDCS) that can be adapted to long duration signals. After change detection and signal segmentation, the next step (not presented in this paper) would be to compute indices like the median frequency of the resting segments to quantify the fatigue. In this paper we only focus on the first problem of detection-segmentation.

3. DCS AS AN EXTENSION OF THE CUSUM ALGORITHM

3.1. Overview of the CUSUM algorithm

Let $(x_1, x_2, \ldots, x_n)$ be a sequence of observed random variables with conditional probability density $f_{\theta_0}(x_k/x_{k-1}, \ldots, x_1)$ before the change time t_0, θ_0 being the parameter vector of the segment S_0 before t_0, and with conditional probability density $f_{\theta_1}(x_k/x_{k-1}, \ldots, x_1)$ after this change time, θ_1 being the parameter vector of segment S_1 after t_0.

Let S_1^k be the sum of the logarithms of the successive likelihood ratios [10]:

$$S_1^k = \sum_{i=1}^{k} s_i = \sum_{i=1}^{k} \log \frac{f_{\theta_1}(x_i/x_{i-1}, \ldots, x_1)}{f_{\theta_0}(x_i/x_{i-1}, \ldots, x_1)}. \quad (1)$$

The decision function is defined as

$$g_k = S_1^k - \min_{1 \le j \le k} S_1^j \quad (2)$$

and the corresponding stopping time is

$$t_s = \min\{k : g_k \ge h\}, \quad (3)$$

where h is a given threshold.

Given that $E_{\theta_0}[s_i] < 0$ and $E_{\theta_1}[s_j] > 0$ (detectability property), an estimated value of change time t_0 can be obtained by the relation

$$t_0 = \max\{k : g_k = 0\}. \quad (4)$$

The CUSUM algorithm can be written in a recursive way as [10]

$$\begin{aligned} g_0 &= 0, \\ g_k &= \max(0, g_{k-1} + s_k). \end{aligned} \quad (5)$$

In the case of independent zero mean Gaussian sequences and when the point is to detect a change of variance, the expression of the likelihood ratio becomes [10]:

$$s_i = \frac{1}{2} \ln \frac{\sigma_0^2}{\sigma_1^2} + x_i^2 \left(\frac{1}{2\sigma_0^2} - \frac{1}{2\sigma_1^2} \right), \quad (6)$$

$$\left(\text{Because: } f_{\theta_0}(x_i) = \frac{1}{\sqrt{2\pi}\sigma_0} e^{-x_i^2/2\sigma_0^2};\ f_{\theta_1}(x_i) = \frac{1}{\sqrt{2\pi}\sigma_1} e^{-x_i^2/2\sigma_1^2} \right). \quad (7)$$

3.2. Application after autoregressive modeling

A signal is AR-modeled if it can be written as

$$x_i = -\sum_{n=1}^{p} a_n \cdot x_{i-n} + \varepsilon_i, \quad (8)$$

where ε_i are the innovations or prediction errors of the signal (white noise). The terms a_i are the coefficients of the model and contain frequency information of the signal. The variance σ_0^2 of the innovations gives the energy of the signal. In general, detection cannot be applied on dependent signals. Therefore the change detection algorithm is applied on the sequences of prediction errors deduced from AR (autoregressive) modeling for S_0 (before change time, $\theta_0 = (a_1^0, \ldots, a_p^0, \sigma_0^2)$) and S_1 (after change time, $\theta_1 = (a_1^1, \ldots, a_p^1, \sigma_1^2)$) [10, 14]:

$$s_i = \frac{1}{2} \ln \frac{\sigma_0^2}{\sigma_1^2} + \frac{(\varepsilon_i^0)^2}{2\sigma_0^2} - \frac{(\varepsilon_i^1)^2}{2\sigma_1^2}, \quad (9)$$

where

$$\varepsilon_i^l = x_i + \sum_{k=1}^{p} a_k x_{i-k}; \quad l = \{0, 1\}. \quad (10)$$

3.3. The DCS algorithm

Many algorithms can be found that detect spectral changes when the parameters are unknown (see, e.g., the Brandt algorithm [10], the divergence Hinkley algorithm [14], DCS algorithm [9, 16]).

The latter (DCS) was developed for detection of changes in signals of long duration. It was based on local cumulative sums of likelihood ratios computed between two local windows estimated around the current time t. The parameters of the two segments, S_b^t ("b" for "before") and S_a^t ("a" for "after"), were estimated using two estimation windows W_a and W_b of identical length N before and after the current time t:

(i) $W_b^t : x_i; i = \{t-N, \dots, t-1\}$ used to estimate the parameter $\widehat{\theta}_b$ of the probability function before the current time t,

(ii) $W_a^t : x_i; i = \{t+1, \dots, t+N\}$ used to estimate the parameter $\widehat{\theta}_a$ of the probability function after the current time t.

At time t, DCS was defined as:

$$\mathrm{DCS}\left(H_a^t, H_b^t\right) = \sum_{j=1}^{t} \log \frac{f_a^j\left(x_j\right)}{f_b^j\left(x_j\right)} = \sum_{j=1}^{t} s_j. \tag{11}$$

When a change occurs at t_M it has been demonstrated [9] that DCS reaches a maximum at this time t_M.

The detection function was expressed as

$$g(t) = \max_{1 \le j \le t} \left[\mathrm{DCS}\left(H_a^j, H_b^j\right)\right] - \mathrm{DCS}\left(H_a^t, H_b^t\right) \tag{12}$$

and the stopping time was:

$$t_s = \inf \{t : g(t) \ge h\}, \tag{13}$$

where h was a given threshold.

When applying the DCS algorithm after AR (autoregressive) modeling, a third window W_p^t was necessary to compute the prediction error after AR parameter estimation.

Figure 2 illustrates the window definition (W_b^t for AR parameter θ_b^t estimation, W_a^t for AR parameter θ_a^t estimation, W_p^t for prediction error estimation), the evolution of DCS around the change time t, and the corresponding evolution of the decision function.

This change detection method has proved to be efficient when applied to uterine EMG [9] or postural muscle activity [17]. However, some limitations of DCS can be underlined that are related to its use in specific configurations: (i) as the estimation windows are used to estimate locally the distribution parameters before and after the current time t, the choice of the window width has a great influence on the detection process; (ii) the detectability property is no longer preserved in the DCS algorithm. Therefore detection fails when the two distributions are very close together (see Figure 3). In fact, the detection function stabilizes after N points beyond the change time without reaching the threshold.

Based on the same basic concept, a modified algorithm was developed to overcome these problems and to ensure the detectability property.

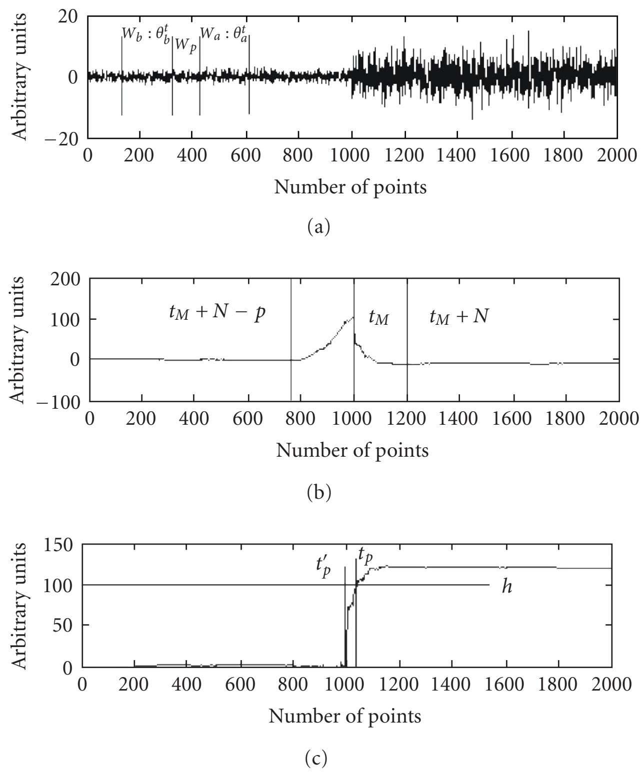

Figure 2: Upper tracing: position of the estimation and prediction windows. Middle tracing: evolution of DCS around the change time t_M. Lower tracing: detection function. For all tracings, x-axis: number of points, y-axis: arbitrary units.

4. THE MODIFIED DYNAMIC CUMULATIVE SUM (MDCS) ALGORITHM

4.1. Variable window width

The algorithm is still based on two sliding windows W_b^t and W_a^t that are used to estimate θ_b^t and θ_a^t at each time t. As for DCS, W_a^t has a constant length N, but W_b^t now includes all samples from 1 to $t-1$. Hence, when both windows correspond to the same distribution (no change in the segment), the parameter estimation is always better for W_b^t than for W_a^t, leading to $E_{\theta_0}[s_i] < 0$.

θ_b^t and θ_a^t are estimated using these new windows:

$$\begin{aligned} W_b^t &: 1 \cdots t-1 \longrightarrow \theta_b^t, \\ W_a^t &: t+1 \cdots t+N \longrightarrow \theta_a^t. \end{aligned} \tag{14}$$

The definitions of the log-likelihood ratios, the cumulative sum, and the detection function remain the same as for DCS. In addition, when the signal samples are dependent, it is still possible to perform AR modeling and to introduce an intermediate prediction window W_p^t.

Figure 4 illustrates this new approach. MDCS is now decreasing before the change time and continuously increasing after that, if the process is not stopped by a threshold crossing.

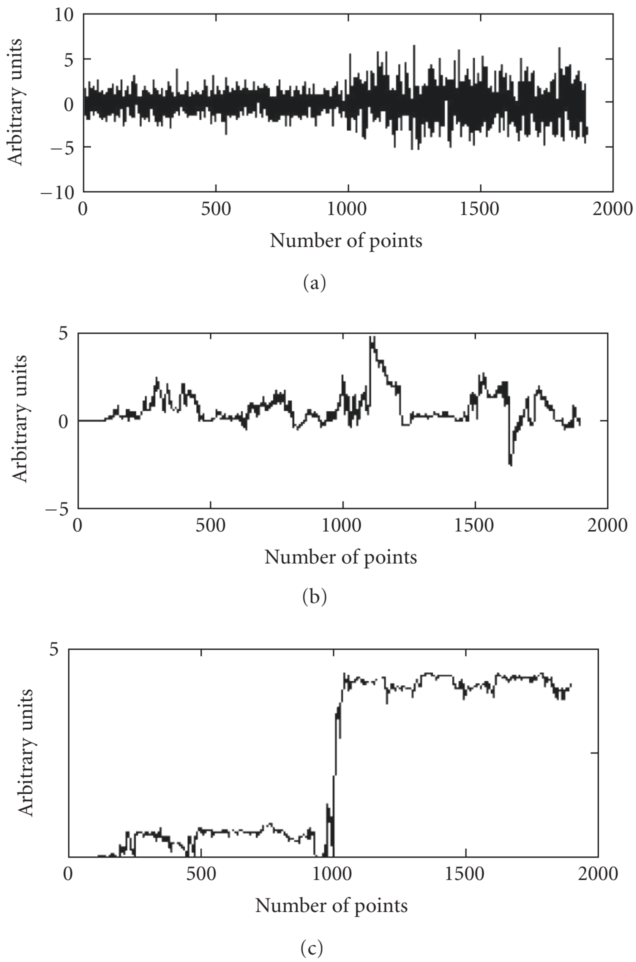

Figure 3: An illustration of a change that was not detected by the DCS algorithm. Upper tracing: signal segment. Middle tracing: DCS evolution. Lower tracing: detection function evolution. For all tracings, x-axis: number of points, y-axis: arbitrary units.

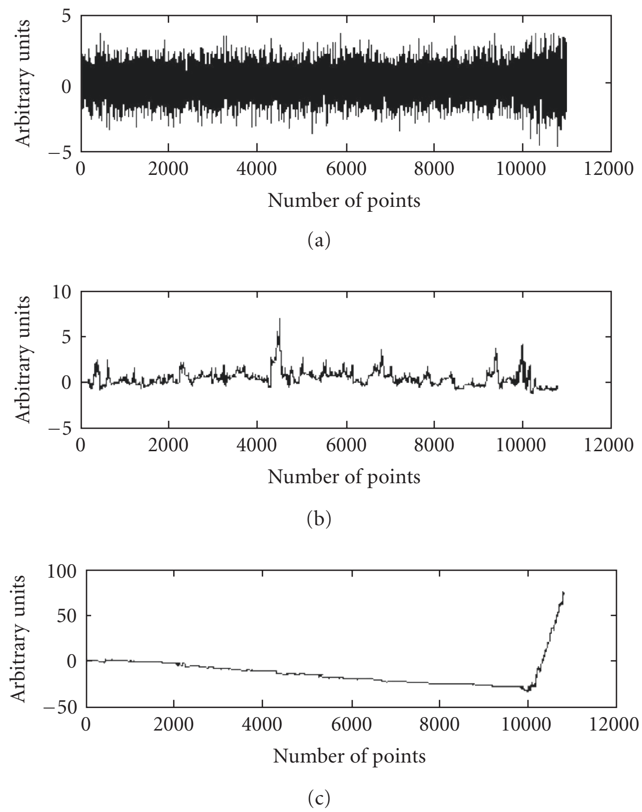

Figure 4: (a) Simulated signal containing a change in variance (from 1 to 2) at point 10000. (b) Evolution of DCS before and after the change time (change not detected). (c) Evolution of MDCS before and after the change time (change detected). For all tracings, x-axis: number of points, y-axis: arbitrary units.

4.2. *Double thresholding*

One of DCS drawbacks was the fact that, between the change time and the stopping time, W_b^t kept increasing, hence including samples taken after the change time to update θ_0 estimates. To solve this problem, the idea was to apply two thresholds (h_L and h_H) to the detection function:

(i) the lower threshold h_L stops θ_0 estimate updating,
(ii) the higher threshold detects the change h_H.

This double thresholding allows a limitation in the bias of θ_0 estimation without increasing the false alarm rate, as was the case before when a threshold that was too low was applied to the detection function.

5. AUTOMATIC CHOICE OF THE THRESHOLDS

One of the most crucial issues in change detection is the choice of the detection threshold h. It mainly depends on the signal characteristics and is generally adjusted by experience or by using a training set of data. Methodologies can be found in the literature to choose the threshold according to the probability of false alarm, and the mean time between false alarms [10, 18]. However, the formulation is asymptotic and difficult to apply in practical use.

In case of a CUSUM algorithm, a very useful factor to choose the threshold h is the Kullback-Leibler distance between two probability densities f_{θ_0} and f_{θ_1} of a random variable x, defined as

$$K(\theta_0, \theta_1) = \int Ln \frac{f_{\theta_0}(x)}{f_{\theta_1}(x)} f_{\theta_0}(x)dx. \qquad (15)$$

The Kullback-Leibler distance can be considered as a distance between these two probability densities. In addition, it is known [10] that the delay for detection is inversely proportional to the Kullback-Leibler distance. If h is the threshold used in the detection algorithm, the relationship between h and the Kullback-Leibler distance can be expressed as

$$E_{\theta_1}(s) = K(\theta_1, \theta_0) = \frac{h}{\tau}, \qquad (16)$$

where τ is the mean delay for detection. Hence the Kullback-Leibler distance can be used to choose the threshold h.

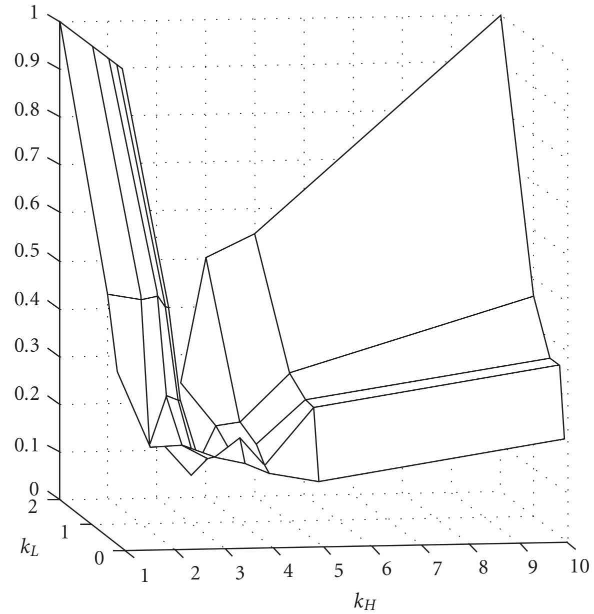

FIGURE 5: Variation of the segmentation error with the low and high threshold values. Thresholds are indicated as the factors k_L (y-axis) and k_H (x-axis) to apply to the mean square value of the Kullback-Leibler distance MS_{KL}.

From (16) we can write $h \approx M \cdot K(\theta_1, \theta_0)$ where M is the number of points after time changes. So we can use an estimation of the Kullback-Leibler distance to calculate the threshold h.

Now considering two AR models $\theta_0 = (a_1^0, \dots, a_p^0, \sigma_0^2)$ and $\theta_1 = (a_1^1, \dots, a_p^1, \sigma_1^2)$, the Kullback-Leibler distance between θ_1 and θ_0 can be expressed as [6]

$$K(\theta_1, \theta_0) = -\frac{1}{2} - \frac{1}{2} \ln \frac{\sigma_1^2}{\sigma_0^2} + \frac{1}{2} \frac{\sigma_1^2}{\sigma_0^2} \left[1 + \sum_{k=1}^{\infty} \left(c_k^{0/1} \right)^2 \right], \tag{17}$$

where the coefficients $c_k^{0/1}$ are the coefficients of the following Taylor expansion:

$$\frac{A_0(z)}{A_1(z)} = 1 + \sum_{k=1}^{\infty} c_k^{0/1} z^{-k}. \tag{18}$$

The following steps are proposed to choose the threshold h automatically.

(1) The signal is first divided into successive segments of equal length N.
(2) The AR model $\theta = (a_1, \dots, a_p, \sigma^2)$ is estimated for each segment.
(3) Then the Kullback-Leibler distance is computed between each pair of successive segments, leading to a sequence of values that are thus sorted in ascendant order.
(4) The sequence is limited to the lowest 90% of values in order to suppress the influence of any possible very large value.
(5) The mean square value MS_{KL} of the remaining distribution of the Kullback-Leibler distances is then computed, providing the low and high thresholds $h_L = N \cdot k_L \cdot \text{MS}_{\text{KL}}$ and $h_H = N \cdot k_H \cdot \text{MS}_{\text{KL}}$, N being the window width.

The determination of k_L and k_H was performed by simulation with the same reference set as that used to build the ROC curves in the previous paragraph. Segmentation was achieved with successive values of k_L and k_H and the number of nondetection and false alarms counted.

Figure 5 shows the variation of the segmentation error (sum of nondetections and false alarms) with respect to both thresholds using the simulation data. The surface presents a minimum at k_L=1 and k_H=3.

6. RESULTS AND DISCUSSION

This method was first tested on simulated signals generated by concatenating segments of random noise filtered at different frequency bands, then to electromyographic recordings.

As an illustration, the segmentation was applied to electromyographic signals recorded during a long term (2h30) experiment assessing the comfort of car seats through a measure of local muscular fatigue. Each experiment was divided into 7 phases lasting from 10 minutes to 30 minutes. Figure 6 shows one of those phases after MDCS segmentation (25 segments).

This new technique of windowing—double thresholds decreases the probability of false alarm especially in the electromyography signals which are long duration signals. This is coming from the fact that the detection function $g(t)$ rises to the second threshold only when a real change occurs. Furthermore, The Kullback-Leibler distance is used to determine these thresholds automatically because the characteristics of the electromyography signals change from person to another and depend on many other parameters. Finally, it is important to notice that this method can be applied to whatever kind of signals presenting changes in frequency or amplitude.

Both methods (DCS and MDCS) were tested on simulated data made of 1000 segments of white noise with a variance change from 1 to 2 and 1000 segments without a change. To compare the results, we chose the ROC curves (receiver operating characteristics) that plot the probability of detection with respect to the probability of false alarms. In general, higher is the curve, better are the results. Figure 7 clearly shows how the modified algorithm improves the overall detection quality.

In these curves presented on Figure 7, we can see that if we need a detection probability equal to 0.9, the false alarm probability given by the DCS algorithm is about 0.1 but it is less than 0.02 for the MDCS method. MDCS decreases the probability of false alarm for a given detection probability.

7. CONCLUSION

The local approach of change detection allows a local estimation of the distribution parameters before and after the current time t. A change is detected in the same way as

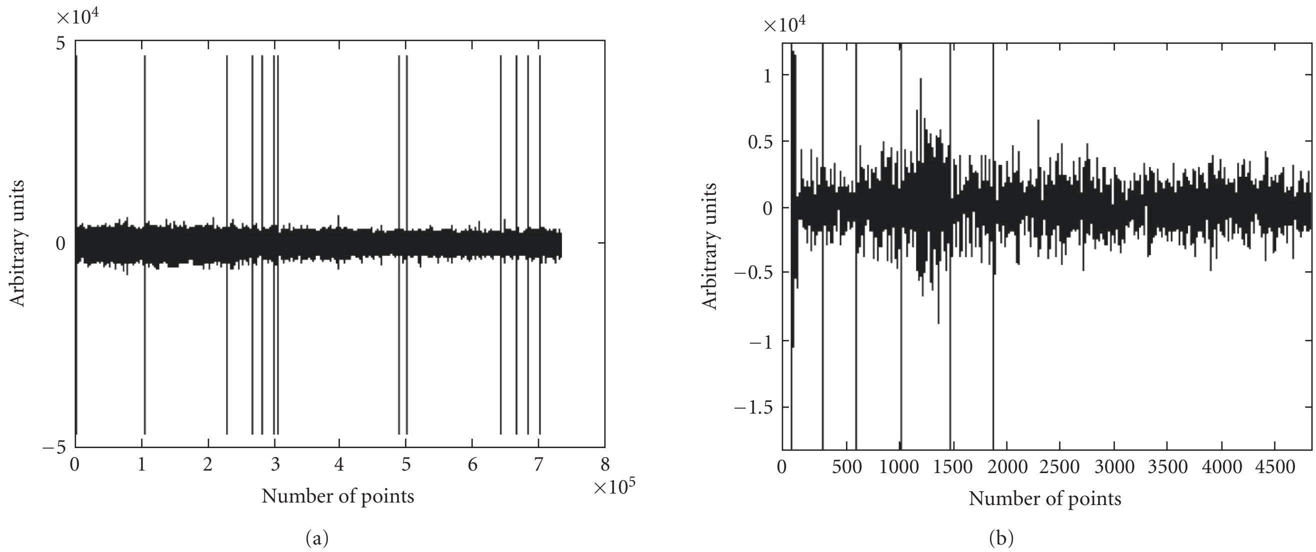

Figure 6: Application of MDCS on a real signal. (a) a 15-minute recording epoch, (b) zoom at the beginning of the signal. This figure shows the detection points. x-axis: number of points, y-axis: arbitrary units.

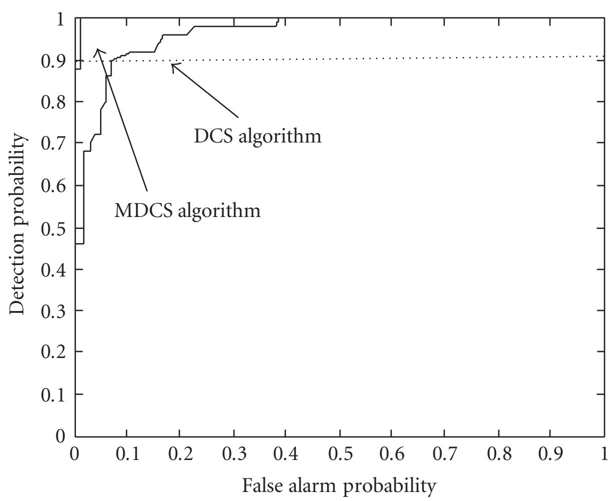

Figure 7: Comparison of DCS and MDCS methods by ROC curves computed from simulated data. x-axis: false alarm probability, y-axis: detection probability.

for the classical CUSUM approach after parameter estimation. A first algorithm (DCS) had been successfully tested on long term recordings related to biomedical signals. However, DCS presented some limitations in its ability to detect slow changes, the main of them being that it did not respect the detectability property. In addition, the threshold of the detection function had to be chosen by expertise or by using reference data sets. The modified algorithm overcomes these problems by a restriction of the estimation window for the segment S_0 (before change point) using a low threshold that is distinct from the detection function threshold itself. In addition, these thresholds are learned automatically by using the Kullback-Leibler distance. As a consequence, MDCS becomes an offline algorithm if applied extensively to each recording to be segmented, since the Kullback-Leibler distance distribution must be computed first for each new recording. However, it seems wise to imagine that the same thresholds could be applied to a class of similar signals such as electromyograms recorded on various muscles and various subjects during the same experimental protocol. Nevertheless this point has yet to be demonstrated.

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