The Sixteenth International Symposium on Artificial Life and Robotics 2011 (AROB 16th '11),
B-Con Plaza, Beppu,Oita, Japan, January 27-29, 2011

Continuous Change Point Detection for Time Series Images Using ESPRT

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Abstract: In order to continuously detect the change point in ongoing time series data, we propose a method using extended sequential probability ratio test (ESPRT). That is, it is a repetition of three stages, where the first stage is prediction model construction, and change point detection as the second stage, and reconstruction of prediction model as the third stage. In this paper, we show experimental results by applying the method to time series data of image storage, where the images are transmitted as compressed data (i.e. JPEG file) from remote monitoring camera systems.

***Keywords*:** Continuous change detection, monitoring camera system, time series images, extended sequential probability ratio test (ESPRT), security

I. INTRODUCTION

Today, monitoring camera systems are widely used in the society [1]. However, because there is a channel capacity limit in the public communication line, remote monitoring systems ordinarily use compressed data (e.g. JPEG file) to send scene images if there happens something abnormal or something changed. For this reason, the camera system is required to become smart enough to judge by itself as to whether something abnormal has occurred or not.

On the other hand, if something moves in the scene image, the quantity of the compressed image tends to be different from the steady situation so far. Based on the characteristics, in our previous paper, we have proposed a method for the change detection using applying the Sequential Probability Ratio Test (SPRT) ([2], [3]) to the scene images of time series [6]. Moreover, in the literature, we have experimented with the real time series images from a monitoring camera and have compared the SPRT the method with the well-known Chow Test [4].

However, we have just only presented the results of first change detection. In fact, we need to continuously deal with the change detection from the time series images, and so that we have to uses the Extended SPRT (ESPRT), in order to know the change time point correctly and reconstruct the next prediction model [5].

In this paper, we show the experimental results of continuous change detection from real time series images, and discuss the performance of the method.

II. SPRT AND CHANGE DETECTION

For the change detection problem, we propose an application of Sequential Probability Ratio Test (SPRT) that has been mainly used in the field of quality control.

1. SPRT ([2],[3])

The SPRT is used for testing a null hypothesis H_0 (e.g. the quality is under pre-specified limit 1%) against hypothesis H_1 (e.g. the quality is over pre-specified limit 1%). In addition, it is defined as follows.

At each stage of successive events $Z_1, Z_2, \cdots Z_i$ that are respectively corresponding to observed time series data, the probability ratio λ_i is computed.

$$\lambda_i = \frac{P(Z_1 \mid \mathbf{H}_1)\cdot P(Z_2 \mid \mathbf{H}_1)\cdots P(Z_i \mid \mathbf{H}_1)}{P(Z_1 \mid \mathbf{H}_0)\cdot P(Z_2 \mid \mathbf{H}_0)\cdots P(Z_i \mid \mathbf{H}_0)} \quad (1)$$

where $P(Z \mid H_0)$ denotes the distribution of Z when H_0 is true and $P(Z \mid H_1)$ denotes the distribution of Z when H_1 is true.

Two positive constants C_1 and C_2 ($C_1 < C_2$) are chosen. If $C_1 < \lambda_i < C_2$, the experiment is continued by taking an additional observation. If $C_2 < \lambda_i$, the process is terminated with the rejection of H_0 (acceptance of H_1). If $\lambda_i < C_1$, the process is terminated with the acceptance of H_0.

$$C_1 = \frac{\beta}{1-\alpha} \qquad C_2 = \frac{1-\beta}{\alpha} \quad (2)$$

where α means type I error (reject a true null hypothesis), and β means type II error (accept a null hypothesis as true one when it is actually false).

2. Procedure

The concrete procedure of structural change detection is as follows.

Step1: Make a prediction expression and set the tolerance band (***a***) (e.g. ***a***=**2**σ_S) that means permissible error margin between the predicted data and the observed one (where σ_S means the standard deviation).

Step2 : Set up the null hypothesis H_0 and alternative hypothesis H_1.

H_0 : Change has not occurred yet.

H_1 : Change has occurred.

Set the values α, β and compute C_1 and C_2, according to Equation (2). Initialize i = 0, $\lambda_0 = 1$.

Remark: The statement of the null hypothesis H_0, "Change has not occurred yet.", means in statistical sense. It means that the generation probability for the data to go out from the tolerance band is less than (or equal to) θ_0 (for instance, 1%). Similarly, the statement of the alternative hypothesis H_1, "Change has occurred." means that the generation probability for the data to go out from the tolerance band is greater than (or equal to) θ_1 (for instance, 99%). Additionally, we suppose that θ_1 is considerably greater than θ_0.

Step3: Incrementing i (i = i+1), observe the following data y_i. Evaluate the error $|\varepsilon_i|$ between the data y_i and the predicted value from the aforementioned prediction expression.

Step4: Judge as to whether the data y_i goes in the tolerance band or not, i.e., the ε_i is less than (or equal to) the permissible error margin or not. If it is Yes, then set $\lambda_i = 1$ and return to Step3. Otherwise, advance to Step5.

Step5: Calculate the probability ratio λ_i , using the following Equation (3) that is equivalent to Equation (1)

$$\lambda_i = \lambda_{i-1} \frac{P(\varepsilon_i \mid \mathbf{H}_1)}{P(\varepsilon_i \mid \mathbf{H}_0)} \qquad (3)$$

where, if the data y_i goes in the tolerance band, $P(\varepsilon_i |H_0) = \theta_0$ and $P(\varepsilon_i |H_1) = \theta_1$, otherwise, $P(\varepsilon_i |H_0) = (1-\theta_0)$ and $P(\varepsilon_i |H_1) = (1-\theta_1)$.

Step6: Execution of testing.

(i) If the ratio λ_i is greater than C_2 (= $(1-\beta)/\alpha$), dismiss the null hypothesis H_0, and adopt the alternative hypothesis H_1, and then End.

(ii) Otherwise, if the ratio λ_i is less than C_1 (= $\beta/(1-\alpha)$), adopt the null hypothesis H_0, and dismiss the alternative hypothesis H_1, and then set $\lambda_i = 1$ and return to Step3.

(iii) Otherwise (in the case where $C_1 \le \lambda_i \le C_2$), advance to Step7.

Step7: Observe the following data y_i incrementing i. Evaluate the error $|\varepsilon_i|$ and judge whether the data y_i goes in the tolerance band, or not. Then, return to Step5 (calculation of the ratio λ_i).

3. Extended SPRT [5]

We extend the definition of detected change point by SPRT. As such extension, we adopt the number tc-***M*** where tc is ordinary aforementioned change point and ***M*** is the number of times when the observed data continuously goes of tolerance zone until the ratio $\lambda_i >$ C_2 The number ***M*** can be obtained from the equation below.

$$\left(\frac{\theta_1}{\theta_0}\right)^M > C_2 \left(= \frac{1-\beta}{\alpha}\right) \qquad (4)$$

Then we have the following equation using Gauss notation. The value of ***M*** depends on the parameters (see Table 1).

$$M = \left\lceil \log_{\frac{\theta_1}{\theta_0}} \frac{1-\beta}{\alpha} \right\rceil \qquad (5)$$

From some experimental results, we have found that, if we adopt the interval [tc-***M***+1, tc] as the existing range of true change point, the hitting (or correct estimation) percentage will considerably increase.

Table 1. Parameter values in SPRT and ***M***.

α	β	θ_0	θ_1	***M***
0.05	0.05	0.1	0.9	2
		0.2	0.8	3
		0.3	0.7	4

III. CONTINUOUS CHANGE DETECTION FOR IMAGE SEQUENCE

In order to continuously detect the structural change of the scene images from a monitoring camera, we apply the ESPRT method to the time series of compressed image data (JPEG file) quantity (Kbyte).

Fig.1 and Fig.2 show two kinds of images when a person has moved into and out of the scene at high speed and low speed, respectively. Fig.3 and Fig.4 show two graphs on time series data of JPEG file volumes, corresponding to Fig.1 and Fig.2, respectively.

We assume that there are four change points in the both of the two kinds of time series images. The first change point is the time when some person appears in the scene image, and the second is when he stops walking, the third when he begins to move again, and the fourth when he moves out of scene.

The results of change detection by SPRT and Chow Test are shown in the graphs in Fig.5 and Fig.6, respectively, where the SPRT detects change points in the case of condition 1(θ_0=0.9, θ_1=0.1). The number of sample points for learning and analysis is five, where those samples are used for deciding prediction model (regression line) in both cases.

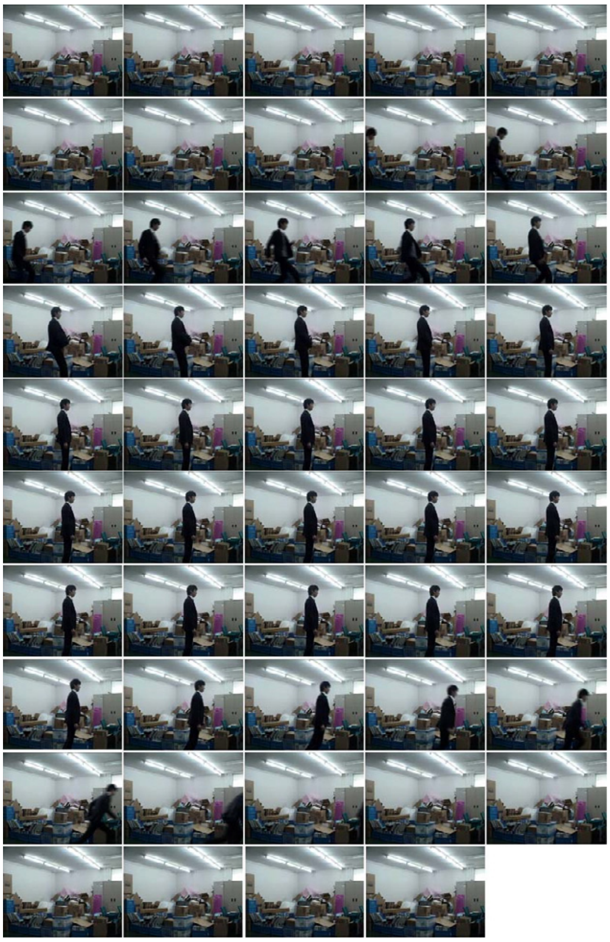

Fig.1. Example of time series images where someone moves in, stops walking, moves again, and moves out at high speed what we call "Fast-In Fast-Out Case". (Time is counted from the upper left to the lower right.)

If SPRT detects the change at tc, the ESPRT estimates the true point as tc-1 under the condition 1.Then after the first detection, next five points from tc-1 to tc+3 will be used as learning samples for reconstructing the next prediction model.

The experimental results show that ESPRT method continuously detects the change point better than Chow Test in the two kinds of time series images.

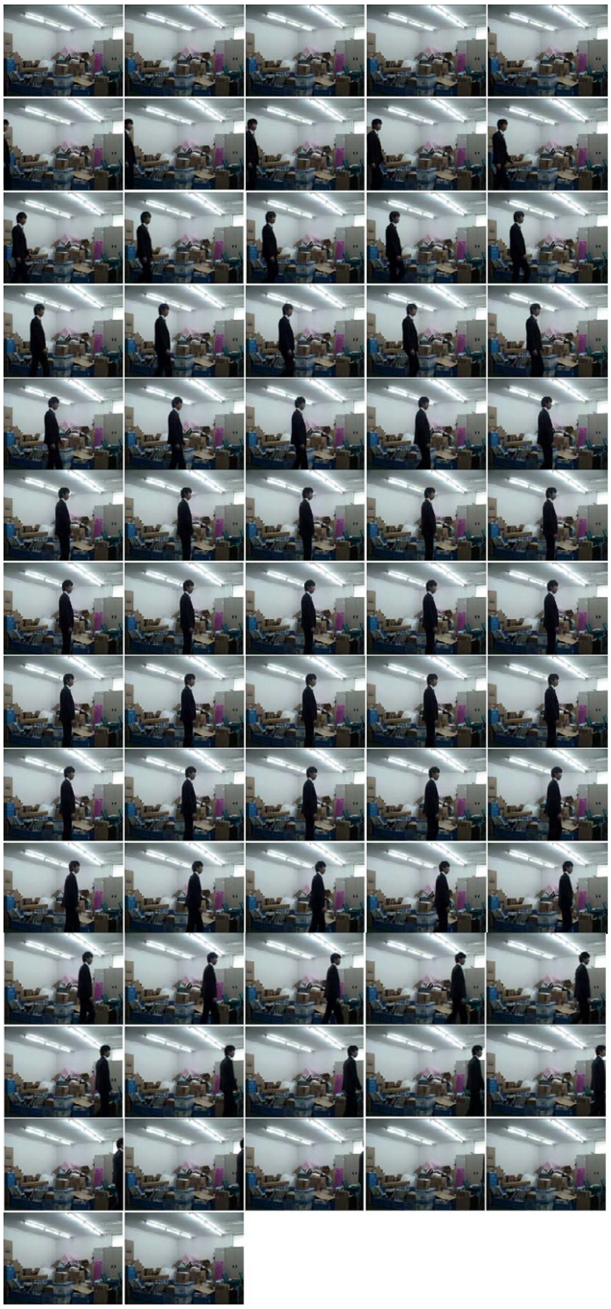

Fig.2. Example of time series images where someone moves in, stops walking, moves again, and moves out at low speed what we call "Slow-In Slow-Out Case". (Time is counted from the upper left to the lower right.)

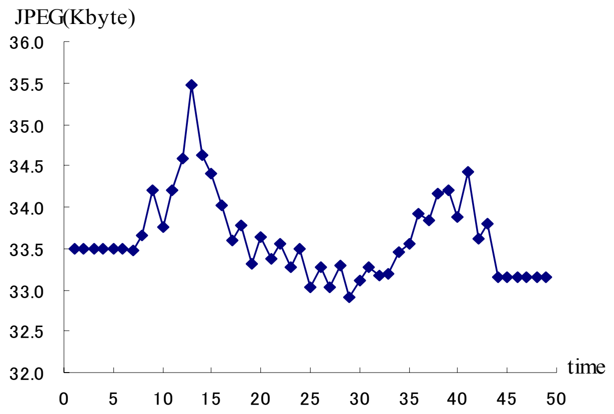

Fig.3. Time series data of JPEG file volumes in Fig.1 (Fast-In Fast-Out Case).

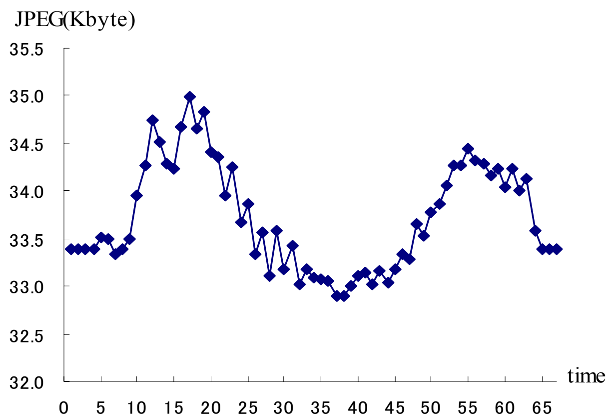

Fig.4. Time series data of JPEG file volumes in Fig.2 (Slow-In Slow-Out Case).

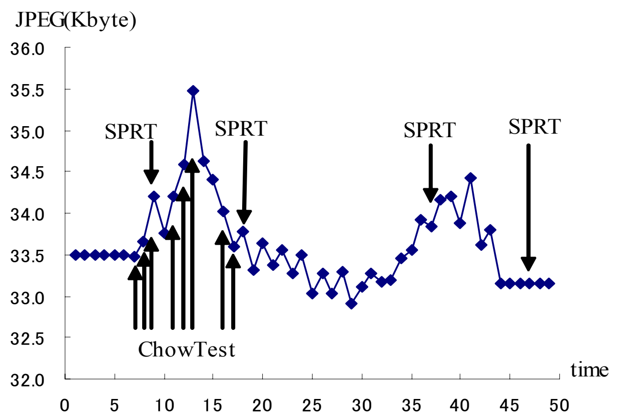

Fig.5. Change detection results by SPRT and Chow Test for the time series data in Fig.3 (Fast-In Fast-Out Case).

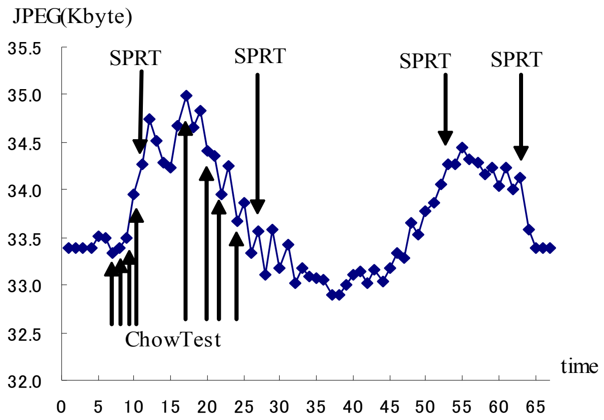

Fig.6. Change detection results by SPRT and Chow Test for the time series data in Fig.4(Slow-In Slow-Out Case).

IV. CONCLUSION

This paper has proposed the ESPRT method for continuous change detection and have shown its effectiveness by experimental results that the method has detected the four change points in two kinds of time series data, more correctly than Chow Test.

REFERENCES

[1]Shinichi Masuda, Tetsuo Hattori (2007), Development of a Wireless Remote Monitoring System Utilizing Multiple Wireless Sensors (in Japanese), IEEJ Trans. IA, Vol.127, No.6, pp.610-617.

[2] A. Wald(1947), Sequential Analysis, John Wiley & Sons.

[3]Hiromichi Kawano, Tetsuo Hattori, Ken Nishimatsu (2008), Structural Change Point Detection Method of Time Series Using Sequential Probability Ratio Test－Comparison with Chow Test in the ability of early detection－(in Japanese), IEEJ Trans. EIS, Vol.128, No.4, pp.583-592.

[4]Chow,G.C. (1960), Tests of Equality Between Sets of Coefficients in Two Linear Regressions, Econometrica, Vol.28, No.3, pp.591-605.

[5] Katsunori Takeda, Tetsuo Hattori, Izumi Tetsuya, Hiromichi Kawano (2010): "Extended SPRT for Structural Change Detection of Time Series Based on Multiple Regression Model", Proceedings of the 15th International Symposium on Artificial Life and Robotics (AROB15th'10), ISBN 978-4-902880-4-4, pp.755-758.

[6] Katsunori Takeda, Tetsuo Hattori, Izumi Tetsuya, Hiromichi Kawano, Shinichi Masuda (2010): "Application of SPRT to Image Data Sequence for Remote Monitoring System", Proceedings of the 15th International Symposium on Artificial Life and Robotics (AROB 15th'10), ISBN 978-4-9902880-4-4, pp.759-762.