Voice Quality Management for IP Networks Based on Automatic Change Detection of Monitoring Data

Satoshi Imai[1], Akiko Yamada[1], Hitoshi Ueno[1], Koji Nakamichi[1], and Akira Chugo[1]

Fujitsu Laboratories Ltd, Kamikodanaka 4-1-1, Nakahara-ku, Kanagawa, Japan
{imai.satoshi, akikoo, ueno.hitoshi, nakamichi, chugo}@jp.fujitsu.com

Abstract. Recently, quality management of IP networks has become an important issue with the development of real-time applications such as IP-phones, TV-conferencing and video-streaming. Specifically, when voice data is mixed with various application data, there are worries that there will be a critical degradation in voice quality. In current management of voice quality, the general scheme is to monitor the voice quality using a preset threshold for the data. However, it's not easy to set a proper threshold for data monitoring in each case, because the characteristics of the monitoring data become more diverse as networks become larger in scale and more complex. We propose an automatic change detection scheme that detects changes in the behavior of the monitoring data with changes in the traffic conditions, without any preset threshold. The essential concept of our scheme is the application of a statistical scheme to sequential data monitoring. We also demonstrate the effectiveness of our proposed scheme when applied to voice quality management.

1 Introduction

With the sophistication of network technologies, the various application services are now deployed on IP networks. Specifically, the VoIP service is coming into general use as an alternative to the public switched telephone network (PSTN) call service. However, the emergence of these various IP services brings new issues to the VoIP service. The main issue is that the voice communication quality is extremely sensitive to the transmission characteristics of the voice packets. The VoIP quality is related to end-to-end delay, jitter and packet loss in the IP network, compared to other services such as E-mail and Web browsing.

- **End-to-end delay**
  is the time required for a voice packet sent by the caller to reach the callee. (This is equivalent to the difference between the packet arrival time at the callee and the packet timestamp that the caller puts on the transmission.) Real-time communication quality falls to a critical level when the delay exceeds a specific value (e.g. 150msec).

- **Jitter**
  is the variation in packet arrival times. (This is equivalent to the difference between each end-to-end delay and the average end-to-end delay.)
  If the packet arrives too early or too late, the playout quality will be bad, because voice codecs require a steady packet stream to provide adequate playout quality.
- **Packet Loss**
  is a phenomenon in which voice packets are discarded on the IP network.
  Voice quality deteriorates because jumpiness and noise are caused by losing a part of the voice signals.

The behavior of these packet parameters depends on changes in the network conditions. In order to sustain VoIP quality, it is necessary to detect the change in network conditions before the VoIP quality deteriorates, and prevent any deterioration in quality.

Our study assumes an active measurement scheme by sending test packets as VoIP quality monitoring schemes, and focuses on a change detection scheme for network conditions (e.g. traffic load) based on analyzing the behavior of the monitoring data. In a change detection scheme, we should preset a suitable threshold to detect changes in the behavior of the monitoring data associated with a change in network conditions. However, as IP networks become large in scale and application traffic becomes more diverse, the behavior of the monitoring data (e.g. end-to-end delay and jitter) detected by active measurement will become nonidentical and more complex. Therefore, it is not easy to preset proper thresholds for data monitoring at all measurement points.

In this paper, we focus on the fact that jitter is extremely sensitive to changes in the network load, and propose a VoIP quality management scheme that detects the change in the behavior of the jitter associated with a change in the network load automatically and in real time by applying a statistical scheme.

The contents of this paper are organized as follows. Section 2 gives the VoIP quality management model and technical issues. Section 3 describes our scheme based on statistical tests. Section 4 presents some simulation results, and Section 5 concludes the paper with a summary and future studies.

2 VoIP Quality Management Model

Generally, the VoIP quality can be affected by even a sharp change in the traffic load which cannot be observed by MIB (which measures only the average load over several minutes duration). Therefore, we focus on an active measurement scheme which observes the behavior of the monitoring data associated with a sharp change in the traffic load, and define the VoIP quality management model shown in Fig. 1.

- The monitoring agents are located at each site, and observe the behavior of jitter on a peer-to-peer session between two agents.

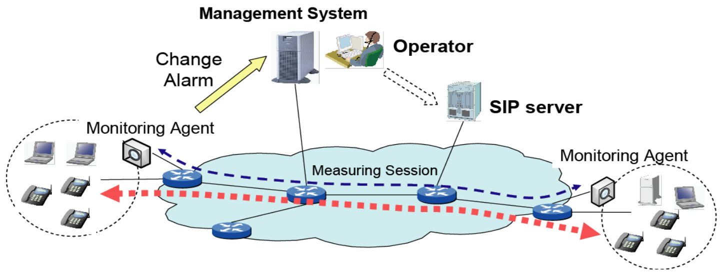


Fig. 1. VoIP Quality Management Model

- When an apparent change in jitter is detected, the monitoring agent advertises a change alarm to the management system or the network operators.
- The management system or the network operators control the specific target (e.g. SIP server) based on the trigger of the change alarm.

2.1 Technical Issues

Recently, in the data mining fields, researches into change detection schemes for data monitoring abound [1, 2]. It is a common issue to design proper thresholds for data monitoring in this fields. Representative schemes include statistics-based approaches, which are schemes that detect changes in the behavior of the monitoring data by i) defining the behaviors of the monitoring data in the normal states as a statistical model; ii) testing whether or not the present monitoring data belongs to a defined statistical model.

However, in order to analyze time-varying and complex data in real time, the data should be analyzed as a time series. Generally, for time-series data there is a strong correlation between past data and present data. Because statistics-based approaches require the assumption of statistical independence between sampled data, it is less effective to apply a direct statistics-based approach to time-series data.

Therefore, we propose a new automatic change detection scheme which has the following characteristics.

[1] Statistics-based change detection for time-series data
The proposed scheme focuses on the independent and normally-distributed residual error signals derived by modeling the time-series for jitter as an auto-regressive (AR) model [3]. As a result, we are able to use the statistics-based approach for time-series data by applying statistical tests to the residual errors in the AR model.

[2] Recursive calculation of statistical data
Every time a test packet is received, the proposed scheme calculates the jitter, and adaptively estimates the distribution of the residual errors in the AR model. Thus, we can detect changes in the behavior of the jitter using a statistical test in real time.

[3] Autonomic learning of normal behavior

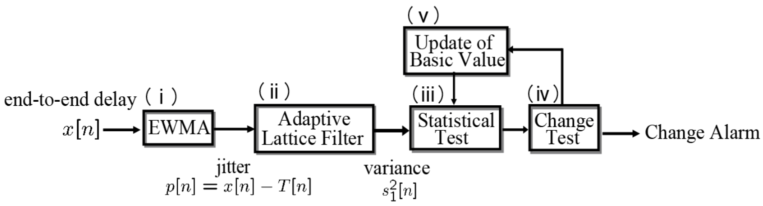


Fig. 2. Process Flow

The proposed scheme learns the normal behavior of the residual errors autonomously. As a result, the designers do not have to set any information about the monitoring data, such as the characteristics of the jitter, beforehand.

3 Automatic Change Detection

In this section, we describe our proposed scheme. Our scheme can detect automatically and instantaneously changes in the behavior of the jitter measured by the monitoring agent. The algorithm is performed as follows. (Fig. 2)

(i) Measure the end-to-end delay $x[n]$ in time n, and calculate the jitter $p[n]$ from $x[n]$ by an exponentially-weighted moving average (EWMA).
(ii) Calculate the sample variance $s_1^2[n]$ of the residual errors in the AR model using an adaptive lattice filter [4, 5].
(iii) Calculate the statistical value and detect the instantaneous change (outlier) from the basic variance s_0^2 by the F-test [6].
(iv) Detect any stationary change in $s_1^2[n]$.
(v) Update the basic variance s_0^2 when a stationary change is detected.

The detailed algorithms on this flow are described below.

3.1 Time-series Model for Jitter

We adopt the AR model as the time series model for the jitter $p[n]$, which is calculated from the end-to-end delay $x[n]$ measured in time $n \in \mathbf{Z}$. The AR model for the jitter p_t $(t = n - W + 1, \cdots, n)$ is defined by

$$p_t = -\sum_{i=1}^{m} a_i p_{t-i} + \epsilon_t. \tag{1}$$

where ϵ_t is the normally-distributed residual error with a mean of 0, and variance σ^2. W is the sampling data size for the estimation of AR parameters a_i $(i = 1, \cdots, m)$, the AR order m is a time-variable parameter which is optimally set by Akaike's Information Criterion (AIC) [3] in time n. In this paper, the jitter $p[n]$ is defined as $p[n] = x[n] - T[n]$, where the mean $T[n]$ of the end-to-end delay $x[n]$ is defined based on EWMA with the forgetting value $0 < \lambda << 1$, which gives

$$T[n] = (1 - \lambda)T[n-1] + \lambda x[n]. \tag{2}$$

Calculation of Residual Error. When the optimal AR model is estimated for the jitter, the residual errors become independent and normally-distributed white noise signals. In order to derive the optimal AR model, we use an adaptive lattice filter algorithm, which can calculate recursively for nonstationary data.

Adaptive Lattice Filter Algorithm

`{Initial value};`
`for` $0 \le m < M$
$\quad \gamma_m[-1] = \rho_m[-1] = \Delta_{m+1}[-1] = 0$
`{Update of times};`
`for` $0 \le n$
$\quad \gamma_0[n] = 0, \;\; \epsilon_0[n] = \rho_0[n] = p[n]$
$\quad E^{\epsilon}_0[n] = E^{\rho}_0[n] = \omega E^{\epsilon}_0[n-1] + p[n]^2$
`{Update of AR's orders};`
`for` $0 \le m < M$
$\quad \Delta_{m+1}[n] = \omega \Delta_{m+1}[n-1] + \frac{\epsilon_m[n]\rho_m[n-1]}{1-\gamma_m[n-1]}$
$\quad k^{\epsilon}_{m+1}[n] = \frac{\Delta_{m+1}[n]}{E^{\epsilon}_m[n]}, \;\; k^{\rho}_{m+1}[n] = \frac{\Delta_{m+1}[n]}{E^{\rho}_m[n-1]}$
$\quad \epsilon_{m+1}[n] = \epsilon_m[n] - k^{\rho}_{m+1}[n]\rho_m[n-1]$
$\quad \rho_{m+1}[n] = \rho_m[n-1] - k^{\epsilon}_{m+1}[n]\epsilon_m[n]$
$\quad E^{\epsilon}_{m+1}[n] = E^{\epsilon}_m[n] - k^{\rho}_{m+1}[n]\Delta_{m+1}[n]$
$\quad E^{\rho}_{m+1}[n] = E^{\rho}_m[n-1] - k^{\epsilon}_{m+1}[n]\Delta_{m+1}[n]$
$\quad \gamma_{m+1}[n] = \gamma_m[n] + \frac{\rho_m[n]^2}{E^{\rho}_m[n]}$
`end.`

The above-described parameter $(1-\omega)*E^{\epsilon}_m[n]$ with the forgetting value $0 << \omega < 1$ in the adaptive lattice filter algorithm is equivalent to the sample variance of residual error $\epsilon_m[n]$ in the number of samples defined by $W = 1/(1-\omega)$. In this paper, the order m to minimize AIC values expressed by

$$\mathbf{AIC}_m[n] = \min_m [\, \log\left((1-\omega) * E^{\epsilon}_m[n]\right) + \frac{2(m+1)}{1/(1-\omega)} \,] \tag{3}$$

is defined as the optimal order $\hat{m}$. In our approach, we detect changes in the behavior of the jitter by observing this sample variance $(1-\omega) * E^{\epsilon}_{\hat{m}}[n]$.

3.2 Change Detection Scheme Based on a Statistical Test

The change detection scheme tests the change in the sample variance $(1-\omega) * E^{\epsilon}_{\hat{m}}[n]$ in the adaptive lattice filter algorithm, every time the end-to-end delay $x[n]$ is measured. To be more precise, the scheme automatically learns the basic sample variance s_0^2 and detects the differences between the basic sample variance s_0^2 and the present sample variance $s_1^2[n] = (1-\omega) * E^{\epsilon}_{\hat{m}}[n]$ by a statistical test.

Our statistical test scheme consists of testing two hypotheses: a null hypothesis (no change) and an alternative hypothesis (change), every time a test packet is received.

Outlier Detection. We treat the scheme which tests the statistical differences between two sample variances (s_0^2 and s_1^2) as a framework to detect any outlier to the sample variance (s_1^2) based on the basic sample variance (s_0^2).

The basic idea of outlier detection is described as follows. Based on the evidence that the residual errors in the optimal AR model belong to a normal distribution, we define basic n_0-samples of the residual errors as

$$[\textbf{Basic Samples}] \quad \epsilon_1^0, \cdots, \epsilon_{n_0}^0 \ \sim N\{0, \sigma_0^2\}, i.i.d \tag{4}$$

While, the present n_1-samples to test the change are defined as

$$[\textbf{Test Samples}] \quad \epsilon_1^1, \cdots, \epsilon_{n_1}^1 \ \sim N\{0, \sigma_1^2\}, i.i.d \tag{5}$$

Testing the differences between the sample variances s_0^2 from the basic samples and the sample variances s_1^2 from the test samples boils down to carrying out an F-test on the following hypotheses:

$$\begin{cases} \mathbf{H_0} : \sigma_0^2 = \sigma_1^2 \\ \mathbf{H_1} : \sigma_0^2 \neq \sigma_1^2 \end{cases} \tag{6}$$

The statistical value based on the null hypothesis ($\mathbf{H_0}$), which is expressed by

$$F_0 = \frac{\frac{n_1 s_1^2}{n_1 - 1}}{\frac{n_0 s_0^2}{n_0 - 1}} \tag{7}$$

belongs to an F-distribution with $(n_0 - 1, n_1 - 1)$ degrees of freedom as shown in Fig. 3. When $F^\alpha(n_0 - 1, n_1 - 1)$ is the upper α point on the F-distribution with $(n_0 - 1, n_1 - 1)$ degrees of freedom and $F_\alpha(n_0 - 1, n_1 - 1)$ is the lower α point, the F-test rule with significance level α are derived as below.

$$\left.\begin{matrix} F_0 > F^{\alpha/2}(n_0 - 1, n_1 - 1) \\ F_0 < F_{\alpha/2}(n_0 - 1, n_1 - 1) \end{matrix}\right. \Rightarrow \text{Accept the alternative hypothesis} \tag{8}$$

Because we premise on the basis that the both s_0^2 and s_1^2 are derived by the adaptive lattice filter, the sample variances s_1^2 are calculated in time n, and both n_0 and n_1 are equivalent to $1/(1-\omega)$. Therefore, the outlier detection rules based on the basic variance s_0^2 with significance level α are defined as

$$\frac{s_1^2[n]}{s_0^2} > F^{\alpha/2}\left(\frac{\omega}{1-\omega}, \frac{\omega}{1-\omega}\right) \Rightarrow \text{An upper outlier has occurred} \tag{9}$$

$$\frac{s_1^2[n]}{s_0^2} < F_{\alpha/2}\left(\frac{\omega}{1-\omega}, \frac{\omega}{1-\omega}\right) \Rightarrow \text{A lower outlier has occurred} \tag{10}$$

Updating the Basic Variances. The update rule for the basic variance s_0^2 is described as below. We expand a "scheme to detect an outlier" to a "scheme to detect a stationary change". The update rule is

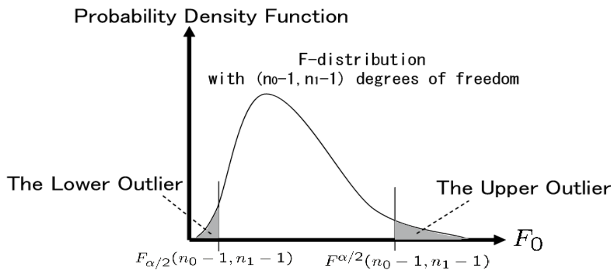


Fig. 3. F-distribution

– Update basic variance s_0^2 when a stationary change is detected.

When k_1 and k_2 are the numbers of upper and lower outlier detections respectively, and N is the trial number of the outlier detection test, the rate of upper and lower outlier detection is shown below.

$$r_1 = k_1/N, \quad r_2 = k_2/N \tag{11}$$

We assume that

– if the rate of outlier detection r_1 or r_2 is under the significance level $\alpha/2$, the basic variance s_0^2 is correct.
– if the rate of outlier detection r_1 or r_2 is much over the significance level $\alpha/2$, the basic variance s_0^2 is changed.

The above assumption are represented as the following hypotheses.

$$\text{Upper Side Change} : \begin{cases} \mathbf{\hat{H}_0} : r_1 \leq \frac{\alpha}{2} \\ \mathbf{\hat{H}_1} : r_1 > \frac{\alpha}{2} \end{cases} \tag{12}$$

$$\text{Lower Side Change} : \begin{cases} \mathbf{\hat{H}_0} : r_2 \leq \frac{\alpha}{2} \\ \mathbf{\hat{H}_1} : r_2 > \frac{\alpha}{2} \end{cases} \tag{13}$$

The problem of testing these hypotheses can be resolved using statistical values which are expressed by

$$Z_1 = \frac{r_1 - \alpha/2}{\sqrt{\alpha/2(1 - \alpha/2)/N}}, \; Z_2 = \frac{r_2 - \alpha/2}{\sqrt{\alpha/2(1 - \alpha/2)/N}} \tag{14}$$

If the trial number N is sufficiently large, the statistical values (Z_1 and Z_2) belong to a standard normal distribution. When the upper $\tilde{\alpha}$ point of a standard normal distribution is $Z^{\tilde{\alpha}}$, the rules to detect whether or not a stationary change has occurred are as expressed below.

$$Z_1 > Z^{\tilde{\alpha}} \Rightarrow \text{ stationary change has occurred on the upper side} \tag{15}$$
$$Z_2 > Z^{\tilde{\alpha}} \Rightarrow \text{ stationary change has occurred on the lower side} \tag{16}$$

When a stationary change is detected by the above-described rules, we update the basic variance s_0^2 to

- $s_0^2 * F^{\alpha/2}\left(\frac{\omega}{1-\omega}, \frac{\omega}{1-\omega}\right) \Leftarrow$ change on the upper side
- $s_0^2 * F_{\alpha/2}\left(\frac{\omega}{1-\omega}, \frac{\omega}{1-\omega}\right) \Leftarrow$ change on the lower side

In our approach, the estimation of the both rates in Equation(11) are determined in real time. If $D[n]$ is a discrete parameter that is 1 when an outlier is detected, and 0 when no outlier is detected, the rate $r[n]$ in time n is calculated using the forgetting value $0 < \eta \ll 1$ as below.

$$r[n] = (1-\eta)r[n-1] + \eta D[n] \tag{17}$$

Where the trial number N is equivalent to about $1/\eta$. In this paper, we set η as $\alpha/2$ based on the significance level for outlier detection.

4 Simulation Analysis of Voice Quality Monitoring

In this section, we evaluate the performance of the proposed scheme on a simulation model that is designed by OPNET. In the simulation, two scenarios are implemented: one scenario is the case with only VoIP traffic, and with a G.711 codec on the network, the other is the case with mixed traffic which includes VoIP, FTP and HTTP traffic on the network. From the simulation results, we show that the proposed scheme enables us to detect sharp changes in the traffic load indirectly by analyzing the behavior of the jitter as below.

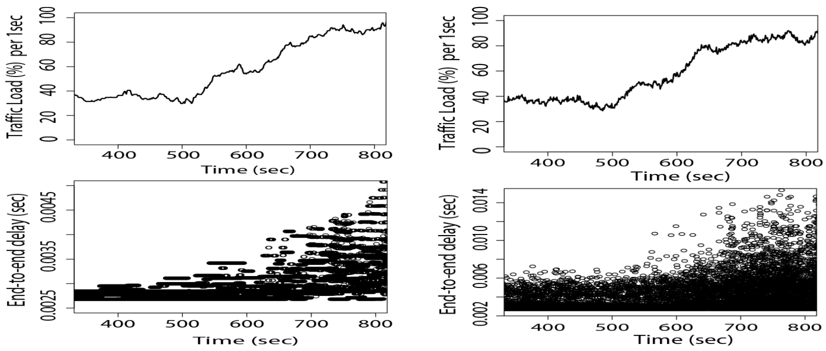
4.1 Simulation Scenarios

When the traffic load per 1 [sec] on the measurement route is increased after 500 [sec] from the stationary load of about 30% in both scenarios, the time-series graphs of the end-to-end delay measured by the monitoring agent are as shown in Fig. 4. The proposed scheme is applied to the end-to-end delay in Fig. 4(a) and Fig. 4(b), respectively. In this paper, we use the forgetting values of $\lambda = 0.01$, $\omega = 0.99$, $\eta = 5e-7$, and the significance levels in the statistical test of $\alpha = 1e-6$, $\tilde{\alpha} = 0.01$.

Relationship Between Load and Jitter. The jitter, which is calculated from the end-to-end delay, has the following characteristics as shown in Fig. 5.

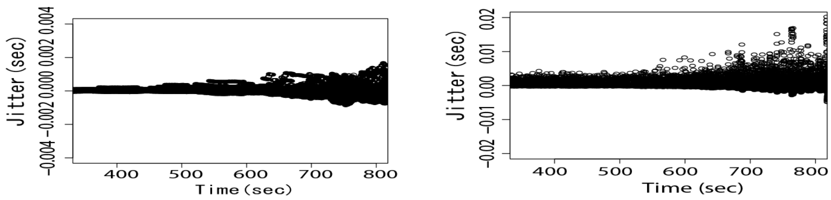
- As the traffic load increases, the jitter also increases.
- The jitter in the mixed traffic case is larger than the jitter in the case with only VoIP traffic.

Because our scheme detects behavioral changes in the jitter associated with sharp changes in the traffic load by observing the behavior of the residual errors in the AR model, we show the relationship between the traffic load and the residual errors. The relationship between the means of the traffic load and the variances of the residual errors per 1 [sec] are shown in Fig. 6. The correlation coefficients below an about 90% load in Fig. 6(a) and Fig. 6(b) are 0.912 and 0.872, respectively. These results show a strong correlation between the traffic load and the variances of the residual errors in both scenarios. Therefore, it is effective to observe the variances of the residual errors in order to detect sharp changes in the traffic load.



(a) VoIP only case (b) Mixed case

Fig. 4. Time-series graphs (Upper: traffic load, Lower: end-to-end delay)



(a) VoIP only case (b) Mixed case

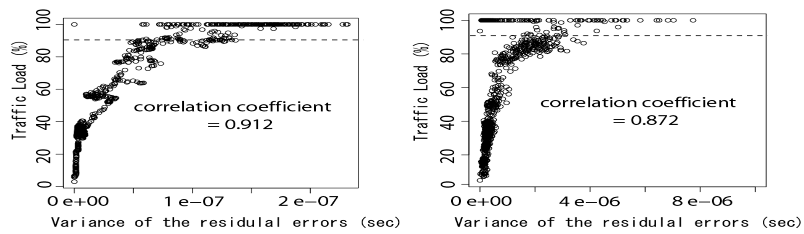
Fig. 5. Jitter calculated from the end-to-end delay in Fig.4

Detection Results. The detection results for the end-to-end delay in Fig. 4 are shown in Fig. 7. The change values in these results are the sum of the change amounts, which indicate $+1$ when it is detected that the jitter increased, and -1 when it is detected that the jitter decreased.

In the simulation results, we can verify that our scheme detects that the variances of the residual errors (i.e. the behavior of the jitter) have changed after the traffic load changes sharply, for example, at about 520 [sec] in Fig. 7(a) or at about 550 [sec] in Fig. 7(b). Therefore, our scheme enables us to detect automatically the changes in the behavior of the jitter associated with the changes in the traffic load, without presetting a threshold for the jitter, based on recursive calculations.

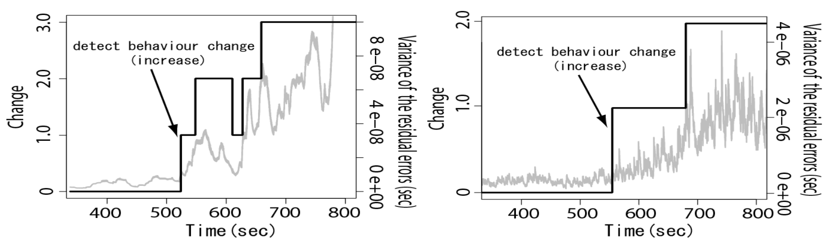
5 Conclusion

In this paper, we focus on the measurement of jitter by a monitoring agent, and propose a change detection scheme based on time-series modeling and a statistical approach, which detects automatically and instantaneously changes in the behavior of jitter associated with sharp changes in the traffic load. From



(a) VoIP only case (b) Mixed case

Fig. 6. Relationships between the means of the traffic load and the variance of the residual error per 1 [sec]



(a) VoIP only case (b) Mixed case

Fig. 7. Simmulation results of automatic change detection

the simulation results, we were able to verify that our scheme is very effective as a scalable system, because it can be operated without presetting any information about the monitoring data.

Future studies will focus on research and development of a control scheme to avoid any deterioration in VoIP quality based on this change detection scheme.

References

1. Lui, C.L., Fu, T.C, and Cheung, T.Y.: Agent-Based Network Intrusion Detection System Using Data Mining Approaches. Third International Conference on Information Technology and Applications (ICITA), Vol. 1. (2005) 131-136
2. Petrovsky, M. I.: Outlier Detection Algorithms in Data Mining Systems, Programming and Computer Software, Vol. 29, Issue. 4. (2003) 228-237
3. Chatfield, C.: The Analysis of Time Series: An Introduction, Sixth Edition. Chapman & Hall/CRC. (2004)
4. Friedlander, B.: Lattice Filters for Adaptive Processing. Proceedings of IEEE, Vol. 70. (1982) 829–867.
5. Singer, A.C.: Universal Linear Prediction by Model Order Weighting. IEEE Trans, Signal Process, Vol. 24, No. 10. (1999) 2685–2699.
6. Bulmer, M.G.: Principles of Statistics. Dover Publications, Inc. (1979)