Recurrence Plot-based Approach to the Analysis of IP-Network Traffic in terms of Assessing Non-stationary Transitions over Time

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Abstract—This paper presents a recurrence plot (RP) scheme approach to the analysis of non-stationary transition patterns of IP-network traffic. In performing a quantitative assessment of dynamical transition patterns of IP-network traffic, we used the values of determinism (DET) defined by the recurrence quantification analysis (RQA). Also, in evaluating fractal-related properties of IP-network traffic, we employed the detrended fluctuation analysis (DFA), which is applicable to the analysis of long-range dependence (LRD) in non-stationary time-series signals. Furthermore, to obtain a comprehensive view of network traffic conditions, we used a self-organizing map, which provides a way to map high-dimensional data onto a low-dimensional domain. When applying this method to traffic analysis, we performed two kinds of traffic measurement in Tokyo, Japan, and derived values of DET and the LRD-based scaling parameter $\alpha$ of IP-network traffic. Then, we found that the characteristic with respect to DET and self-similarity seen in the measured traffic fluctuated over time, with different time variation patterns for two measurements. In training the self-organizing map, we used three parameters: average throughput, variation ratio of DET, and $\alpha$ value. As a result, we visually confirmed that the traffic data could be projected onto the map in accordance with traffic properties, resulting in a combined depiction of the effects of the DET and network utilization rates on the time-variations of LRD.

Index Terms—Detrended fluctuation analysis, network traffic, non-stationary transition, recurrence plot

I. INTRODUCTION

Measurement-based studies especially in the 1990s have revealed that traffic behaviors in actual IP networks are self-similar, demonstrating fractal-like variations [1]-[4]. The concept of self-similarity is related to the occurrence of similar patterns at different scales in finite-dimensional distributions of a time-series signal. Previous studies have shown that aggregated traffic in real-world networks has long-range dependence (LRD), in which a process is characterized by an autocorrelation function that decays with a lag time. Simulation-based studies for evaluating the effects on a network system have also demonstrated that the LRD seen in the IP-network traffic fluctuation can affect network performance levels in terms of the network link bandwidth and buffer responses [5]. Characteristics of IP-network traffic in actual environments vary randomly over time; that is, the characteristics of the probability distributions of IP packets change dynamically in the time domain. In Refs. [6]-[9], for example, Takayasu et al. pointed out that network traffic behaviors change with the phase transition patterns and that their fractal-like behaviors are affected by the packet density and its variation pattern in the time domain. These studies have contributed to the analysis by demonstrating that phase transitions and power laws apply to changes in actual IP-network traffic density. Furthermore, in order to evaluate the time-variation patterns of traffic’s LRD and packet density in actual environments, self-organizing scheme-based approaches have been also presented [10],[11]. In these previous studies, however, the dynamical transitional patterns of IP-network traffic have not been fully explained, so the fractal-related characteristics of traffic changes remain to be analyzed.

This paper describes an analysis of IP-network traffic in terms of evaluating its non-stationary transition patterns. To clarify the dynamical changes of actual IP-network traffic, we used a recurrence plot (RP), which is effective for visualizing non-stationary variation patterns of dynamical systems [12], [13]. In addition, to obtain quantitative information associated with RPs, we applied the recurrence quantification analysis (RQA) [14]-[16] to measuring the degree of non-stationary variation patterns of IP-network traffic. Furthermore, in order to integrate multiple variables obtained from measured traffic data sets, this paper used a self-organizing map, which is an effective tool for clustering relative relationships in high-dimensional input data [17], [18]. The concept of RP-based analysis is reviewed in Section 2, in which fractal-related analysis using the detrended fluctuation analysis (DFA) [19]-[23] is defined. The basic flow of the self-organizing map is also presented in this section. Section 3 of this paper presents analytical results for IP-network traffic observed in actual environments. Based on measured traffic data sets, this paper shows that the proposed scheme is effective as a way of displaying how IP-network traffic conditions change over time.
II. METHOD OF ANALYZING NON-STATIONARY TRANSITION PATTERNS OF IP-NETWORK TRAFFIC

Researchers have pointed out that fractal-like behaviors of IP-network traffic are affected by packet density and its variation pattern [6]-[9], as described in the introduction. As a way for measuring the dynamical transition patterns of IP-network traffic, we used the recurrence plot (RP). Its basic concept is reviewed in this section. This section also reviews the concept of the detrended fluctuation analysis (DFA) to derive LRD-based properties of IP-network traffic, and the flow of the self-organizing map used to visualize the properties of IP-network traffic is presented.

A. Analysis using recurrence plot approach

The RP approach provides a qualitative interpretation of hidden patterns of dynamical systems [12]. It enables us to investigate the m-dimensional phase space trajectory by means of a two-dimensional visualization. By using RPs, we can efficiently check non-stationary variation patterns of time-series data.

Here, let \( x(i) (i = 1, 2, 3, \ldots, N) \) be a one-dimensional stochastic process with time i. The dynamics of time-series data can be expressed by a reconstruction of the phase space trajectory \( X(i) \):

\[
X(i) = (x(i), x(i+\tau), \ldots, x(i+(m-1)\tau)),
\]

where \( m \) and \( \tau \) are an embedding dimension and a time delay, respectively. Then, the distance between two state vectors \( X(i) \) and \( X(j) \) (i, j = 1, 2, 3, \ldots, N) can be defined as follows:

\[
D(i, j) = |X(i) - X(j)|.
\]

The RP visualizes the relationships between two state vectors within a two-dimensional square matrix of size \( N \times N \). In this process, a threshold distance is generally set for plotting recurrence points, which fall in the neighborhood of a fixed size. Instead of plotting the recurrences in two values (i.e., black and white) by setting a threshold level, the distance \( D(i, j) \) can also be used, which helps checking the phase space trajectory of target data [13]. If phase space trajectory returns to itself and runs close for some time, the diagonal patterns can be seen in the RP. The single dot or short diagonal segments in the RP suggests that the phase space trajectory is unstable.

The recurrence quantification analysis (RQA) has been introduced as a way of measuring quantitative information with respect to RPs [14]. It defines measures of complexity using the recurrence point density and diagonal structures in RPs. When analyzing the dynamical time-variation patterns of IP-network traffic, we focus on a parameter called determinism (DET) [14]-[16], which measures the ratio of recurrent points forming line segments that are parallel to the main diagonal, as follows:

\[
\text{DET} = \frac{\sum_{l=1}^{l_{\text{max}}} l \cdot p(l)}{\sum_{l=1}^{l_{\text{max}}} l \cdot p(l)} \times 100 \%,
\]

where \( p(l) \) is the frequency distribution (or histogram) of the lengths \( l \) of diagonal lines in the RP. The threshold, \( l_{\text{min}} \), excludes diagonal lines that are formed by the tangential precession of the phase space trajectory.

B. Measuring fractal-related properties of IP-network traffic

To measure the fractal-related properties of IP-network traffic, we use the DFA scheme [19]-[23] to analyze the traffic’s degree of long-range dependence (LRD), which affects the performance of network systems.

The many previous studies presented so far have been based on the assumption that the target network traffic is stationary or wide-sense stationary, which is often difficult to find in the real world. The DFA has been introduced as a way of measuring long-range power-law correlations or LRD of non-stationary time series signals.

Here, let \( x = \{x(i); i = 1, 2, 3, \ldots, N\} \) be a one-dimensional stochastic process with time i. We define the following integrated signal \( y(k) \):

\[
y(k) = \sum_{i=1}^{k} (x(i) - \mu),
\]

where \( \mu \) is the mean of \( x(i) \). Next, we divide the integrated time series \( y(k) \) into boxes of equal length \( n \). We then find the least-squares line that fits the data in each box of length \( n \). After that, \( y(k) \) is detrended by subtracting the local trends \( y_d(k) \) in the following way:

\[
F(n) = \left[ \frac{1}{N} \sum_{k=1}^{N} (y(k) - y_d(k))^2 \right]^{1/2}.
\]

The above computation is repeated across a broad range of scales to characterize the relationship between the box size \( n \) and the average root-mean-square fluctuation function \( F(n) \). A power-law relationship between them indicates the presence of scaling given by \( F(n) \sim n^{\alpha} \), which means that the process obeys the scaling law characterized by the scaling exponent \( \alpha \). The fractal-like nature of the fluctuation is described by the scaling exponent \( \alpha \), which represents the long-range power correlation or LRD of the signal. If the target process is similar to white noise, then \( \alpha \) is close to 0.5. If the process is correlated or persistent, \( \alpha > 0.5 \); if the process is anti-correlated or anti-persistent, \( \alpha < 0.5 \). Namely, \( \alpha \) values increasingly greater than 0.5 indicate an increasing degree of LRD for the time-series signal; i.e., the \( \alpha \) value corresponds to the Hurst parameter when \( 0.5 < \alpha < 1.0 \) [19]-[23].

The important advantage of DFA lies in its applicability to non-stationary time series; i.e., the scaling behaviors of non-stationary traffic can be analyzed with this method, although conventional methods such as R/S analysis cannot be used for non-stationary signals. Furthermore, a DFA-based method can be a more effective tool for estimating the degrees of LRD than conventional methods. For example, comparisons between DFA-based and other methods were presented with respect to the values and confidence intervals of estimating LRD in [23]; white noise-based evaluations revealed that this scheme can provide better results compared to conventional methods such as R/S analysis. As a result, this method has been successfully applied to evaluate the characteristics of data such as DNA and economic indexes [19]-[23]. The \( \alpha \) values obtained through this analysis allowed us to use the self-organizing scheme as described in the next section.
C. Analysis using the self-organizing map

The self-organization algorithm can convert complex, nonlinear statistical relationships among multi-dimensional data into simple geometric relationships in a low-dimensional domain. It calculates multi-dimensional parameters so that they optimally denote the domain in which relationships of primary data are preserved topologically. In this paper, a two-dimensional map is employed to map the measured traffic data.

The basic training process of the self-organization model is defined as [17], [18]

\[ w(t+1) = w(t) + h_{c(x,i)}(x(t) - w(t)), \]  

where \( w \) is the weight vector, \( x \) is the n-dimensional input vector, \( h_{c(x,i)} \) is the neighborhood function, \( i \) specifies a node in the output layer, and \( t \) is the regression step index. In this process, the input vector \( x \) is compared with all \( w_i \), and the subscript \( c(x) \) is defined by the Euclidean condition

\[ \| x - w_c \| = \min_i \| x - w_i \|, \]  

where \( w_c \) is the winner that best matches \( x \). Here, the initial value of \( w_i \) is set to a random value, and the Gaussian-type neighborhood function can be expressed by

\[ h_{c(x,i)} = a(t) \exp \left\{ -\| r_c - r_i \|^2 / 2\sigma_c^2(t) \right\}, \]  

where \( 0 < a(t) < 1 \) is the learning rate parameter, \( r_c \in \mathbb{R}^2 \) and \( r_i \in \mathbb{R}^2 \) are the vertical locations on the grid, and \( \sigma(t) \) corresponds to the width of the neighborhood function. In addition, assuming that \( T \) is the number of total training iterations, \( a(t) \) and \( \sigma(t) \) can be defined as

\[ a(t) = a(0) \left( 1 - \frac{t}{T} \right), \]  

\[ \sigma(t) = \sigma(T) + (\sigma(0) - \sigma(T))(1 - \frac{t}{T}). \]  

The procedure of this self-organizing training process is described as follows:

(a) Initialize \( w_i \) to a random value;
(b) Input \( x(t) \), one at a time;
(c) Calculate eq. (7), and find \( w_c \);
(d) Calculate eq. (6) using eqs. (8) - (10), and
(e) Repeat from (b).

To increase the training efficiency, the algorithm is performed in two phases. In the first phase, a relatively large initial neighborhood radius is used to tune the map approximately. Then, in the second phase, the initial neighborhood radius is set to a small value to fine tune the map.

In checking the projected data sets in the map, the distance between them generally reflects their similarity or dissimilarity. However, unseen relationships between high-dimensional data (i.e., walls or boundaries among nodes) can sometimes exist in the output layer of the map. To demonstrate these relationships in the map, we use the unified distance matrix (U-matrix), which is effective for visualizing steep topological differences among nodes [24], [25].

Considering the Euclidean distance in a two-dimensional rectangular topology of size \( (X \times Y) \), the U-matrix in this analysis can be calculated by using the distances \( d_x, d_y, \) and \( d_{xy} \), as follows:

\[
U = \begin{pmatrix}
\text{du}(1,1) & \text{dx}(1,1) & \cdots & \text{du}(1,Y) \\
\text{dy}(1,1) & \cdots & \cdots & \cdots \\
\text{du}(2,1) & \cdots & \cdots & \cdots \\
\text{dy}(2,1) & \cdots & \cdots & \cdots \\
\vdots & \vdots & \vdots & \vdots \\
\text{du}(1,Y) & \text{du}(Y,1) & \cdots & \text{du}(X,Y)
\end{pmatrix}
\]  

\[ \text{dx}(x, y) = \| w_{x,y} - w_{x+1,y} \|, \]  

\[ \text{dy}(x, y) = \| w_{x,y} - w_{x,y+1} \|, \]  

\[ \text{dxy}(x, y) = \| w_{x,y} - w_{x+1,y+1} \|^{1/2} + \| w_{x,y+1} - w_{x+1,y} \|^{1/2}/2. \]

where \( w_{x,y} \) is the calculated weight vector, and \( du \) and \( dy \) is calculated by using the mean of surrounding eight distances (see Appendix) [24], [25]. Namely, the U-matrix combines several distances into one matrix of size \((2X-1) \times (2Y-1)\) in a two-dimensional map. The U-matrix elements can be generally indicated by the depth allocated in the two-dimensional domain (or the difference of color in the map).

When investigating the time variation patterns of IP-network traffic, we integrate several parameters by using the self-organizing map. In this analysis, data sets of \( N \) samples of IP-network traffic are set over time, and the time-shift between consecutive sets is \( M \). Next, we derive several variables for the training from each data set. Then, the self-organizing map is trained on input data and a visual interpretation of the data is displayed in a two-dimensional domain, the output layer of the map.

III. CASE STUDY: ANALYSIS OF MEASURED NETWORK TRAFFIC

A. Measurement of IP-network traffic

When measuring IP-network traffic for the analysis, we set traffic measuring devices at two locations. The NTT Musashino R&D Center (Tokyo, Japan) was connected to the Internet via a 17-Mbps leased line, and IP packets entering the center from the Internet were measured via a router at the terminating point of the line by a traffic measuring device. Also, an access provider in Tokyo and the Internet were connected via a 1-Gbps switch, and the flow of IP packets between the access provider and the Internet was measured by a traffic measuring device attached to the switch. We call these measurements A and B, respectively.

To measure the network traffic throughput (= the amount of traffic per second), we set the time resolution of the traffic measuring device to 10 ms at 10:00 a.m. on Dec. 3, 2002 for measurement A, and at 5:10 a.m. on May 28, 2003 for measurement B. Then, the total number of sampling points for analysis was 40,000 (400 s).

Measured traffic throughputs normalized by the bandwidth in measurements A and B are shown in Fig. 1, where the time resolution is 100 ms for the main part and 10 ms for the upper part (inset). The fluctuations in the main part appear to be...
non-stationary for both cases: the measured traffic throughput for measurement A tends to saturate after around 120 s (12,000 sample points) to 200 s (20,000 sample points); measured traffic throughput for measurement B tends to saturate around 220 s (22,000 sample points) to 280 s (28,000 sample points). Also, the bursty nature of the traffic is visible in the inset for both measurements, indicating that self-similar features were present in the apparently non-stationary body of fluctuations. However, we can see that the fluctuation patterns, or the degrees of fluctuations, changed when the measured throughput saturated for both cases. Namely, the results show that the fractal-like characteristics of IP-network traffic in these measurements seemed to change with non-stationary transitions in the IP networks.

Then, traffic throughput of allocated data sets derived from Fig. 1 are shown in Fig. 2, where the average values are plotted in the center of each 100-s period. Here, the number N of sampling points for one data set was 10,000 (100 s), and the time-shift number M between consecutive data sets was 2,000 (20 s); i.e., the data sets for calculations were set to 2,001 to 12,000, 4,001 to 14,000, ..., and 30,001 to 40,000 samples (the number of total data sets = 15). Results show that the average throughput (normalized average throughput) for measurement A tended to increase over time, while that for measurement B peaked at approximately 220 - 280 s, each reflecting basic time-variation patterns in Fig. 1.

**B. RP-based analysis of measured traffic**

The RPs obtained for both measurements are shown in Fig. 3, where the distance of eq. (2) is plotted in stead of setting a threshold distance [13]. Here, based on the average mutual information and the false nearest neighbors [26], [27] in addition to the embedding theory by F. Takens [28], the time delay and embedding dimension were set to 5 and 3 for measurement A, and 10 and 3 for measurement B, respectively. In these RPs, the darker domains correspond to points where the state space reconstruction is characterized by long distances while domains with short distances correspond to light depth; e.g., the upper-right part in Fig. 3(a) corresponds to the domain where the dynamical changes in data were smaller. Results in Fig. 3 also show that there are few diagonal patterns perpendicular to the main diagonal for both measurements, meaning that the measured traffic did not contain so many periodic time-variations for each case.

The calculated values of DET (%DET) for both measurements are shown in Fig. 4, where the radius (or the threshold distance) for counting recurrent points was set to 100, and the lowest number of upward diagonal recurrent points required to define a deterministic line was set to 10, respectively. Results show that the time periods, in which the values of DET tend to be higher, correspond to the domains where there are non-stationary transition changes in measured traffic in Fig. 1; e.g., the DET values for measurement A tend to be higher around 20 - 40 s, 130 - 270 s, and 310 - 340 s; those for measurement B tend to increase especially from around 220 - 280 s. Namely, we can say that the degree of fluctuation, which affected the non-stationary transition patterns, for measurement A was higher than that for measurement B on average in these periods.
In evaluating the result in Fig. 4, the time period of one data set and the time shift between consecutive data sets were set to 100 and 20 s, respectively, and we define the variation ratio of DET of each data set as the sum of DET for the time period of $t = t_1 - t_1 + 100$ s divided by the sum of DET for the time period of $t_0 - t_0 + 100$ s, where $t_0$ and $t_1 (= t_0 + 20)$ are start times of the previous and the target data sets, respectively. Then, the variation ratio of DET for allocated data sets derived from Fig. 4 are shown in Fig. 5, where the values for each data set are plotted in the center of each 100-s period for calculations.

Looking at the variation ratio of DET for measurements B, their variation patterns seem to reflect the pattern of average throughput in Fig. 2 clearly. Namely, we see that the value tends to be more than 1 during 150 - 250 s, which means that the degree of non-stationary transitions of measured traffic continued to increase during this period. Also, the tendency for the variation ratio of DET for measurement B to decrease to less than 1 after 250 s indicates that the value of DET in Fig. 4 (b) was turned to decrease during this period. These tendencies clearly reflected aggregation patterns of the average throughput in Figs. 1 and 2.

On the other hand, the variation ratio of DET for measurement A seems to change randomly compared with that for measurement B. The IP-network traffic for measurement A tended to aggregate in accordance with continuous non-stationary fluctuations during this period, so the variation ratio of DET did not exhibit a clear tendency. Thus, we can conclude that the non-stationary transition patterns of IP-network were different for each measurement.

C. LRD-based analysis of measured traffic

In this section, we show an LRD-based analysis of measured traffic and discuss the results using RQA-based measures. When calculating the scaling parameter $\alpha$ of the DFA approach, the number of samples in one data set was set to 10,000. Examples of log-log plots of $n$ vs. $F(n)$ for measurements A and
B are shown in Fig. 6, where data sets whose normalized throughputs were less than 0.5 and above 0.7 on average were calculated. In Fig. 6, there are basic trend lines for ranges of 0.7 - 0.8 \( \leq \log_{10}(n) \leq 3.1 - 3.2 \) for each measurement, although the different slopes can be seen in a different local range of \( \log_{10}(n) \) for data 3 in measurement B, meaning that there existed much more complex stochastic structures with respect to scaling behavior in data 3.

![Log-log plots for measurements A and B](image)

Fig. 6. Examples of log-log plots of \( n \) vs. \( F(n) \) for measurements A and B.

Then, derived \( \alpha \) values of allocated data sets, with a time period of 100 s and a time shift of 20 s, for measurements A and B are shown in Fig. 7, where the results were plotted in the center of each time period (100 s) for calculations. Here, in the calculation of \( \alpha \) values from log-log plots of \( n \) vs. \( F(n) \), the results change with respect to the ranges of \( \log_{10}(n) \); for example, the \( \alpha \) value for data 1 in measurement A changes; e.g., 0.77 for \( 0.70 \leq \log_{10}(n) \leq 3.0 \) and 0.79 for \( 0.70 \leq \log_{10}(n) \leq 3.2 \). The following discussion is concerned with \( \alpha \) values defined for the best line in ranges of around \( 0.70 \leq \log_{10}(n) \leq 3.2 \), because our aim is to comprehend basic scaling tendencies of traffic data and to simplify the DFA-based analysis. When we checked all data sets, the relative differences for \( \alpha \) values were less than 2 to 3%.

Looking at the \( \alpha \) values for measurements B, the variation patterns of the \( \alpha \) values seem to be correlated with the average throughput and the variation ratio of DET in Figs. 2 and 5. Namely, the \( \alpha \) values tended to increase when the average throughput increased or when the variation ratio of DET values was more than 1. In the case for measurement A, we see that the \( \alpha \) values tend to increase after around 250 - 300 s but do not seem to have a correlation with the variation ratio of DET values in Fig. 5. We can estimate that traffic’s LRD-based properties for measurement A varied with a decreasing degree of fluctuations in accordance with continuous non-stationary variations in this period, demonstrating that the \( \alpha \) values tended to increase after around 250 - 300 s, in which the average throughput for measurement A almost saturated.

These results seem to be due to the network system’s nature; i.e., because i) the degree of aggregation of IP-network traffic and ii) the margin of total network bandwidth for measurement B were higher than those for measurement A, so the measured traffic throughput for measurement A fluctuated more widely on average and tended to saturate more quickly than that for measurement B. As a result, the time-variation properties associated with LRD were different when comparing the results for measurements A and B.

In Refs. [6]-[9], Takayasu et al. suggested that fractal-like behaviors of IP-network traffic can be affected by their packet density and time-variation patterns. In these studies, it has been pointed out there exists a certain threshold level of IP-network traffic density, at which the phase transition patterns of them can change; e.g., \( 1/f \) fluctuations of IP-network traffic behaviors can change with the packet density. In this study, we took a RQA-based approach, which defines the measure of complexity using the recurrence point density and diagonal structure in the RP, in order to examine fractal-based properties of IP-network traffic with respect to their non-stationary transition patterns. As a result, we confirmed that a larger degree of DET or average throughput tended to reflect increases in the degree of LRD of IP-network traffic, although their time-variation patterns can be different for different locations. Thus, analysis using RP-based measures can be
D. Analysis using self-organizing map

This paper applied a self-organizing scheme to the measured traffic data and thus evaluated the time variations of measured traffic data. In this analysis, we used three parameters derived from a measured traffic data set: the average throughput (normalized average throughput), the variation ratio of DET, and the $\alpha$ value. The average throughput is related to the degree of aggregation of measured traffic or used bandwidth of the IP network; i.e., increases to a certain degree in this value lead to decreases in the degree of traffic's fluctuations. The value of DET corresponds to the occurrence of non-stationary transitions of measured traffic, and the variation ratio of DET, whose value is more than 1, reflects the increasing degree of non-stationary fluctuations of IP-network traffic in the time domain. The $\alpha$ value corresponds to the degree of LRD of measured traffic, so increases in this value lead to increases in the degree of LRD of IP-network traffic and to lower network performance.

The data sets in Figs. 2, 5 and 7 were used in training a topologically rectangular map, and the map size was set to $10 \times 10$. In addition, based on the quantization error defined by the mean of $||x - w_c||$ [18], we set the number of total training iteration for the self-organizing map to 10,000. To raise the efficiency of training, we performed the training in two phases [18]: in the first phase, with training number of 1,000, the initial value of the learning-rate parameter $a(0)$ was set to 0.5, while in the second phase it was set to 0.05. In addition, parameters of the neighborhood radius were also altered: the initial value $\sigma(0)$ and final value $\sigma(T)$ in the first phase were set to 5 and 1, while the corresponding values in the second phase were 2 and 1, respectively.

Figure 8 shows a visualization result projected onto the two-dimensional U-matrix domain in which the distances between neighboring map units and the cluster structure of maps are visualized [24],[25], where the reference axes are set as $x$ and $y$, and the order of data set from the beginning is set for both measurements.

Here, we allocated the coordinates $(x, y)$ ($x = 1, \ldots, 10$ and $y = 1, \ldots, 10$) to the center of map units; i.e., the coordinate grids $(x, y)$ of the form $(1,1), \ldots, (10,1), (1,2), \ldots, (10,2), \ldots$ and $(1,10), \ldots, (10,10)$ were allocated. In addition, maps of the corresponding values of the input variables are shown in Fig. 9, where each parameter is split into several domains.

First, we see the following characteristics of the input variables:

- The average throughput tends to increase along the $x$- and $y$-axes, and the upper-right region corresponds to the domain where the value was the highest. The variation ratio of DET is the lowest at central-left region and tends to increase along the $x$-axis, with the values in the bottom-right region being the highest of all, meaning that the bottom-right region corresponds to the domain where the degree of non-stationary fluctuations of measured traffic increases. The $\alpha$ value is the lowest value at the bottom-left region and tends to be higher in the upper-left and bottom-right regions, meaning that the upper-left or bottom-right region corresponds to the domain where the patterns of measured traffic are most likely to affect the network system in terms of LRD.

In the map of the time-based sets of traffic data, we see the following points:

- The 15 sets of data for measurement A shift from the central-left region, to the upper region, and finally to the central-right region in the map. Therefore, these results visually demonstrate that values of average throughput and the degree of LRD tended to increase especially after the 3rd data set for measurement A during this period. We also see that the variation ratio of DET for measurement A is within a limited range compared with that for measurement B.
- The 15 sets of data for measurement B shift from the bottom-left region, to the bottom-right region, to the upper-left region, and then to central-left region in the map, which constitutes visual confirmation that values of all parameters were dramatically changing within this time period. When we look at the $\alpha$ values for measurement B, for example, we see that some data sets that are located at upper-left or bottom-right region were relatively high, resulting in the value of B[11] being the highest.
• In checking the differences due to the U-matrix, we see that some data sets such as B[7-10] or B[11-14] are distinguished from data sets for measurement A, which seemed to be due to the differences in the variation ratio of DET and the $\alpha$ value.

• In addition, to evaluate the positions of projected data, we calculated the center of balance of each data set by checking the coordinate grids for the center of map units, where the data are located. As a result, the centers of balance were (5.00[1.58], 4.80[1.30]) for the data sets of 1st - 5th for measurement A, (7.00[0.71], 8.60[1.52]) for the data sets of 6th - 10th for measurement A, (7.40[3.13], 9.40[1.34]) for the data sets of 11th - 15th for measurement A, (2.20[1.79], 1.20[0.45]) for the data sets of 16th - 20th for measurement B, (9.20[1.31], 2.20[1.31]) for the data sets of 6th - 10th for measurement B, and (1.00[0.00], 7.80[1.92]) for the data sets of 11th - 15th for measurement B, respectively, where [ ] represents standard deviation of each value. Namely, in terms of quantitative evaluations for five-unit data sets, we see that projected data for measurement B dynamically shifted from the bottom-left, to the bottom-right, and then to the upper-left regions in the map, while those for measurement A tended to be at central or upper-right regions in the map.

As a result, we can efficiently check that the degree of LRD for measurement B tended to increase with increasing and decreasing the variation ratio of DET, while that for measurement A tended to be stable compared with measurement B. We thus visually confirmed our technique’s ability to project traffic data onto a two-dimensional domain in a way that reflects their properties. The proposed method projects data with multi-dimensional input parameters onto a two-dimensional space, so that we can effectively evaluate changes in IP-network traffic conditions over time. Here, we must be aware that the properties of LRD can change with the bandwidth and the type of network systems. Therefore, further analysis using several kinds of data sets should be undertaken to evaluate applicability of the proposed scheme.

IV. CONCULUSION

This paper applied the RP-based approach in order to analyze how non-stationary transition patterns of IP-network traffic change over time. Also, in performing a quantitative evaluation, we derived the values of DET defined by the RQA. When evaluating the fractal-based properties of IP-network traffic, we measured the degree of LRD of measured traffic by applying the DFA approach, which provides a way of measuring the degree of long-range power-law correlation or LRD of time-series signals that are not necessarily stationary. Furthermore, for an analysis in which multiple aspects of network conditions are taken into account, this paper applied a self-organizing approach in a simple evaluation of how the non-stationary transition patterns of IP-network changes over time.

Based on measurements in actual environments, we derived the value of DET and the LRD-based parameter of IP-network traffic and confirmed that an increasing degree of DET or a larger value of the average throughput reflected increases in the degree of LRD of IP-network traffic. The map produced by the self-organizing algorithm reflected the effects of both the variation ratio of DET and the network bandwidth utilization on the degree of LRD.

Future studies will be concerned with further analysis using various kinds of calculation conditions and further evaluations of the applicability of this method to various network environments.

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