An Adaptive Routing Algorithm of self-similar Traffic based upon The Prediction of Fractal Time Series and GA

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https://doi.org/10.15017/3000254

出版情報：経済論究. 108, pp.29-41, 2000-11-28. 九州大学大学院経済学会
バージョン：
権利関係：

An Adaptive Routing Algorithm of Self-similar Traffic based upon the Prediction of Fractal Time Series and the GA

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SUMMARY

This paper deals with an adaptive routing algorithm of self-similar traffic based upon the prediction of fractal time series and the GA (Genetic Algorithm).

Mathematical results show that the superposition of many ON/OFF sources exhibit the self-similarity. At first, the self-similar traffic is represented by using a convolution of the input signal and the impulse response function which is developed by using a set of scaling functions. The prediction method is derived by usingthe fact that the impulse response possess the self-similarity due to the fractal property even if the time scale is expanded. By using the fluid flow model where the input traffic is assumed to be fractal, the delay on the output link is predicted by our method. In the adaptive routing algorithm treated in our paper,the predicted delay on the output link is broadcasted as well as observed delay to find out shortest path in the next time point. By using the predicted delay and the observed delay to formalize routing tables, packets can be sent through more relevant path. Even more, by using these two kinds of delay, the time interval T for updates can be taken larger than in conventional algorithm. Conventional routing algorithms only generate the shortest path from the source to the destination, even if some alternative path is available. In the adaptive algorithm, we utilize the GA to find out some alternative path if the communication delay become large. The algorithm realizes a kind of load balancing by using the alternative paths. The performance of the adaptive algorithm is compared to conventional ones. As a result, the mean delay on the output link become about 20% smaller, and the variance of the delay become remarkably small.

Keywords Adaptive Routing, Fractal,Self-similar Traffic, Prediction, Genetic Algorithm

1. Introduction

Incearsing demand for integrated communication such as multi-media traffic on the internet claims more effective routing algorithm on a high-speed communication infrastructure[1]. The basic function to be performed by any computer network s the provision of effective paths for an end user. In conventional routing algorithm such as the internet, the whole of the hop count metric are directly broadcasted to nodes[2][3], However, if the size of network is large, the global network to be forwarded become large, and its performance may be degraded. An alternative we employ is the routing algorithm based upon the status of nodes to suppress the updates exchanged in the network. The pertinent information about the delay on outgoing links is forwarded to nodes in a distributed system. Each node individually maintains a list (table) of its best next hop (outgoing link) to each destination. The best path is determined based on a cost such as the number of hops, delay, throughput and error rate as well as processing capacity of switching node. These cost values are broadcasted and received by each node as update in a distributed manner at each time interval T.

If the interval T between updates of routing table is small,the messages suffer original packet traffic. On the other hand, if T is large, these paths generally remain fixed for the duration of operation, and the routing table may not provide appropriate information any more. As an adaptive routing algorithm to resolve these crucial problems, in our algorithm, we utilize also the predicted delay on outgoing links as well as the observed delay[4].

In the adaptive routing algorithm treated in our paper, the predicted delay on the outgoing link is broadcasted as well as observed delay to update the routing tables. Evenmore, by using these two kinds of delay, the time interval T can be taken larger than in conventional algorithm.

Especially, the mathematical result about the ON/OFF sources states that aggregate network traffic exhibits self-similar or long-range dependency[5]-[9]. An extensive statistical analysis for LAN traffic confirms the self-similarity. However, the theory has not been applied positively to the prediction of network traffic.

In previous papers we showed the prediction method of fractal time series by using the time scale expansion[10]-[13]. We use the fact that aggregation of many ON/OFF sources exhibits self-similarity or long-range dependency[1]. At first, the times series is represented by a convolution of the input signal and the impulse response function which is expanded by using a set of scaling functions. Then, the prediction method is derived by using the fact that the impulse response possess the self-similarity due to the fractal geometry even if the time scale is expanded. The prediction method is applied to estimate the delay of packets on the output link. The information of delay is also used for the calculation of routing table.

Under heavy offered load, shortest path simple route turn out not to be optimum, then multiple or bifurcated paths are generated. Packets at a node are assigned to one of several outgoing link on a probabilistic base. We use the Genetic Algorithm (GA) to find out these alternative[15][16]. The adaptive algorithm is evaluated by using the simulation study. As a result, the mean delay on the output link become about 20% smaller, and the variance of the delay become remarkably small.

In the following discussion, Section 2 shows the basic idea of adaptive routing and result of aggregation of ON/OFF sources. In Section 3, we show the prediction method of self-similar traffic by using the time scale expansion. We also give a metric to check the fractal property by using the wavelet transform. Section 4 shows the adaptive routing algorithm based upon the prediction of self-similar traffic, and the path generation by the GA. In Section 5, the performance of the adaptive routing algorithm is evaluated by using simulation studies.

2 . Routing algorithm and fractal time series

2.1 Routing algorithm utilizing predicted delay

The distributed routing algorithm is based on the premise that the best total path from a source node to a destination is the sum of many individual node-to node best path. Each node individually maintains a list (table) of its best next hop (outgoing channel)to each destination. The best path is determined based on a cost such as the number of hops, delay, throughput and error rate as well as processing capacity of switching node. These cost values are broadcasted and received by each nodes as update in a distributed manner.

For example, in the RIP (Routing Information Protocol), the whole of the hop count metric is directly broadcasted to nodes. In this case, the routing information message contains huge table,if the size of network is large(2). On the other hand, in the routing algorithm which exchanges only the status of outgoing link at each node such as delay, the message exchanged in the network is restricted(3). In our paper, we use the status of outgoing link to calculate the routing table.

(1) Utilizing predicted delay

In the routing algorithm based on the link information,the shortest path is estimated by conventional algorithm such as the Dijkstra's algorithm. Routing tables are reorganized by exchanging the cost message information at every time interval, say T. If the interval T is small, the updates are sent frequently and its transmission suffers original packet traffic, even though we have better routing tables. On the other hand, if the interval T is large, routing table may not give appropriate path anymore after time T.

As an adaptive routing algorithm to resolve these crucial problems, in our algorithm, we utilize also the predicted delay on outgoing links as well as the observed delay(4). Originally, the observed delay in the buffer is a kind of past information about the network. By using the predicted delay and the observed delay to formalize routing tables, packets can be sent through more relevant path. Even more, by using these two kinds of delay, the time interval T can be taken larger than in conventional algorithm.

(2) Alternative path found by the GA

Once one thinks in terms of single path

routing, it is natural to choose the shortest, or more generally, the least cost path whenever alternate paths exit. The shortest path algorithm shows the best path for each packet, however, it may occurs the case where many path (flows) use the same link (outgoing path), and packets have large delay, especially for heavy offered load cases. Because, the shortest path is estimated independently for each packet, and shortest path turn out not to be optimum any more. Then, it is necessary to find out second-best path (alternative multiple or bifurcated path), and to distribute offered load. We apply the GA to generate alternativepath. In the GA, a certain node on the best path found by the Dijkstra's Algorithm is replaced by another adjacent node, and the path before and after the alternative node are used for the alternative path.

These alternative path are generated at time interval T, however, the total number of alternative path is limited by deleting the path having large delay from the routing table.

2.2 Fractal time series generated by ON/OFF sources

Mathematical results show that the superposition of many ON/OFF sources with strictly alternating ON/OFF periods can produce aggregated network traffic that exhibits the self-similarity or long-term dependency[(6)-(9)]. The proof of this fundamental result was given by Taqqu, Willinger and Sherman[(6)(7)].

Suppose that there is one stationary binary time series $W(t)$ which is the state of the packet generated. $W(t)=1$ means that there is a packet at time t (ON period), and $W(t)=0$ means there is no packet (OFF period). The length of ON and OFF periods are i.i.d, and are independent. An OFF period always follows an ON period. Suppose now that there are M i.i.d sources by distinguishing these sources by the superscript m, $W^m(t)$. The superposition of packet count at time t is $\sum_{m=1}^{M} W^{(m)}(t)$. Rescaling time by a factor T, we have next aggregated packet count in the interval $[0, Tt]$.

For large M and T, the function behaves statistically like

$$TMt\mu_1/(\mu_1+\mu_2)+(T^{2H}L(T)M)^{1/2}\sigma B_H(t) \quad (1)$$

where $B_H(t)$ is a fBm (fractional Brownian Motion) with Hurst parameter H. To specify the distribution of the ON/OFF periods, let $f_1(x)$, $f_2(x)$ denote the distribution function of the length of ON period and OFF period, and their distribution functions are $F_1(x)$, $F_2(x)$. Then the complementary distribution functions

$$F_{1c}(x)\sim 1_1 x^{-\alpha 1}L_1(x),\ 1<\alpha_1<2 \quad (2)$$

$$F_{2c}(x)\sim 1_2 x^{-\alpha 2}L_2(x),\ 1<\alpha_2<2 \quad (3)$$

where μ_1, μ_2 are mean length of ON/OFF periods, σ_1, σ_2 are variances of ON/OFF periods. The functions $L_1(x)$, $L_2(x)$ are slowly varying function at large x, and are constants or the functions $\log x$, $(\log x)^{-1}$ which are asymptotic to a constant. $\sigma_{\lim}$ is represented by using $L_1(x)$, $L_2(x)$, μ_1, μ_2, σ_1, σ_2, α_1, α_2.

Extensive statistical analyses confirmed the presence of self-similarity of fractal properties in measured Ethernet LAN traffic and also in the wide area traffic such as TELNET and FTP(6)-(9).

3. Prediction of fractal time series

We assume that the aggregated traffic $x(t)$ on the nodes of computer networks is approximated by a fBm whose pattern of oscillation can be controlled by the fractal dimension. Then we apply the prediction method given by authors to the aggregated traffic $x(t)$(10)-(13).

Model fitting

For the problem of optimal prediction, we assume at first $x(t)$ is linearly dependent on the past of $x(t)$ as

$$x(t)=\int_0^{t_0} h(t,\ t-\tau)x(\tau)d\tau,\quad t>t_0 \tag{4}$$

where $h(t,\ \tau)$ is a time-variant impulse response function.

Suppose that the impulse response function $h(t,\ \tau)$ of linear time-variant system is expanded by using a set of scaling functions $\phi(t)$ as follows.

$$h(t,\ \tau)=\sum_{i=0}^{\infty}\sum_{j=0}^{\infty} h_{ij}\phi_{Ni}(t)\phi_{Nj}(\tau) \tag{5}$$

where $$\phi_{ij}(t)=\phi(2^i t-j) \tag{6}$$

$$\phi(t)\begin{cases}1, & 0<t\leq 1;\\ 0\ ; & otherwise\end{cases} \tag{7}$$

The coefficients h_{ij} of the impulse response function need to be chosen so that the square error $E=\sum(x(t)-\hat{x}(t))^2$ between observed $x(t)$ and the prediction $\hat{x}(t)$ obtained by equation (4) is minimized. Differentiating E with respect to h_{ij}, we obtain the increment of h_{ij} for successive optimization.

Prediction

Suppose the time series $x(t)$ is observed in the period $T_s<t<T_e$ $(T_1=T_e-T_s)$, and in the period $0<t<T_2$ $x(t)$ is predicted by using the time scale expansion. Define following related to the fractal property.

$$b=a^D,\quad a=T_2/T_1,\quad T_2>T_1 \tag{8}$$

The constant D is the fractal dimension of the time series $x(t)$. The fractal dimension D is limited in a range so that the time series bear the fractal property.

$$1<D<2,\quad H=2-D \tag{9}$$

where H is the Hurst parameter.

Then, by using the fractal property of $x(t)$, the following equation is approximately held in $0<t<T_2$.

$$x(t)=b^{-1}\int_0^{bt_0} h\left(\frac{t}{b},\ \frac{t-\tau}{b}\right)x(\tau)d\tau \tag{10}$$

It means, in the period $0<t<T_2$ where the time scale in $T_s<t<T_e$ is expanded a times, there are b pieces of fractal geometry contained in $T_s<t<T_e$. It is preferred to take the range of prediction $0<t<T_2$ comparable to the observation period $T_s<t<T_e$. Then, $a=2$ or $a=3$ is suggested.

Calculation of h_{ij}

Now, we show details of calculation of h_{ij}. For simplicity, the time is descretized and the integral is replaced by the summation. In equation one step (interval is one) ahead value is fitted.

By substituting equation (5) into equation (4), we have

$$x(n+1)=\int_0^n \sum_{i=0}^{\infty}\sum_{j=0}^{\infty} h_{ij}\phi(n-i)\phi(n-\tau-j)x(\tau)d\tau \tag{11}$$

where $t_0=n$ and $t=n+1$.

Since the scaling function in equations (6), (7) have the effect to remove the term where $\phi(t)=0$, then we have a simple expression for $y(n+1)$ as

$$x(n+1)=\sum_{j=1}^{B} h_{nj}\theta(n-j) \tag{12}$$

where $\theta(n-j)$ is obtained by the integral of $x(t)$ as

$$\theta(n-j)=\int_0^{n-j}\phi(n-\tau-j)x(\tau)d\tau \tag{13}$$

By using the property of the scaling function

$$\theta(n-j)=\int_{n-j-1}^{n-j} x(\tau)d\tau \tag{14}$$

To minimize the square error between $x(t)$ and the prediction $\hat{x}(t)$ obtained by equation (12), we have derivatives with respect to h_{ij} as

$$\Delta h_{nj}=-2(x(n+1)-y(n+1))\theta(n-j) \tag{15}$$

In the same way, we have representation for equation (10) in discrete time as

$$x(bn+b)=b^{-1}\int_0^{bn} h\left(\frac{n}{b},\ \frac{n-\tau}{b}\right)x(\tau)d\tau \tag{16}$$

For the calculation of $x(bn+b)$, we have

$$x(bn+b)=b^{-1}\sum_{j=1}^{B} h_{ij}\Theta(n-j) \tag{17}$$

$$\Theta(n-j)=\int_{bn-bj-b}^{bn-bj} x(\tau)d\tau \tag{18}$$

Table 1 shows the mean prediction error for 1-step ahead prediction for fBm. As is seen from the result, the prediction error (defined as $|x(t)-\hat{x}(t)|/x_{\max}-x_{\min}$ ranges from 0.17% to 25.0%, and are very small.

Table1. Prediction error of fbm

D	1.80	1.50	1.25
error	0.25	0.19	0.17

3.1 Prediction of Waiting Packets in Queue

In the following, the prediction method for the self-similar traffic is applied to the prediction of waiting packets in a queue of fluid flow approximation. Suppose that $J(t)$ denotes the input traffic to the queue, C denotes the output multiplexer's link capacity, and $Q(t)$ is the total amount of packets outstanding at the multiplexer output link at time t.

Then ,while $J(t)<C$, all arriving packets are transmitted immediately over the output link. When $J(t)$ exceeds C, a queue will be built up at the rate $J(t)-C$. We approximate it by a time-continuous function. Then,we can write

$$\frac{dQ(t)}{dt}=\begin{cases} J(t)-C, & if\ Q(t)>0,\ or\ J(t)>C \\ 0, & otherwise \end{cases} \tag{19}$$

Thus while $Q(t)>0$, it is integral of the process $J(t)-C$.

$$Q(t)=\int_{t_0}^{t} J(u)du-C(t-t_0) \tag{20}$$

where t_0 is the most recent moment when $Q(t)=0$.

In the following simulation study, we show the prediction error for $Q(t)$ can be made small.

Suppose that the input traffic $J(t)$ is a fBm whose maximum amplitude is normalized to 20, and $C<40$. The interval of time t is one. Then the 1-step ahead prediction of number of waiting packet in buffer is obtained by using equation (20). Namely, we have 1-step ahead prediction of $J(t)$ by using the prediction method of fractal time series, then we

Table2. Relative error of prediction for $Q(t)$(%)

Link capacity	C=25	C=20	C=15
error	1.2	2.2	4.8

obtain the value of $Q(t)$ at 1-step later by using equations (13)(14)(20). We define the prediction error of $Q(t)$ as the difference between $Q(t)_1$ obtained by using observed $J(t)$(fBm) and estimated $Q(t)_2$ where $J(t)$ is estimated by using the prediction method of the fractal time series. Table 2 shows the mean value of relative error of prediction $|Q(t)_1 - Q(t)_2|/|J(t)|$ where $|J(t)|$ is the maximum amplitude of $J(t)$.

As is seen from Table 3, the error of prediction is relatively small for one-step ahead prediction if the link capacity is not small.

4. Wavelet transform of fractal time series

We present some results required from the theory of orthonormal wavelet expansion [14]. The wavelet expansion is used to estimate the parameters of the fractal time series and to test the fractal property. Orthonormal wavelet expansion of function employ following form

$$x(t)=\sum_n^N\sum_m^M x_n^m \psi_n^m(t) \tag{21}$$

$$x_n^m=\int_{-\infty}^{\infty} x(\tau)\psi_n^m(t)d\tau \tag{22}$$

where $\psi_n^m(t)$ is defined by basic wavelet function $\psi(t)$ as follows.

$$\psi_n^m(t)=2^{m/2}\psi(2^m t-n) \tag{23}$$

The numbers n,m are the integer dilation and translation indices, respectively[8].

If $x(t)$ is fBm, $x(t)$ is wide-sense stationary with spectrum, and it has the associated time-average spectrum $S(\omega)$ which is in inverse proportion to ω (decay like $1/\omega^N$)[7]. We can therefore define a limiting spectrum for the nonstationary $x(t)$ through

$$S(\omega)=\sigma^2\omega^{-\gamma} \tag{24}$$

$$\gamma=5-2D \tag{25}$$

On the other hand, we have following statistics based upon the characteristics of the Wavelet expansion.

$$\mathrm{var}(x_n^m)=\sigma^2\omega^{-\gamma m} \tag{26}$$

Now, we turn to our main result for the estimation of D. By taking the logarithm of equation (20), we have a linear function of index m. If $x(t)$ is a fBm, then

$$\sum_m(\log(\mathrm{var}(x_n^m))-2\log\sigma-\gamma m)^2=0 \tag{27}$$

This result shows that by fitting a regression line to $\log(\mathrm{var}(x_n^m))$ with respect to the variable m, two parameters of $x(t)$ (σ nad γ) are estimated. Moreover, the root mean square error of the difference

$$R_\omega=\left(\sum_m(\log(\mathrm{var}(x_n^m))-c_0-c_1 m)^2\right)^{1/2}/(MX_\gamma) \tag{28}$$

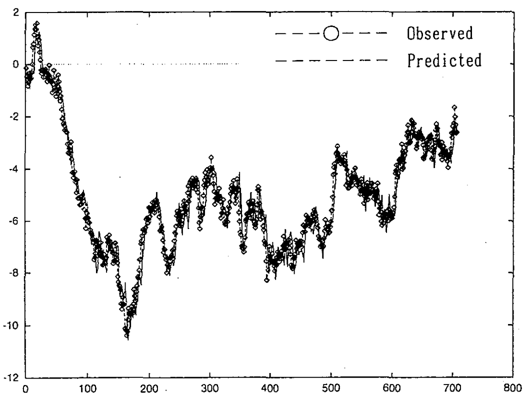

Fig.1 Prediction of fbm

provides a measure to test whether $x(t)$ possess fractal property where M is the range of m and Xr is the difference between the maximum and minimum of $\log(\mathrm{var}(x_n^m))$. If the time series $x(t)$ test the fractal property.

5. Routing Algorithm

5.1 Routing table

Routing tables are used to steer individual packets to the appropriate outgoing link. Routing tables used in this paper contains following information.

(1) routes for each destination.

(2) probabilities for selection of alternative path.

(3) estimated delay of outgoing links.

A route shows each adjacent nodes from a source to a destination. A routing table may include several paths for the same source-destination pair, because is fractal, then $R_\omega=0$ theoretically. However, it depends on the computational precision. By many simulation studies, we have a mean value as $R_\omega=0.006$ for the fBm.

To determine the threshold value of R_ω, we estimate R_ω by using the time series generated by the AMRA model. Because the ARMA model has the spectrum which exponentially decrease and is regarded as the counter part of the fractal time series. Table 3 shows the R_ω for several value of degree of AR part and MA part. By using the result, we use the $R_\omega=0.03$ as the threshold value to our algorithm generate alternative paths by using the GA besides the best path (default path). The path used for each packet is selected by using the probabilities assigned to each path. For example, two routes $R_1=(1, 2, 3, 11)$ and $R_2=(1, 4, 5, 11)$ are used at the probabilities 0.7 and 0.3. Estimated delay for R_1 and R_2 are also included in the routing table.

Table3. R_ω of ARMA model

P	3	2	2	1	1	1
Q	2	2	1	2	2	1
R_ω	0.057	0.037	0.034	0.052	0.129	0.046

At first, routing tables contain only the shortest path (route) obtained by the Dijkatra's algorithm. Upon receiving the message about the observed and predicted delay on outgoing link from every nodes, a node will update its routing table. It must select its best path based on the received information. At the same time, a node will find alternative second-best path by using the GA to distribute offered loads. Because, the shortest path is found out independently only by using the delay information on the transmission link. Therefore, the cases may happen many packets are send on the same link which has very small transmission delay in the previous time point. Then, the delay of these packets may remarkably increase due to the concentration of the traffic.

One alternative path is generated ateach time interval T. However, to keep the size of routing tables to be a certain size, alternative path with smaller probability of usage are deleted from the table, and the number of paths is restricted in a range.

5.2 Applying the GA

We have already indicated that, under heavy offered load, a network reaches a steady state of performance rather than a decreasing one, and many packets are transmitted over the same output link based upon the best path. To prevent the depletion of resources within the network, it is necessary to generate multiple or bifurcated alternative paths, and packets on a node are assigned to one of several outgoing link on a probabilistic base. These multiple paths are generated by using the GA as follows.

(1) Consider a shortest path A between nodes m and n obtained by the Dijkstra's algorithm.

(2) Select a intermediate node j between m and n at random.

(3) Replace the node k by node k which is adjacent to node j and is selected at random.

(4) Find the shortest path between m and k, and between k and n, then the path is a alternative path B for the path A.

The probability p_i with which a packet is assigned a outgoing link i is defined by using the whole delay on each path, namely, is in proportion to the inverse of the delay of the route.

$$P_i = delay_i / \sum_{k \in S} delay_k$$

where S is the set of outgoing links. The crossover operation in the system means the exchange of path included in a pair of route. At first we find a set of common nodes included in the route A and B which are both start at the same node. Then we select a node I from the set of nodes. Then, we take the first half before I on the route A, and add the latter half after I from on the route B. In the same way, we generate a new route by using the first half of the route B and the latter half of the route A. After generating two route, we select one of them who has smaller delay for the packet transmission.

In the routing table several paths (about 3 in the simulation) are listed for each source-destination pair, and one of the paths is selected with the probability proportional to the inversion of delay. The GA operation is applied when we update the routing table.

6. Simulation study

6.1 Aggregation of ON/OFF sources

To illustrate the adaptive routing algorithm, consider a computer network including nodes and terminals which are identical to ON/OFF sources chosen as follows.

(1) Number of nodes: about 15

(2) terminals in nodes: about 10

(3) output link from nodes : 2, 3 or 4

(4) speed of output link : 1.5 Mbps

(5) average length of message : 10 Kbyte

(6) routing algorithm : Dijkstra algorithm

The parameter to generate the input traffic are given as follows.

(1) mean arrival interval to terminal : from 10 to 50 sec

(2) length of aggregation of traffic : T_a= 15 sec

The results explain self-similar phenomena in network traffic in terms of superposition of many ON/OFF sources. Figure 2 shows a result of simulation to check whether or not the resulting synthetic traffic look like actual self-similar traffic at different time scale. Figure 3 shows the logarithm of the wavelet coefficients for the traffic.

As can be seen, our synthetic traffic passes the visual test easily. Table 4 shows the R_ω for the aggregated traffic depending on the length of the aggregation of the traffic on each node. As Table 4 shows, the R_ω has very little dependency on the length of aggregation of traffic. Similarly striking agreement between synthetically generated traffic and actual self-similar traffic we obtain in a number of different scenarios, e.g. choosing many M, selecting different α for the ON/OFF period distribution.

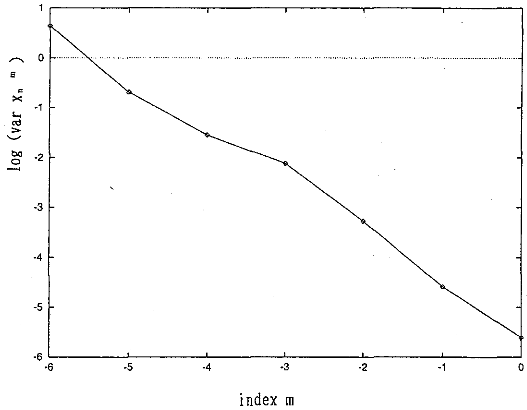

Fig.3 Example of logarithm of wavelet coefficients

Table4. R_ω of aggregated traffic

T_a	10	15	20	25	30
R_ω	0.025	0.030	0.029	0.031	0.031

6.2 Comparison of routing

The improvement obtained by the adaptive routing algorithm can be seen in Fig.4, where the mean response time versus mean response time performance is displayed (dotted line). For comparison, the performance of conventional scheme is also shown (solid line), in which only the observed delay information is utilized to find out the shortest paths and no alternative paths are found by the GA.

These results exhibit clearly the improvement gained in the entire small arrival interval range of by using the adaptive routing algorithm. Simulation of packet transmission shows that adaptive scheme is in average superior to the conventional algorithm in all of the range of mean arrival interval. In particular, we note that mean arrival interval is small (under heavy traffic condition), there is a value of it over which the mean response time become very large in the conventional scheme, however, in the adaptive routing

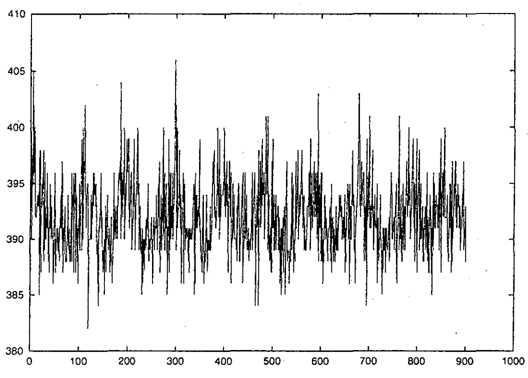

Fig.2 Aggregated traffic on a certain node

algorithm the network can still deliver the packets to the destination with finite delay.

We now examine the performance of adaptive routing algorithm for two restricted cases.

(Case 1) Relatively large number of output links.

In this case, the number of output link in each node is chosen relatively large, for example, its mean value is 4.

(Case 2) Only designated nodes can generate packets.

In this case, only designated nodes in the network can generated the packets, and the destination node are also restricted.

Tables 5 and 6 show the result of mean response time T_r depending on the mean arrival interval I_a. We again note an important improvement in using the adaptive routing algorithm over the conventional scheme.

6.3 Routing by uisng only GA

Two important questions remain : how to estimate the improvement given by the prediction of transmission delay and the and one given by the GA in the adaptive routing algorithm. To briefly illustrate this point, we consider following two cases of routing algorithm.

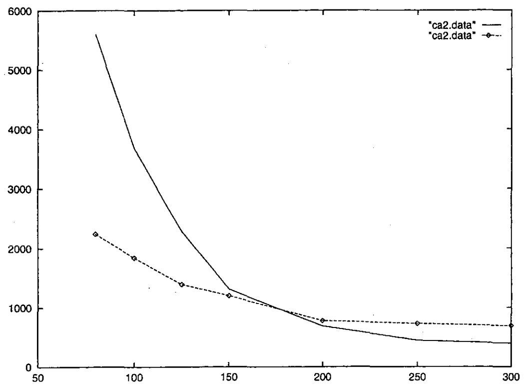

Fig.4 Mean response time versus mean arrival interval

Table5. Mean response time (Case 1, msec)

I_a	12500	16000	20000	24000	32000	40000
T_r	2464	2032	1440	1290	896	832

Table6. Mean response time (Case 2, msec)

I_a	12500	16000	20000	24000	32000	40000
T_r	2680	2032	1652	1312	928	832

(Case A) Scheme using only the GA

In the conventional algorithm based upon the shortest path, we find alternative path by using the GA.

(Case B) Scheme using predicted delay

In the conventional algorithm based upon the shortest path, we use observed delay and also predicted delay, but do not use the GA for finding alternative paths.

Tables 7 and 8 summarize the result for two cases, and show the mean response time versus mean arrival interval. By comparing the result with Fig.3 and Tables 2 and 3, it turns out that the effect solly given by the adaptive algorithm is relatively small which use the predicted delay, and is not relevant to prevent the increase of response time, especially, in the heavy traffic condition.

On the other hand, the routing algorithm utilizing the alternative paths obtained by the GA suppress the response time in the large input intensity. However, the mean response time in Case A is about 20% larger than in the case of original adaptive routing algorithm.

7. Conclusion

This paper showed an adaptive routing algorithm of self-similar traffic based upon the prediction of fractal time series and the GA (genetic Algorithm). At first, the self-similar traffic is represented by using a convolution of the input signal and the impulse response function which is developed by using a set of scaling functions. The prediction method is derived by using the fact that the impulse response possess the self-similarity due to the fractal geometry even if the time scale is expanded. In the adaptive routing algorithm treated in our paper, the predicted delay on the output link is broadcasted as well as observed delay to find out shortest path in the next time point. In the adaptive algorithm, we utilize the GA to find out some alternative path if the offered load become large. The algorithm realizes a kind of load balancing by using the alternative paths. The performance of the adaptive algorithm is compared to conventional ones. As a result, the mean delay on the output link become about 10% smaller, and the variance of the delay become remarkably small.

Table7. Mean response time (Case A, msec)

I_a	12500	16000	20000	24000	32000	40000
T_r	4066	2992	2096	1296	816	512

Table8. Mean response time (Case B, msec)

I_a	12500	16000	20000	24000	32000	40000
T_r	3536	2608	2001	1328	832	736

The remaining problems are a kind of long-term prediction of traffic and the application to the QOS, and further works will be done on the basis of the paper.

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