A Traffic Predictor Based on Adaptive Fuzzy Clustering Technique for IP-based Networks

Yau-Hwang Kuo and *Mong-Fong Horng*[*]

Department of Computer Science and Information Engineering, National Cheng Kung University
Department of Electrical Engineering, Kao-Yuan Institute of Technology[*]
Email : yhkuo@cad.csie.ncku.edu.tw

Abstract

A traffic predictor is significant to ensure the reliability and utilization of network resource in the next generation Internet. An adaptive approach based on fuzzy clustering technique for traffic estimation in resource protocols is proposed. The proposed traffic estimator is deployed to learn the knowledge about the traffic flows and generates a set of cluster representing the profile of flow characteristics. Different from the past k-mean clustering, the proposed clustering algorithm does not need the prior information of cluster number. The size of cluster set is fully determined by target pattern set. By matching the derived cluster set of flow patterns with the current flow pattern, the future flow is estimated and predicted. In experiments, two kinds of traffic flow are used to verify the algorithm performance, periodic flow and Poisson flow. Results show excellent performance of the proposed predictor. The prediction errors, in average, are near 15.4% and 3.56% for periodic flow and Poisson flow, respectively.

I. INTRODUCTION

Interactive multimedia communication has become one of the most promising technologies on the Internet. To provide good multimedia communication services on the Internet, we need a mechanism consisting of admission control, flow control and resource management to guarantee the end-to-end Quality of Service (QoS) for users is urgently needed. Unfortunately, the existed IP-based Internet lacks some significant properties to realize the goal of offering feasible multimedia services with tolerable packet delay and loss. To solve this problem, many new architectures and protocols for resource reservation had been presented. In the reservation protocol, discriminative delivery is the most important mechanism for developing QoS delivery. All flows should be admitted to have a reasonable sharing of network bandwidth before starting transmission. Obviously, how to determine the bandwidth sharing is the key point to QoS guarantee. The conventional scheduler serving in a steady round-robin is incapable of dynamic bandwidth allocation. In this paper, we propose a traffic predictor based on a novel fuzzy clustering technique to assist the traffic scheduler of reservation protocol, such as RSVP. In the new generation Internet, network resources are no longer to be used without permission and arbitrary allocation. All network resources, especially the bandwidth, have to be allocated by a resource administrator for all connection requests to guarantee the admitted connection to obtain an agreed service quality. In such a new networking architecture, traffic predictor is frequently introduced to help the scheduler decide the transmission order of all incom-

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* The co-author also is a PhD. candidate of the department of computer science and information engineering at National Cheng-Kung University.

ing effectively and efficiently so that the congestion can be avoided [1]. Consequently, each admitted connection could be served with the beforehand promised QoS level. Because of the traffic variation, the bandwidth of the networking device for each connection also has to be allocated dynamically to meet the promised QoS level. Besides, since the traffic condition in a connection depends on different applications, the data flow rate of an admitted connection varies with time in multimedia applications, such as VoD and I-phone. The varying flow rate results in the difficulties of traffic scheduling, buffer control and data loss handling.

In the previous studies, most of the traffic prediction focused on multimedia application on ATM [2,3] by using neural network [2,5-6] or fuzzy logic [1,3,7] respectively. However, the applicability of neural network approach is argued [8] because a neural network has to learn a complicated mapping between past and future arrivals. In the proposed approach, the traffic patterns are preprocessed by the proposed fuzzy clustering to extract the traffic characteristics. By using the proposed fuzzy clustering technique, the representative clusters of traffic patterns are obtained to indicate the characteristics of the flow traffic. Based on the derived cluster set, arrived flow pattern is used to estimate traffic flow and predictor the future flow rate precisely. By the proposed clustering approach, the proposed traffic estimator features high estimation speed, high estimation accuracy and high adaptability, so it is suitable for various interactive multimedia communication services on high-speed networks.

2. ADAPTVE TRAFFIC PREDICTOR BASED ON FUZZY CLUSTERING

High-Speed network supporting multimedia services are able to handle bursty traffic and satisfy various Quality-of-Service (QoS) and bandwidth requirements. In the discussion of QoS issues, datagram loss probability and end-to-end delay are concerned most. For instance, one of the most common-used video compression standards is the MPEG standard defined by ISO Motion Picture Expert Group. In a MPEG video service connection, the traffic rate is viewed as a variable bit rate (VBR) traffic with high peak rates relative to its average rate. To maintain a stable frame rate at replay, the end-to-end delay of all datagram should be guaranteed and the datagram delayed out of bound will be discarded. Thus a sufficient bandwidth is required to solve the delay problem. However, excessive bandwidth may cause low bandwidth utilization. Some efforts tried to smooth a VBR traffic stream to a constant bit rate (CBR) traffic, but they often brought on redundancy in realization and caused datagram loss while the flow rate is in a bursty. In multimedia service, the diverse characteristic of multimedia bitstream makes it difficult to offer an efficient and effective allocation of bandwidth for all admitted connections. The proposed predictive scheduler is shown in Fig. 1. Different from non-predictive schedulers, we use a traffic estimator to predict the rate of flows by analyzing the arrival patterns for each connection. The traffic estimator based on a novel fuzzy clustering technique extracts knowledge about the target flow characteristic. By using the learned knowledge, a pattern-matching scheme is deployed to rapidly predict the future flow rate.

A new architecture of QoS router for the next generation Internet is shown in Fig. 1. There are three main components to be realized. They are a packet classifier, traffic estimator and packet scheduler. An adaptive clustering algorithm is proposed to develop high-performance traffic predictor in this paper. By mean of the robust nonlinear decision of fuzzy logic, it helps to evaluate rapidly the flow rate, promote the bandwidth utilization and improve packet loss. Consider an arbitrary traffic flow *f(t)* to be estimated and predicted, we have a sampled flow value *f(k△t), for k=0, 1, 2,…*and *△t* is the period of sampling flow pattern. For simplicity, f(k△t) is denoted as f(k). From the flow sample *f(k)*, a set of flow patterns *P={p(k)}* is obtained by

$$P(k)=\{f(k\triangle t), f((k-1)\ \triangle t)\}, \ldots, f((k-n+1)\triangle t\ ) \quad (1)$$

In different kinds of Internet service, diverse characteristic is observed and analyzed generally in statistics to derive either mathematical correlation or flow tendency. The complicated and inflexible model usually result is an infeasible solution.

In our approach, an adaptive clustering algorithm is developed to derive the correlation between successive flow patterns and to realize the traffic prediction. Clustering algorithm is used to cluster the generated traffic patterns and to find the desired characteristic. Fuzzy c-means is a well-known clustering algorithm to analyze a given data set. However, we have to specify the cluster number before starting the c-mean algorithm. In network applications, the prior knowledge is not available. On behalf of the insufficiency, in the traffic estimation problem, the flow variation may vary greatly that causes the unpredictability about the number of clusters. Thus, we propose a new clustering algorithm to release the constraint on cluster number *c* as follows

Step 1. Initialize two cluster centers c_1 and c_2 in the pattern space as landmarks and generate a proximity matrix *M*

$$M^2 = \begin{bmatrix} 1 & \mu_{12} \\ \mu_{21} & 1 \end{bmatrix} \quad (2)$$

and

$$\mu_{ij} = \frac{1}{1+\left|c_i - c_j\right|} \quad (3)$$

where μ_{ij} is a menbership grade indicating the similariry between c_1, and c_2 as well as | . | is an Euclidean distance between two patterns

Step 2. Given a flow pattern p_j, we refresh the evaluation matrix by

$$E = \begin{bmatrix} M^K & U^T \\ U & 1 \end{bmatrix} \quad (4)$$

and

$$U = (u_{K+1,1}, u_{K+1,2}, \ldots, u_{K+1,K}) \quad (5)$$

where $u_{ij} = \frac{1}{1+\left|c_i - p_j\right|}$ is the silimarity grade representing the slimiarity between c_i and p_j, U^T is the transport vector of *U* and *N* is the dimension of square matrix *M*. It is obvious that *E* is an unity diagonal square matrix with dimension *(K+1)*.

Step 3. Evaluate the possibility of the new patttern becoming a cluster center from the element $\{e_{ij}\}$ of matrix *E*;

$$\text{if} \quad e_{K+1,j} < \min_{i \neq j}\{e_{ij}\} \quad for\ j=1, 2, \ldots, K \quad (5)$$

then p_j will be a new cluster center c_{k+1} , *K* is increased by one and the proximity matrix M^{K+1} is upgraded according to

$$M^{K+1} = E \quad (6)$$

else p_j is assigned to cluster *i* given by

$$i = \max_{1 \le i \le N}\{e_{i,K+1}\} \quad (7)$$

Step. 4 Replace all cluster centers with the cluster centroid, given by

$$c_i = \frac{\sum_{j=1}^{n_i} p_j^i}{n_i} \qquad (8)$$

Step. 5 Goto Step 2.

The initial landmarks specify the minimum dissimilarity betwween two different cluster centers. The similarity menbership function used here is bounded in the intrval of [0, 1]. In this clustering scheme, the similarity instead of specifying a cluster number in the method of fuzzy c-means, we define a minimum vigilance via the initial landmark in initialization. When a pattern with dissimilarity exceeding the vigilance, a new cluster is created for this pattern, otherwise this pattern will be classified to the cluster that is the nearest one to it. Meanwhile, the cluster receiving new clasified patterns will upgrade its center by the new centroid of all patterns in it. The obtained cluster set is representative for the traffic characteristic of flow *f(k)* through the clustering process of flow patterns of *f(k)*. Sicen all flow patterns would be classified to a certain cluster, the averagement of all flow patterns of a cluster is called cluster center. Thus the cluster centers means a suitable and reasonable prediction baseline to find the prediction f_{k+1} such as the $Prob(f((k+1)= f_{k+1} \mid f((k)= f_k , f((k-1)= f_{k-1},\ldots, f((k-n+1)= f_{k-n+1} \;)$ is maximized, where $Prob(|)$ is conditional probability. In the proposed traffic predictor, a new-generated flow pattern is matched with the learned cluster centers individually and sequentially to predict the future flow rate. Given a center matrix C with K clusters derived from the fuzzy clustering mentioned above,

$$C = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_K \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ \vdots & \vdots & \vdots & \vdots \\ c_{K1} & c_{K2} & \cdots & c_{Kn} \end{bmatrix} \qquad (10)$$

The row vector c_i is a center derived from the clustering of flow patterns *{p(k)}*. A clusteri matching scheme is used to estimate the traffic flow when a new flow pattern arrives. To obtain a N-step prediction We partition the matrix C as

$$C = \left[\begin{array}{cccc|ccc} c_{11} & c_{1,2} & & c_{1,n-N} & c_{1,n-N+1} & & c_{1,n} \\ c_{2,1} & c_{2,2} & & & & \ddots & \\ & & \ddots & & & & \ddots \\ c_{K,1} & & & c_{K,n-N} & c_{K,n-N+1} & & c_{K,n} \end{array}\right]$$

$$= \left[\begin{array}{c|c} v_1^i & v_1^o \\ \vdots & \vdots \\ v_K^i & v_k^o \end{array}\right]$$

(11)

The sets of row vectors $\{v^i\}$ and $\{v^o\}$ are the input pattern and output patterns of the traffic predictor respectively. That is the traffic predictor will decide the mapping between $\{v^i\}$ and $\{v^o\}$ by matching $\{v^i\}$ with the corre-sponding values of each cluster center. The $\{v^o\}$ derived from the corresponding values of the best-matched cluster center will yield the proper prediction.

Because of the high demand on computation efficiency on network application, the time consumption of traffic predictor is usually argued. In this paper, the network training does not occur at each time instance when a pat-tern is received. The occurrence of clustering process depends on the difference between the receiving flow pattern and the extracted traffic characteristic. When the difference exceeds the vigilance, the clustering process is activated. In the following experiment, it shows that, in many traffic conditions, the clustering process is activated at the short beginning of flow. That is, the proposed traf-fic predictor is effective and efficient. Thus, after the pre-dictor has extracted the representative knowledge enough, the occurrence of learning will not increases until the traffic characteristic changes. Different from the conventional approach, the efficiency of estimator is improved.

3. EXPERIMENTS

In order to approve the performance of the proposed traffic predictor precisely, three flow conditions are adopted in experiments. The first flow type named periodical flow that equips either a variation period or a certain self-similarity. Owing to the encoding characteristics of MPEG video, such kind of flow type is quite normal in video flow. The second is Poisson flow. In a Poisson flow, the interarrival time of two successive packets is characterized by a random variable with Poisson distribution. Generally, in communication networks, it is well known that flows are Poisson flows with different mean values. The third flow type used in experiments is real peer-to-peer video flow measured in local area network.

The prediction performance on periodical flow is shown in Fig. 2. The solid line depicts the flow to be predicted and the dash line shows the result predicted by the proposed predictor. To verify the prediction performance on jounce flow, the target flow is synthesized by sine waves with variant frequencies. From Fig.2, the target flow periodically jounces between 1 Mbps and 9 Mbps. It should be noted that, in all experiments, the traffic predictor has no information about the target flow, such as mean rate and the others. Practically, the proposed predictor operates in a on-line manner by mean of receiving the contiguous-varying flow and meanwhile estimating and predicting the flow rate in the next time instance. In the experiment on periodical flow, the prediction error rate is about 3.42 % and the derive cluster set is composed of 20 clusters. Fig. 3 shows the evolution of the number of the obtained clusters through the proposed adaptive fuzzy clustering algorithm. Clearly, the increasing of cluster number with time indicates the learning process of the proposed predictor. However, after reaching the level of mutual learning, the cluster number remains steady. It means that the later flow variation does not bring any new learning information. Comparing Fig.2 with Fig.3, it is very interesting to find that, in periodical flow, the learning time is shorter than the flow variation period from various experimental examples. In other words, the proposed clustering algorithm exhibits a very positive performance in learning.

The prediction result of Poisson flow is shown in Fig.4. Unlike periodical flow, since Poisson flow does not equip with a periodical variation, it is more difficult to estimate and predict a Poisson flow than a periodical flow. Nevertheless, the experimental result shows an acceptable performance in Fig. 4. Although the cluster number largely increases, the prediction error remains about under 15%. In the third experiment, a real video flow sampled from the film 'Titanic' is taken as the test data. The prediction result is shown in Fig. 5. Although the burst prediction is not good enough, the average accuracy should be acceptable.

Experiencing the three testing flow types mentioned above, the traffic predictor based on the proposed adaptive fuzzy clustering algorithm demonstrates excellent performance on each test. In particular, it shows an extremely good and stable performance on periodical flow. Furthermore, from different experiments, the proposed clustering algorithm can actually learn new flow characteristics adaptively and dynamically which works as the traffic predictor's knowledge base to promote the prediction performance. Besides, in the proposed clustering algorithm, cluster number is not required any more before clustering analysis. All we have to do is to establish the possible minimal distance between two nearest clusters, named vigilance. And then, the proposed clustering algorithm will adaptive increase the cluster number on its own. This is a great difference compared with the previous fuzzy c-mean clustering algorithm

As mentioned above, in the initialization of adaptive clustering, two predefined clusters are used as landmark to analyze flow patterns. The initial landmarks determine the minimum vigilance of similarity between two different clusters. By adjusting the vigilance, we have different traffic characteristic after clustering. The different sets of initial landmarks caused by different vigilance produce various cluster sets. Table 1 shows predictor performance on Poisson flows under conditions of different extracted cluster sets.

Table 1. The prediction performance of different vigilance.

No. of resulted Clusters	5	10	20	40	80	160
Estimation Accuracy	86.5 %	89.2 %	89.7 %	87.8 %	91.4 %	91.1 %

In fact, a higher vigilance value could derive fewer clusters from traffic flow. That is, a cluster could accommodate those patterns with higher dissimilarity. Likewise, the set of fewer clusters accelerates the prediction speed in pattern matching. However it may degrade the prediction accuracy.

By mean of traffic prediction, traffic scheduler could allocate bandwidth of flows in advance according to the produced prediction so that the bandwidth efficiency is improved. The non-predictive scheduler, because of the lack of the adjustability of bandwidth allocation, either has a low bandwidth utilization or high buffer occupancy. In Fig. 6, the comparison of the buffer occupancy caused by a packet scheduler with non-predictive and the proposed predictor depicts that the proposed predictor not only improves the bandwidth efficiency but reduces the requirement of buffer size. That is the buffer occupancy is slight if the predictor works well. It is also seen that in a non-predictive scheduler, the buffer likely overflows when a bursty duration arrives. However, scheduling with our traffic predictor, a slight variation of buffer occupancy definitely helps packet loss ratio and network resource management, even in case of small buffers.

4.CONCLUSION

In this paper, we also propose a new clustering algorithm in comparison with fuzzy c-means, having the expressive benefit of releasing the constraint that specifies the number of cluster in prior. Based on new clustering algorithm, we also propose the architecture of adaptive predictor in reservation protocol. Since the proposed clustering algorithm can adaptively generate necessary cluster to generalize the characteristic of analyzed data patterns. Thus, the dynamic property of our clustering scheme has the benefits that can handle the successive data and dynamically adjust the cluster locations to represent the flow pattern characteristic. It is an important improvement enable clustering to be applicable in continuous dynamic system, such as multimedia network. While comparing with the nearest neighborhood clustering, our scheme has the variable boundary for each cluster that modifies the property of fixed boundary in the nearest neighborhood clustering. In experiments, the presented traffic predictor indeed has an excellent performance on real VBR streams of video service. The accuracy of predictor is acceptable in network applications. In the next generation Internet, a discrimination delivery is the trend of network protocol design. Network resource should be reserved for admitted connections to guarantee

QoS in transmission. The traffic predictor helps the resource reserved more efficiently and dynamically.

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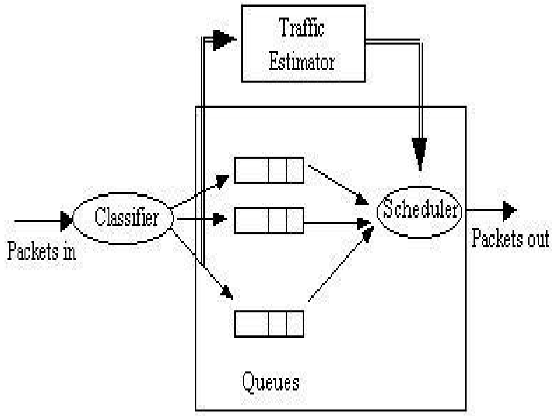

Fig. 1. A new architecture of QoS router in the next generation Internet.

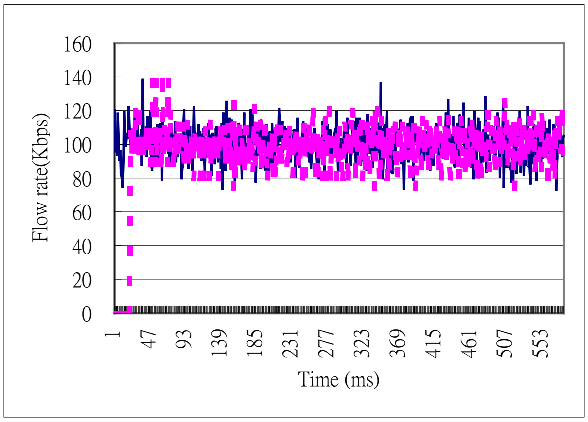

Fig. 4. The prediction performance of Poisson flow.

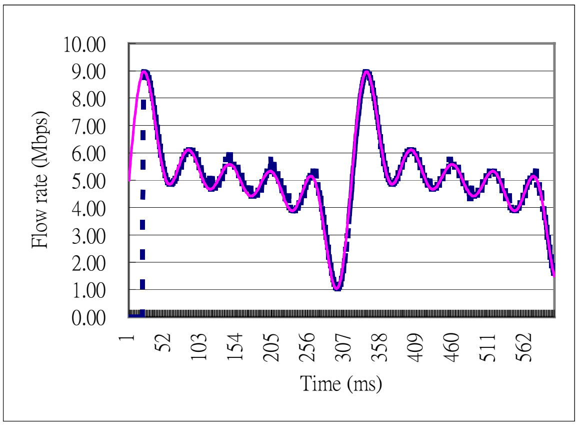

Fig. 2. The prediction performance of periodical flow.

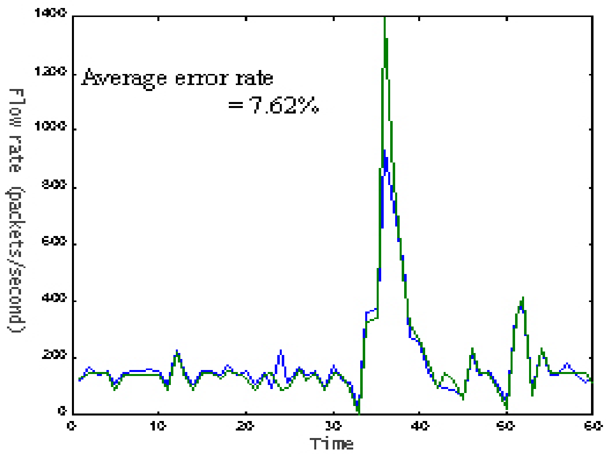

Fig. 5. The prediction performance of real video flow.

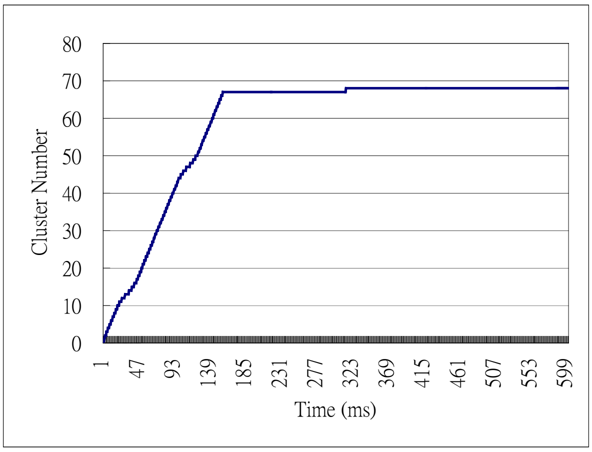

Fig. 3. The evolution of learned cluster number in clustering analysis of periodical flow patterns.

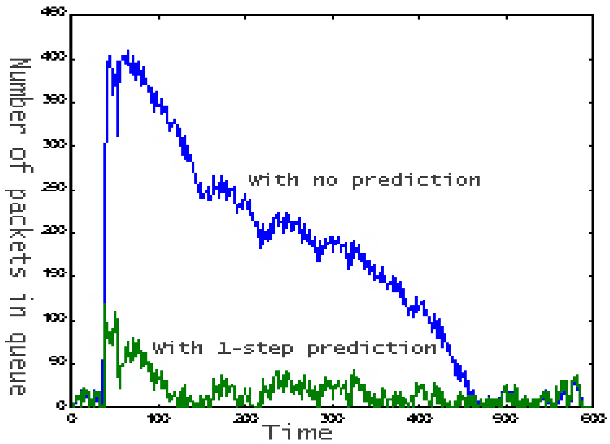

Fig. 6. The buffer occupancy of video flows with predictive scheduling and non-predictive scheduling.