Efficient Traffic Prediction Algorithm of Mutimedia Traffic for Scheduling the Wireless Network Resources

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Abstract— **Real-time variable bit rate (VBR) video traffic generated from multimedia applications, such as MPEG-coded video, is expected to be large portions of the traffic in future wired/wireless networks. The nature of VBR traffic and its Quality of Service (QoS) constraints increase a number of challenges on network resource managements and operational utilizations. Thus, accurate traffic prediction based dynamic resource allocation and scheduling can significantly improve network performance substantially while satisfying QoS requirements. In this paper, we propose a novel prediction algorithm of MPEG-coded real-time VBR video traffic for IEEE 802.11e Wireless LANs (WLANs). Based on statistical property of traffic stream, our algorithm performs a prediction of the next frame size for I-, P-, and B-frames. Simulation study using real-world MPEG-4 coded video traces shows that the proposed algorithm achieves much better performance than ANFIS, LMS, and NN methods. In addition, the applicability of our prediction algorithm to IEEE 802.11e WLAN is discussed.**

I. Introduction

Recently, by the explosive growth of multimedia applications, there will be a requirement of Quality of Service (QoS) guarantee in wireless environments. Especially, over Wireless LAN (WLAN) which is today's dominant wireless access mechanism [1], an efficient delivery of multimedia traffic, such as real-time variable bit rate (VBR) video stream, has received many research attentions from both academia and industry. However, due to the nature that real-time VBR video streams have high traffic burstiness, it is very difficult to achieve the desired QoS requirements of video transmission and the efficient utilization of network resources. To meet the challenges, there have been attempts to adaptively allocate network resources, i.e., network bandwidth, by predicting the traffic dynamics in advance [2][3][4]. Hence, accurate VBR video traffic prediction algorithm can significantly help the design of efficient resource allocation and network performance enhancement.

In this paper, we propose a novel MPEG-coded real-time VBR video traffic prediction algorithm to predict the next frame size for I-, P-, and B-frames. According to the observed past traffic patterns, our algorithm obtains traffic properties using Cubic Spline interpolation method [13], and predicts next video frame size. Thus, network bandwidth is dynamically allocated based on the predicted traffic volume in time. While most of existing prediction algorithms requires sophisticated computation and modeling, we only use several simple numerical methods for the prediction, hence it is very easy to implement our algorithm in real network fields. Furthermore, our accurate prediction can improve the scheduling and resource management in IEEE 802.11e based WLAN.

The rest of this paper is organized as follows. In Section 2, we briefly introduce several previous works on VBR video traffic prediction, and describe the characteristics of MPEG-coded video traffic. Section 3 presents the details of our proposed prediction algorithm. The performance evaluation conducted by thorough simulation is presented in Section 4. Finally, in Section 5, we discuss the applicability of our proposed scheme to IEEE 802.11e WLAN scheduling [1] algorithm as a future work, and make the conclusion of the paper.

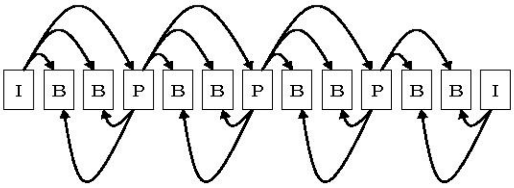
II. Related Works

This section first gives an overview of MPEG-coded video. MPEG standards define the guidelines of the video and audio compression methods. We also introduce several VBR video traffic prediction schemes briefly.

There are several encoding schemes in MPEG standards, MPEG-1, MPEG-2 and MPEG-4. MPEG encoder compresses a video signal at a constant bit rate into VBR stream [14]. MPEG video generates the three types of frames, namely, Intra-frame (I-frame), Predictive-frame (P-frame) and Bidirectional-Predictive-frame (B-frame), during the compression. The I-frame is encoded using information only from the picture itself. In other words, it needs no reference from any other frames. The P-frame is encoded using motion compensation prediction, and predicted from a previous I-frame or other P-frame. The B-frame is encoded in reference to either previous or next I-frame or P-frame. The three MPEG frames are typically arranged in a deterministic periodic pattern called, group-of-picture (GOP). Note that in this paper MPEG-4 video is chosen for the study since it plays a main role in various video applications today. For the MPEG-4 video, GOP is usually consists of 12 frames as following repetitive pattern: IBBPBBPBBPBB, called GOP pattern. The GOP can be characterized by the distance between two

This work was supported by the IT R&D program of MIC/IITA. [2006-S-058-02, Development of Network/Service Control Technology in All-IP based Converged Network]

consecutive I-frames. Fig. 1 depicts the GOP coding structure of MPEG-4 video with a length of 12 and these frame dependencies. In here, we do not present the details of MPEG encoding algorithm [14].



<Figure 1. GOP Coding Structure of MPEG-4>

Generally, in network research fields, the main purpose of traffic prediction is an efficient utilization of network resources, such as network bandwidth. A number of traffic prediction schemes for VBR video traffic have been proposed. In [2], *Adas* proposed an adaptive linear traffic predictor for real-time VBR video traffic prediction using Least Mean Square (LMS). Due to its simplicity and relatively good performance, LMS scheme has been referred in many studies. Based on LMS scheme, *Yoo* developed an adaptive traffic prediction algorithm considering the effects of video scene changes [4]. *Yoo*'s algorithm produces better performance than LMS scheme for video applications that have a heavy fluctuation in scene changes. The two traffic prediction algorithms use the adaptive approach that the algorithm continually updates the predictor weight coefficients with time. To consider the nonlinearities in the traffic characteristics, Neural Network (NN) based prediction algorithms also have been studied [11].

III. TRAFFIC PREDICTION USING CUBIC SPLINE (TPCS)

This section presents the details of our proposed traffic prediction algorithm, called TPCS. Typically, MPEG-coded VBR video traffic exhibits complexity and burstiness on traffic characteristics according to the encoding type and its original scenes. Hence, each VBR traffic stream has different statistical properties. To extract more accurately the statistical property from video traffic, TPCS estimates *probability density function* (PDF) using Cubic-spline interpolation method [13], and utilizes PDF for the prediction of next frame.

In this section, we first briefly introduce Cubic-spline interpolation method which is used for the PDF estimation. Thereafter, the details of proposed prediction algorithm are elaborated.

A. Cubic-Spline Interpolation

We use Cubic-spline interpolation method which is widely used in piecewise polynomial approximation [13], for PDF estimation. Cubic-spline interpolation fits a polynomial to a set of data points, borrowing from the idea that is to connect every adjacent pair of control points by a cubic. Note that each pair of control points has a different cubic. The individual cubic functions are then joined together at the control points into a "smooth curve." The complete fitting function, i.e. the smooth curve, over the entire range is called Cubic-spline function, $f(x)$. Suppose we have n control points, (c_i, y_i), $i = 0,\ldots, n-1$. The $f(x)$ is represented by the collection of n-1 cubic segments, $S_i(x)$, of following form:

$$S_i(x) = \alpha_i(x-c_i)^3 + \beta_i(x-c_i)^2 + \gamma_i(x-c_i) + \delta_i \qquad (1)$$

$$where,\ c_i \le x \le c_{i+1}\ and\ i = 0,\ldots,n-2$$

Then, the $f(x)$ is calculated as:

$$f(x) = S_i(x)\ \ on\ \ [c_i, c_{i+1}]\quad for\ i = 0,\ldots,n-2 \qquad (2)$$

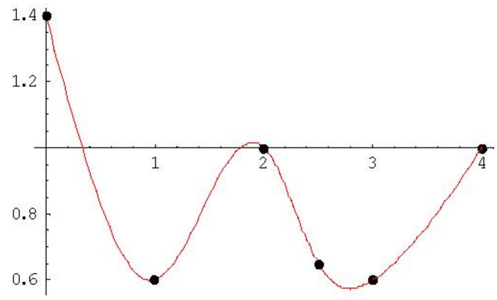
For each cubic segment, $S_i(x)$ in (1), the four unknowns, α_i, β_i, γ_i and δ_i can be derived from following equations and finally the $f(x)$ is obtained.

$$\begin{aligned} S_i(c_i) &= y_i \\ S_i(c_{i+1}) &= S_{i+1}(c_{i+1}) \\ S_i'(c_{i+1}) &= S_{i+1}'(c_{i+1}) \\ S_i''(c_{i+1}) &= S_{i+1}''(c_{i+1}) \end{aligned} \qquad (3)$$

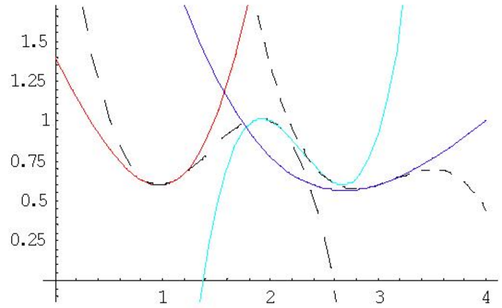
Therefore, we can estimate the PDF of random variable x, $f_X(x)$, as:

$$f_X(x) = f(x) \Big/ \int_{c_0}^{c_{n-1}} f(x)\ dx \qquad (4)$$

Fig. 2(a) shows an example set of six control points, (0, 1.4), (1, 0.6), (2, 0), (2.42, 0.65), (3, 0.6) and (4, 0), and its Cubic-spline function. Also, cubic segments for the control points are shown in Fig. 2(b).



(a) An example of control points and its Cubic-spline function



(b) Cubic segments between two adjacent control points

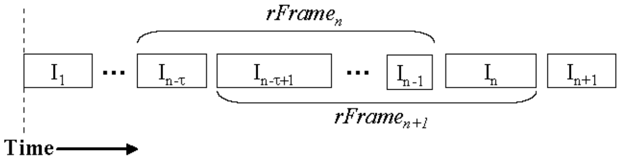
<Figure 2. Cubic-spline Interpolation>

B. *Real-time VBR Video Traffic Prediction (TPCS)*

TPCS first separates the video frames into I, P, and B subgroups by GOP pattern, and measures the size of frames within each subgroup. Then, from the measurements, TPCS estimates PDF of the frame size for each type of frames, and utilizes it for the next frame prediction.

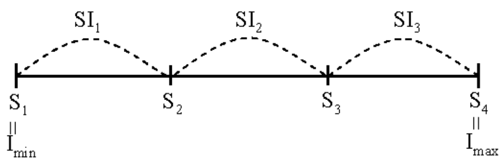
TPCS considers the last n fames it measured for the next frame prediction. In other words, to predict the size of i-th frame, TPCS first estimates PDF of the frame size using the last n frames which are from $(i-n)$-th frame to $(i-1)$-th frame. Then, based on PDF, TPCS predicts the size of next frame, i.e., the i-th frame. In this paper, we define the frames used for PDF estimation and the number of the frames as $rFrame_i$ and *wSize*, respectively.

Suppose that a TPCS has been measured n I-frames, I_1, I_2, …, I_n and its *wSize* is τ. To predict the size of next frame, I_{n+1}, TPCS estimates PDF of the frame size for the last τ frames (i.e., $rFrame_{n+1}$) using Cubic-spline interpolation. The $rFrame_{n+1}$ is the frames from $I_{n-\tau+1}$ to I_n as shown in Fig. 3.



<Figure 3. *rFrame* and the prediction step>

We first find the maximum, I_{max}, and the minimum, I_{min}, among $rFrame_{n+1}$. Then, we divide the closed interval $[I_{min}, I_{max}]$ into three subintervals equally and let SI_1, SI_2 and SI_3 be each subinterval respectively as shown in Fig. 4.



<Figure 4. Three subintervals>

For the convenience of description, we assume that

SI_1 is on $[S_1, S_2)$

SI_2 is on $[S_2, S_3)$

SI_3 is on $[S_3, S_4]$

Based on the frame size, we categorize every frame of $rFrame_{n+1}$ into each subinterval. For example, if the size of a frame is $[S_2, S_3)$, the frame belongs to SI_2. Let us denote the number of frames belonging to a subinterval SI_i as q_i. In this way, we choose the control points, c_i as:

$$c_i = \left(\left\lceil \frac{S_{i+1} - S_i}{2} \right\rceil, q_i \right)$$

$$where, \quad i = 1, 2 \ and \ 3$$

Note that TPCS uses the three control points, c_1, c_2 and c_3, for the Cubic-spline interpolation. As a result of the interpolation described above (1), (2), and (3), Cubic-spline function, $f(x)$, is obtained and we computes PDF of the frame size for the $rFrame_{n+1}$, $f_X(x)$, by (4). In addition, the mean, μ_n, and the standard deviation, σ_n, can be derived from $f_X(x)$ easily. Finally, TPCS predicts the size of I_{n+1} as:

$$\overline{I_{n+1}} = \mu_n + \frac{E_n}{\sigma_{n-1}} \times \sigma_n \qquad (5)$$

where, $\overline{I_{n+1}}$ is predicted value of I_{n+1}, and E_n is the difference in frame size between the predicted value and the actual value and is calculated as $I_n - \overline{I_n}$. Note that E_n and σ_{n-1} are obtained from previous prediction step. In other words, E_n is prediction error for the frame I_n and σ_{n-1} is derived from the PDF used for the frame I_n prediction. This means that TPCS learns the information about previous prediction, and utilizes it for next prediction. For P- and B- frame, the prediction algorithm is applicable without any modification.

IV. PERFORMANCE EVALUATIONS

Using several real-world MPEG-4 video traffic traces, we conduct the simulations to compare the performance of TPCS and three famous prediction algorithms in literature, (1) Adaptive Network-based Fuzzy Inference System (ANFIS) based prediction algorithm [9], (2) the normalized Least Mean Square (LMS) prediction [2], and (3) the neural network (NN) based MPEG-4 video traffic prediction scheme (NN) [11].

The video traffic traces used in this study are obtained from [12].Each of the video traces has been encoded using the three types of different quality levels and we use high-quality traces for the simulation study. The following video sequences were chosen for training; Aladdin, Jurassic Park I, Die Hard III, and Ard Talk. The details of traffic characteristics and encoding scheme about the video traces are available in [12]

A. *Performance Metric*

In our performance evaluation, we use the performance metrics, root mean square error (RMSE). RMSE is the ratio between the sum of the square of the prediction error and the sum of the square of the actual values. It is represented by the following equation:

$$RMSE(\%) = \frac{\sum (F - \overline{F})^2}{\sum F^2} \times 100$$

$$where, \ F: actual\ value$$
$$\overline{F}: predicted\ value$$

Note that in the paper [9] the author already utilized RMSE for the performance metrics. In addition, the video traffic traces used in [9] are the same with the traces that we conducted in this paper. Thus, we also use the results of RMSE in [9] for ANFIS, LMS, and NN.

B. *Prediction Results*

Table 1 shows the results of performance evaluation in terms of RMSE. In the simulation, *wSize* for TPCS is fixed for all the simulations as five. From the table 1, we can observe that TPCS makes more accurate prediction than ANFIS, LMS, and NN in most cases. The predictions of TPCS are somewhat inaccurate compare to other prediction schemes. However, for P-frame, TPCS always outperformed than other three prediction algorithm. In addition, it also offers the good performance for B-frame prediction except for Aladdin and ARD Talk. The performance results indicate the success of our proposed algorithm in predicting real-time VBR video traffic.

V. CONLUSIONS

In this section, we first discuss the applicability of our prediction algorithm to IEEE 802.11e WLAN scheduling algorithm. Then, finally, we summarize our contribution and conclude this paper.

A. Applicability of TPCS to IEEE 802.11e scheduling

IEEE 802.11e is an enhanced version of legacy IEEE 802.11 to provide QoS to applications required [1]. In the IEEE 802.11e, a new Hybrid Coordination Function (HCF) has been proposed to enhance the QoS by combining and extending the mandatory Distributed Coordination Function (DCF) and optional Point Coordination Function (PCF) in IEEE 802.11. There are two categories of medium access in HCF, a contention-based channel access and a controlled channel access, named as Enhanced DCF (EDCF) and HCF Controlled Channel Access (HCCA), respectively. EDCF provides a probabilistic QoS support by using eight Traffic Categories (TCs) for different traffic types of flows. This method is well suited for bursty traffic flows with unknown traffic requirements.

On the other hand, HCCA is used to grant access to traffic flows and provides the parameterized QoS support by considering QoS requirements of each traffic flow. One of the main purposes of HCCA is to support multimedia traffic streams which are mostly the delay sensitive service. To be effective, Hybrid Coordinator (HC) in HCCA is needed to schedule the traffic stream efficiently. Although IEEE 802.11e standard introduces a reference scheduler, it is only well suited for the traffic flows with strict constant bit rate (CBR) characteristics. In other words, to calculate transmission opportunity (TXOP) which is a time duration a station is allowed to transmit a burst of data frames, the reference scheduler only considers averaged values, e.g. mean packet size and mean data rate. Hence, the reference scheduler allocates a fixed TXOP for each flow, and each flow is serviced in fixed Service Interval (SI).

The scheduling method can provide guaranteed service to the flows with CBR characteristics. However, in the case of real-time VBR video traffics, because the bit rate and frame size are very fluctuating, it is very difficult to compute efficient TXOPs for each flow. Some previous researches showed that the reference scheduling algorithm for real-time VBR video traffic causes high queue buildup at each station, and eventually leads large packet delays and dropped packets. In addition, the static scheduling based on averaged value is not desirable because a significant amount of time will be wasted due to the bursty nature of VBR video traffic.

If Access Pointer (AP) can predict the traffic characteristics accurately, the scheduling in IEEE 802.11e can be performed efficiently. We propose that AP in WLAN predicts the next frame size and its expected arrival time using TPCS. Thus, AP utilizes the prediction results for TXOP allocations and SI computations. The prediction results of TPCS discussed Section IV strongly asserts that AP is able to obtain the accurate information about the traffic characteristics.

B. Concluding Remarks

This paper proposed a novel prediction algorithm for real-time VBR MPEG-coded video traffic, called TPCS. To capture the statistical properties of traffic, TPCS estimates PDF using Cubic-spline interpolation method, and utilizes it for the prediction of next frame. The simulation results conducted with real-world VBR video traffic showed that the proposed algorithm significantly improves the prediction accuracy in comparison with ANFIS, LMS, and NN. Thus, we argue that TPCS improves the efficiency of scheduling, i.e., TXOP allocation and SI computation, in IEEE 802.11e WLANs. As a future works, the details of scheduling scheme will be studied.

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<Table 1. RMSE of I-, P-, B- frames for TPCS, ANFIS, LMS and NN>

Movie	Frame Type	TPCS	ANFIS	LMS	NN
Aladdin	*I*	2.03	2.11	2.35	2.60
	P	3.97	10.60	12.48	10.30
	B	3.57	3.12	3.88	8.20
Jurassic Park I	*I*	1.01	0.69	0.80	0.80
	P	1.60	3.28	3.88	4.00
	B	1.52	2.40	2.28	2.20
Diehard	*I*	1.98	2.90	4.41	2.90
	P	2.52	7.25	12.30	9.00
	B	1.59	3.55	3.44	4.00
Ard Talk	*I*	1.12	0.77	1.76	0.90
	P	2.59	5.03	6.10	5.90
	B	1.41	1.12	1.42	3.20