Adaptive MPEG Traffic Prediction

*Souhwan Jung, and **Jisang Yoo

Abstract

This paper addresses traffic prediction issues on MPEG. A new adaptive traffic prediction scheme is proposed using MPEG picture characteristic that picture traffic depends on the coding mode of that picture, that is, I, P, and B mode. Our prediction scheme, which is based on picture decomposition (PD) and the cross-correlation of the different types of pictures, has better performance in predicting bursty MPEG traffic than that of the first-order autoregressive (AR) prediction scheme. Our simulation results show that the performance is further improved about 15% by utilizing the cross-correlations between pictures.

I. Introduction

The Asynchronous Transfer Mode (ATM) has emerged as the international standard[1, 2] for multiplexing and switching techniques in Broadband Integrated Services Digital Networks (B-ISDN). It provides for the integrated support of several types and classes of services that have a very wide range of traffic characteristics and service requirements. For example, an electronic mail service does not have critical delay requirements, but is sensitive to data loss. On the other hand, voice needs to be transported in real-time, but can tolerate some loss without adversely affecting voice quality. However, this is not the case in video communications since they are highly sensitive to the loss of bits.

Since the International Standard Organization (ISO) provided a standard for multimedia applications, called the Moving Picture Experts Group (MPEG) [3], there has been a great deal of effort devoted to characterizing MPEG video. MPEG video uses a two-layer coding scheme, in which a different coding flow is applied on a picture-by-picture basis to obtain higher compression ratios. As a result, MPEG traffic is so bursty that it is difficult to manage it on networks. Accurate traffic prediction enables us to forecast network congestion so that we can prevent it by allocating more bandwidth in advance.

A simple prediction model using the mean and standard deviation was proposed for bandwidth estimation in [4]. In that model, the standard deviation of video traffic is usually too large to be used for predicting the traffic of the next picture. An autoregressive (AR) model with a Gaussian process was presented in [5] to model an encoded video source. This model is suitable for less bursty traffic such as data traffic, but not for very bursty traffic such as an MPEG video. Yegenoglu et. al [6] proposed a motion-classified AR model that uses a different AR parameter set as a function of their motion changes. This model uses three transition states, viz., high-motion, medium-motion, and low-motion. The problem is that of determining the duration of each state. All of these approaches can be used for an encoded VBR video, but they do not take full advantage of the characteristics of MPEG video which uses a picture-dependent coding scheme.

In this paper, we investigate how to predict VBR video effectively in ATM networks. In our prediction scheme, we use the characteristics of MPEG video that generate variable bit rate streams according to the picture types. Our picture-decomposed prediction scheme outperforms the typical autoregressive scheme with the same order prediction due to the increase of the autocorrelation property. By utilizing cross-correlations between different types of pictures, performance is enhanced further by about 15%. The result is from that the cross-correlation property contributes to the performance additionally. In autoregressive scheme, only the autocorrelation property of the signal is used for the prediction. Our method that uses both the autocorrelation and cross-correlation properties of the decomposed signals can be effective for predicting signals that can be readily decomposed into subsignals.

The remainder of the paper is organized as follows. In Section 2, the coding scheme for MPEG video and its statistical characteristics are briefly discussed. In Section 3, our traffic prediction schemes which are based on picture

---

*Department of Info. and Telecom. Engineering, Soongsil University
**Department of Electronics Engineering, Kwangwoon University
Manuscript Received: July 30, 1997.

decomposition are presented, and their performance is compared with that of AR prediction. Finally, our concluding remarks are presented in Section 4.

Ⅱ. Mpeg Video and Statistics

The moving picture experts group (MPEG) is a working group of the International Standard Organization (ISO) to develop a standard for video and associated audio on telecommunication channels as well as local area networks. The MPEG activities cover video and the associated audio compression and the issue of audio-visual synchronization. There are three phases in MPEG standardization. The MPEG first-phase (MPEG-1) video compression standard, aimed primarily at coding video for digital storage media with rates of 1 to 1.5 Mbps is well suited for a wide range of applications at a variety of bit rates[7]. The second phase of MPEG (MPEG-2) is aimed at coding video signals created by CCIR 601, e.g., 720 pixels, 480 lines, 30 frames per second, 2 to 1 interlace at bit rates of 2 Mbps or higher[8]. The third phase of MPEG (MPEG-4) addresses the coding of video signals at very low-bit rates[9, 10]. The scope of MPEG-4 is to code generic audio-visual signals at bit rates from 10 to 64 kbps. We will briefly describe the coding algorithm of MPEG video to understand the characteristics of MPEG traffic.

MPEG video coders use different coding schemes for each type of picture, and can achieve a compression ratio of up to 200. As a result, the generated traffic is highly fluctuating over time, that is, bursty. The burstiness measure most widely used is the peak-to-average ratio (PAR)[5]. The peak rate of MPEG video is up to five times higher than the average rate due to the coding schemes and picture types. The statistics of MPEG traffic of various video scenes are presented in Table 1. Due to large fluctuations, the standard deviation is usually comparable to the mean of the traffic.

Samples of real MPEG video traffic at the frame level are shown in Figure 2. Inspecting traffic at the frame

Table 1. Statistics of MPEG traffic at the frame level.

scenes	mean (cell/frame)	standard deviation	peak (cell/frame)	peak-to-average ratio
star trek	111	99	474	4.27
football	202	180	1004	4.97
bike	90	86	304	3.38
table tennis	173	182	582	3.36
us	60	52	263	4.38

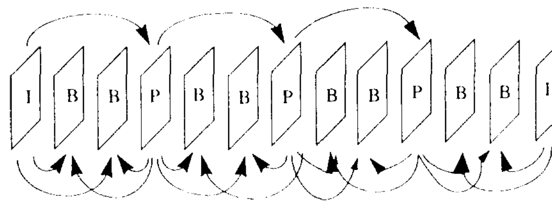
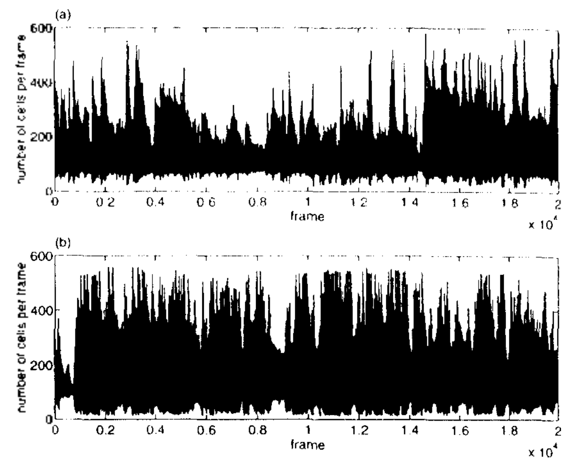


Figure 1. MPEG group of pictures (GOP).



(a) CNN News (b) Princess Bride

Figure 2. Samples of MPEG traffic at the frame level.

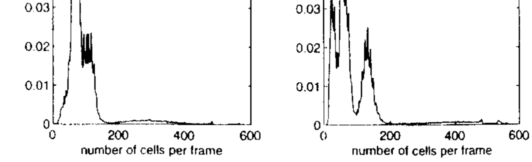


Figure 3. Distributions of MPEG traffic at the frame level.

level, it is observed that the rate of an I frame or a P frame is much higher than that of a B frame, regardless of GOP format. This results from the fact that the bidirectional prediction and large quantization steps are used for B frames. It is also observed that the bit rate of an I frame is, in general, higher than that of a P frame, but that is not the case of a scene change since the P frame is coded the same as an I frame when the energy of the prediction error is higher than that of the original frame.

The distributions of two MPEG traffic source at the frame level are presented in Figure 3. The scenes are CNN News and the movie Princess Bride. Both scenes are about 90 minutes long, and it is difficult to discern from the figure exactly what the distributions resemble. The density in low bit rates is high for both scenes. This result is natural since MPEG videos are coded based on the GOP. Note that a GOP has more B pictures than I or P pictures in this case, and a B picture generates lower bits than an I or P picture. It can also be noted that the distributions do not resemble the Gaussian function. A study shows that the VBR video traffic resembled a Gamma function[11]. But, from our observations, the distributions of MPEG video basically depend on scene and motion changes of the sequence. More extensive studies on mathematical modeling of distributions are required. We will investigate the statistics of MPEG traffic at the slice level to look at more details of traffic variations.

A number of analysis studies on traffic at the frame level and cell level have been performed so far[13-15]. The analysis at the frame level has focused on source modeling, and the analysis at the cell level has focused on a queueing model of the average delay. We will look at the statistics of traffic at the slice level. A slice is assumed as a single horizontal set of macroblocks. When the video data are packetized into a ATM cell, the packetizer has to wait for a while until it collects a quantity of data to packetize. After collecting data, the packetizer encapsules the data into a number of cells, and sends them to networks. The period for the data collection can be a frame, slice, or even macroblock. The interval of a frame, 1/30 sec in general, is not a small delay for packetization since the queueing and propagation delays will be added to this. Data bits less than a cell are generated from a macroblock with the picture of size 352×240. It is a desirable assumption, therefore, that the generated data are collected during a slice interval and then packetized.

In general, the statistical characteristics of MPEG videos show that MPEG traffic is quite bursty at the frame level, and have a distribution that is not a specific function. From the perspective of network side, bursty traffic is difficult to manage since they are apt to cause congestions and buffer overflows. To predict and prevent congestions and buffer overflows due to the burstiness, traffic modeling and resource allocation for VBR video source are important issues that have to be addressed for the spread of video communications over ATM networks.

Ⅲ. Traffic Prediction

3.1 Autoregressive (AR) Prediction

Many prediction schemes have been developed for time series analysis. The autoregressive (AR) and autoregressive moving average (ARMA) predictions are among the major prediction methods that are widely used. A number of studies show that they can model VBR video sources [4, 6]. The different usages of AR and ARMA depend on the shape of the autocorrelation function. It is known that AR is effective for a signal with a linearly decreasing autocorrelation function. On the other hand, ARMA is the choice for a signal with an exponentially decreasing autocorrelation function[16]. In this section, we will review some of the theoretical background for AR prediction scheme, and then investigate its performance for MPEG video streams.

Suppose that Xn is a random sequence of the bit rate at the n-th frame. The m-th order AR prediction is given by

$$X_n = \sum_{k=1}^{m} a_k X_{n-k} + e_n \tag{1}$$

where the is the prediction coefficient and is the prediction error. The prediction coefficients are obtained by the Yule-Walker equation[17] as shown in Appendix,

$$\begin{bmatrix} r_0 & r_1 & \cdots & r_{m-1} \\ r_1 & r_0 & \cdots & r_{m-2} \\ \vdots & \vdots & & \vdots \\ r_{m-1} & r_{m-2} & \cdots & r_0 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_m \end{bmatrix} = \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_m \end{bmatrix} \tag{2}$$

The performance of the AR prediction scheme was investigated by varying the prediction order m. The test data is the bike scene with a GOP size of 6 (IBBPBB). The mean prediction error vs. the order of the AR prediction is shown in Figure 4. At a low order of m=1 or 2, the performance of the AR prediction scheme is very poor since the correlation of two consecutive frames (I and B, or P and B) is very low. The prediction error, however, drops quite a bit at m=3 and 6. This is due to the fact that the previous P or I pictures were included when predicting a new P or I picture. For example, at m=3, two B pictures and an I (or P) picture were used to predict a new P (or I) picture. At m=6, a previous I picture, a P picture, and four B pictures were used to predict an I or P picture. After m=6, the performance converges to a certain value. We conclude that the prediction order m should be greater than or at least equal to the GOP size of traffic to obtain good prediction results.

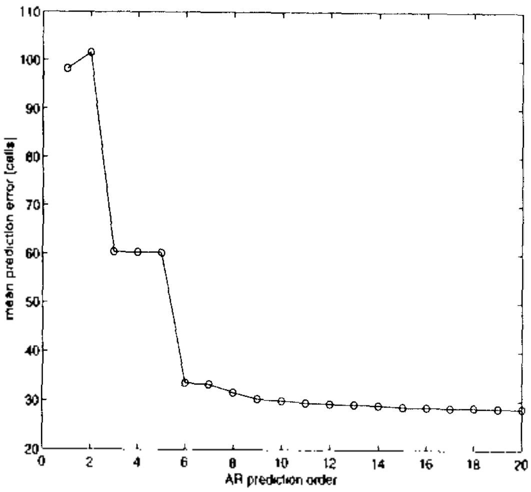


Figure 4. Performance of AR prediction.

3.2 Picture-Decomposed (PD) Prediction

Since MPEG video is bursty and changes dynamically on a picture-by-picture basis depending on the coding mode, the correlation between consecutive pictures is very low, but relatively high between the pictures encoded in the same mode. Figure 5 shows a five-second (150 pictures) video traffic signal from the bike scene. A pseudo-periodic peak traffic is from I pictures, and the medium traffic is from P pictures, and the lowest traffic is from B pictures. This is a general characteristic independent of a flexible GOP sequence because the traffic depends on the coding mode, not on the sequence.

The autocorrelation functions of the bike scene and of the I, B, and P pictures are shown in Figure 6. The autocorrelation for the original signal shows significant fluctuation in Figure 6-(a), but the autocorrelation of the

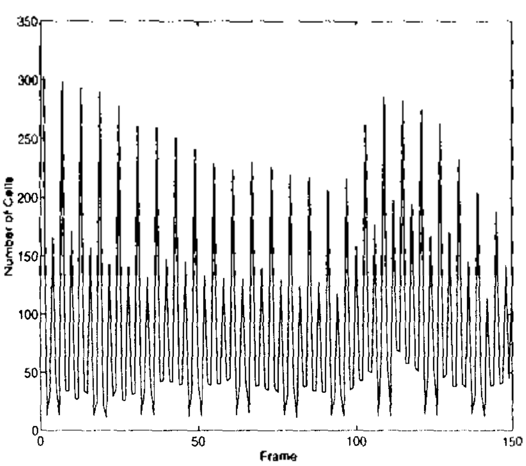


Figure 5. Traffic signal of MPEG video: *bike* scene.

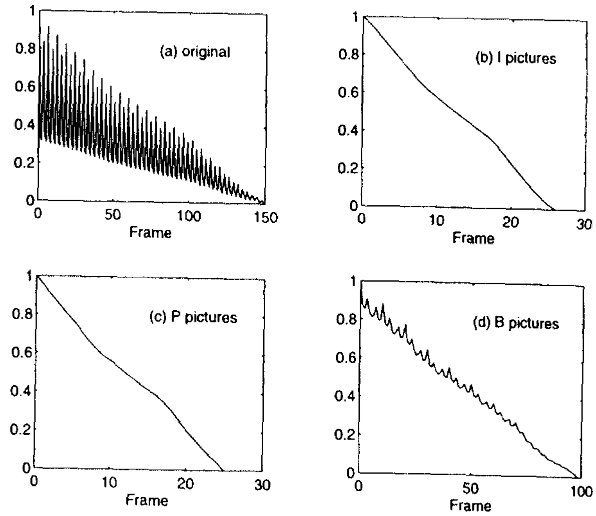
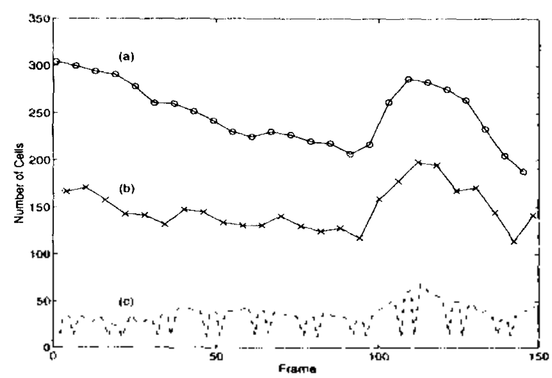


Figure 6. Autocorrelation functions of *bike* scene and decomposed pictures.



(a) I pictures (b) P pictures (c) B pictures

Figure 7. Traffic signals of the decomposed pictures.

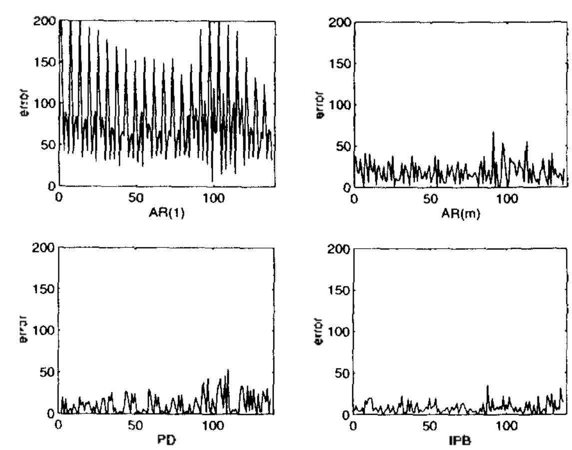


Figure 8. Prediction errors of four different prediction schemes for *bike* scene.

decomposed pictures in Figure 6-(b) decreases smoothly. Examining the first autocorrelation function, we find that the first autocorrelation coefficient of I pictures only is much higher than that of the original traffic. The main idea in this scheme is to decompose the traffic signal into three subsets of pictures coded in the same mode because traffic variations in the same coding mode pictures are relatively small. For example, the bit rate of I pictures changes moderately so that the bit rate of a current I picture will be predictable from the bit rate of the previous I picture. The same argument also holds for P and B pictures.

The results in Figure 7 depict the decomposed signals from the bike scene to show clearly that the signal can be readily decomposed into three components. The autocorrelation functions of the decomposed signals decreases smoothly for all I, P, and B picture types, from which we see that the decomposed signals have high correlations between consecutive pictures.

The first autocorrelation coefficients of the traffic signal before and after decomposition of several scenes are presented in Table 2 which shows that the first autocorrelation coefficient increases dramatically by picture decomposition. For example, in the bike scene, the first autocorrelation coefficients of the I, P and B pictures have increased to 0.96, 0.95, and 0.87 from 0.33 before decomposition. Other scenes like table tennis, flower garden, and US show similar characteristics.

The traffic changes in decomposed signals are generally moderate and are the result of motion or scene changes. This implies that the decomposed signals can be used for motion or scene analysis of MPEG video.

Table 2. Autocorrelation coefficients.

scene	ac(all)	ac(I)	ac(P)	ac(B)
bike	0.33	0.96	0.95	0.87
table tennis	0.27	0.94	0.95	0.96
flower garden	0.39	0.96	0.95	0.98
us	0.49	0.96	0.93	0.89

Table 3. Mean prediction error [cells/frame].

scene	GOP(m)	mean	AR(1)	AR(m)	PD	IPB
bike	6	90	98.3	22.7	16.5	10.7
table tennis	6	173	202.6	41.8	22.1	19.6
us	9	60	61.1	22.1	22.8	21.2
startrek	12	111	109.9	41.8	43.2	41.8
football	12	202	215.6	44.6	47.4	36.9

Since the traffic of the pictures coded in the same mode have a high correlation and the autocorrelation function of the traffic shows a linear decrease, we used the AR model for predicting the traffic of the decomposed pictures. The first order AR prediction model based on our frame decomposition scheme is given by [7],

$$X_i(n) = (1-a_i)\,\eta + a_i X_i(n-1) + e, \quad i \in \{I, P, B\} \tag{3}$$

where $X_i(n)$ is the traffic from the n-th picture with type i, $X_i(n-1)$ is the traffic from previous picture with the same type I, η is the mean of the traffic signal, a_i is the first autocorrelation coefficient of picture type i, and is white Gaussian process.

3.3 IPB-Based Prediction

In this section, we provide an extension of the picture-decomposed (PD) prediction scheme. The basic notion in this scheme is that cross-correlation between different types of pictures can be used to enhance the performance of the PD prediction scheme. Thus, all different types of pictures are used to predict the current frame. The difference in this scheme from the AR prediction is that the prediction coefficients are estimated using both the autocorrelation and cross-correlation coefficients of decomposed signals. Note that in the high-order AR prediction scheme, the prediction coefficients are derived from the autocorrelation coefficients of the whole signal.

A predicted frame of each type is expressed by

$$\hat{I}_n = a_{11} I_{n-1} + a_{21} P_{n-1} + a_{31} B_{n-1} \tag{4}$$

$$\hat{P}_n = a_{12} I_{n-1} + a_{22} P_{n-1} + a_{32} B_{n-1} \tag{5}$$

$$\hat{B}_n = a_{13} I_{n-1} + a_{23} P_{n-1} + a_{33} B_{n-1} \tag{6}$$

where the is the prediction coefficient. To find the prediction coefficients that minimizes the prediction error, we take the derivative of the squared prediction error with respect to the coefficients. For I frames in Equation (4), the squared prediction error is given by

$$\begin{aligned} e_I &= E[(I_n - \hat{I}_n)^2] \\ &= E[(I_n - (a_{11} I_{n-1} + a_{21} P_{n-1} + a_{31} B_{n-1}))^2] \end{aligned} \tag{7}$$

where is the squared prediction error for I frames only. By taking the derivative of Equation (7) with respect to, we obtain

$$r_I(0) a_{11} + r_{IP}(0) a_{21} + r_{IB}(0) a_{31} = r_I(1) \tag{8}$$

$$r_{IP}(0)a_{11} + r_P(0)a_{21} + r_{PB}(0)a_{31} = r_{IP}(1) \quad (9)$$

and

$$r_{IB}(0)a_{11} + r_{PB}(0)a_{21} + r_B(0)a_{31} = r_{IB}(1) \quad (10)$$

where is the k-th normalized set of autocorrelation coefficients of a decomposed signal x and is the k-th normalized cross-correlation coefficient of decomposed signals x and y. Equations (8) through (10) can be expressed as a matrix equation by

$$\begin{bmatrix} r_I(0) & r_{IP}(0) & r_{IB}(0) \\ r_{IP}(0) & r_P(0) & r_{PB}(0) \\ r_{IB}(0) & r_{PB}(0) & r_B(0) \end{bmatrix} \begin{bmatrix} a_{11} \\ a_{21} \\ a_{31} \end{bmatrix} = \begin{bmatrix} r_I(1) \\ r_{IP}(1) \\ r_{IB}(1) \end{bmatrix} \quad (11)$$

Similarly, the prediction errors for P and B frames are given by, respectively,

$$e_I = E[(P_n - \hat{P}_n)^2] \quad (12)$$

and

$$e_B = E[(B_n - \hat{B}_n)^2] \quad (13)$$

The prediction coefficients for P and B frames can be obtained by taking the derivatives of Equations (12) and (13). Finally, the prediction coefficients are obtained via the matrix equation

$$\begin{bmatrix} r_I(0) & r_{IP}(0) & r_{IB}(0) \\ r_{IP}(0) & r_P(0) & r_{PB}(0) \\ r_{IB}(0) & r_{PB}(0) & r_B(0) \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{22} & a_{23} \end{bmatrix} = \begin{bmatrix} r_I(0) & r_{IP}(0) & r_{IB}(0) \\ r_{IP}(0) & r_P(0) & r_{PB}(0) \\ r_{IB}(0) & r_{PB}(0) & r_B(0) \end{bmatrix} \quad (14)$$

Equation (14) can be extended to a m×m matrix equation if we treat all frames in a GOP size m to be of different types. For example, in a GOP of IBBPBB, Equation (14) becomes a 6×6 matrix equation. This scheme is different from the higher order AR prediction scheme in that the autocorrelation coefficients are estimated for each type of the decomposed signals, and the cross-correlation between two different types of signals are also used. Note that in the high-order AR prediction scheme, only the autocorrelation of the original signal is used.

3.4 Performance Comparison

In this section, the performance of our prediction schemes based on picture decomposition is compared with that of the AR prediction scheme. The various video scenes were used for simulation. Figure 8 shows the performance of four prediction schemes.

The first one is a result of the first order AR prediction. The vertical axis is the prediction error in units of the number of cells. Since the correlation between consecutive frames is very low in this case, the performance is quite poor. The second case is the m-th order AR prediction scheme with m equal to the GOP size (m=6 here). The prediction error decreased considerably relative to that of AR(1). The third one is the case of the PD prediction scheme. The performance of the third scheme is better than that of the second one even though only the first order AR prediction was used for the decomposed signal. Finally, the performance of IPB-based prediction is presented. This scheme clearly has the best performance of all.

The mean prediction errors for various video traffic of different GOP sizes are presented in Table 3. The unit of the prediction error is the number of cells. In the table, m is the size of the GOP, and PD denotes picture-decomposed prediction. As shown in the table, the IPB-based scheme shows the best performance, and the AR(m) and PD show similar performance. In general, the first order AR(1) scheme is quite poor for MPEG video traffic since the traffic from consecutive frames has low correlation.

Ⅳ. Conclusions

In this study, the features of MPEG video coding schemes and statistical characteristics have been addressed. Since MPEG video is bursty and the traffic has low correlation, prediction schemes used for packet data are not effective in VBR video signals. A new prediction scheme was proposed, based on the notion that if a signal is decomposed according to its coding mode, then the decomposed signals have higher correlation than the original signal. The prediction scheme based on picture decomposition (PD) has better performance in predicting MPEG traffic than the autoregressive (AR) method. By extending to IPB-based prediction that utilizes the autocorrelation and cross-correlations between pictures, our simulation results show that the performance has been improved about 15%. This is caused from that the contribution of the cross-correlation property is additional. Our scheme can be effectively used for predicting non-MPEG signals that can be readily decomposed into subsignals.

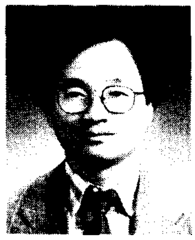
References

1. R. Handel, M. N. Huber, and S. Schroder, *ATM Networks: Concepts, Protocols, Applications*, 2nd ed., Reading, MA: Addison-Wesley, 1994.
2. R. O. Onvural, *Asynchronous Transfer Mode Networks: Performance Issues*, Artech House, 1994.
3. D. Le Gall, "MPEG:a video compression standard for multimedia applications," *Commun. ACM*, Vol. 34, No. 4, pp. 46-58, April 1991.
4. P. Pancha, and M. El Zarki, "Bandwidth-allocation schemes for variable-bit-rate MPEG sources in ATM networks," *IEEE Trans. Circuits Syst. Video Technol.*, Vol. 3, No. 3, pp. 190-198, June 1993.
5. M. Nomura, T. Fujii, and N. Ohta, "Basic characteristics of variable rate video coding in ATM environments," *IEEE J. Selected Areas Commun.*, Vol. 7, No. 5, pp. 752-760, June 1989.
6. F. Yegenoglu, B. Jabbari, and Y. Q. Zhang, "Motion-classified autoregressive modeling of variable bit rate video," *IEEE Trans. Circuits Syst. Video Technol.*, Vol. 3, No. 1, pp. 42-53, February 1993.
7. ISO/IEC/JTC1/SC29/WG11 Draft of Rec. H.262, "Generic Coding of Moving Pictures and Associated Audio," September 1993.
8. R. Aravind, G. L. Cash, D. L. Duttweiler, H. M. Hang, B. G. Haskell, and A. Puri, "Image and video coding standards," *AT&T Technical Journal*, Vol. 72, No. 1, pp. 67-88, Jan./Feb. 1993.
9. D. Anastassiou, "Current status of the MPEG-4 standardization effort," *SPIE Proceedings-Visual Commun. Image Processing 94*, Vol. 2308, pp. 16-24, September 1994
10. I. Corset, S. Jeannin, and L. Bouchard, "MPEG-4: Very low bit rate coding for multimedia applications," *SPIE Proceedings-Visual Commun. Image Processing 94*, Vol. 2308, pp. 1065-1073, September 1994.
11. D. P. Heyman, A. Tabatabai, and T. V. Lakshman, "Statistical analysis and simulation study of video teleconference traffic in ATM networks," *IEEE Trans. Circuits Syst. Video Technol.*, Vol. 2, No. 1, pp. 49-59, March 1992.
12. R. M. Rodriguez-Dagnino, M. R. K. Khansari, and A. Leon-Garcia, "Prediction of bit rate sequences of encoded video signals," *IEEE J. Select. Areas Commun.*, vol. 9, no. 3, pp. 305-314, April 1991.
13. S. K. Chan and A. Leon-Garcia, "Analysis of cell inter-arrival from VBR video codecs," IEEE INFOCOM 94, pp. 350-357, June 1994.
14. D. P. Heyman and T. V. Lakshman, "Source models for VBR broadcast-video traffic," *IEEE Trans. Networking*, vol. 4, no. 1, pp. 40-48, February 1996.
15. B. Melamed, D. Raychaudhuri, B. Sengupta, and J. Zdepski, "TES-based video source modeling for performance evaluation of integrated networks," *IEEE Trans. Commun.*, vol. 42, no. 10, pp. 2773-2777, October 1994.
16. D. Montgomery and L. Johnson, *Forecasting and time series analysis*, McGraw-Hill, 1976.
17. S. Haykin, *Adaptive Filter Theory*, 2nd ed., Prentice Hall, New Jersey, 1991.

Acknowledgment

The authors would like to thank the Soongsil University for supporting this work.

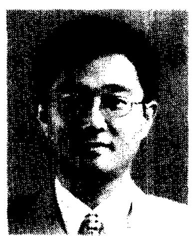
▲Souhwan Jung



Souhwan Jung received the B.S. and the M.S. degrees in Electronics Engineering from Seoul National University, Seoul, Korea, in 1985 and 1987, respectively, and the Ph.D. degrees in Electrical Engineering from the University of Washington, Seattle, in 1996.

He is a professor of Information and Telecommunication Engineering at the Soongsil University, Seoul, Korea. From 1988 to 1991, he was a technical staff in Korea Telecom., Seoul. His current research interests include multimedia traffic management, ATM and high-speed communication network protocols, switch architectures, video compression, and network design for VOD services.

▲Jisang Yoo



Jisang Yoo was born in Seoul, Korea, in 1962. He received the B.S. and M.S. degrees from Seoul National University, Seoul, Korea, and the Ph.D. degree from Purdul University, west Lafayette, IN, all in electronics engeneering, in 1985, 1987, and 1993, respectively.

From September 1993 to August 1994, he worked as a senior Research Engineer in the Industrial Electronics R&D Center, Hyndai Electronics Industries Co., Ltd., Ichon, Korea, in the area of image compression and HDTV. From 1994 to 1997, he was an Assistant Professor with the Department of Electronics Engineering of the Hallym University at Chunchеou, Korea. He is current an Assistant Professor with the department of Electronics Engineering of Kwangwoon University, Seoul, Korea. His research interests are in signal and image processing and computer vision.