

# VBR MPEG Video Traffic Dynamic Prediction Based on the Modeling and Forecast of Time Series

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**Abstract**—The variable-bit-rate traffic characteristic brings a large complication to the dynamic bandwidth allocation and renegotiation of network. To solve this problem, this paper proposes a dynamic prediction scheme of MPEG video traffic. We first advance an initial reversible transformation to the original video GoP sizes and then design an algorithm based on the ARMA process modeling to fit the transformed smooth sequence. At last we take advantage of the multi-step forecast of the series to perform a dynamic prediction for original GoP sizes. An experimental study has shown the good effect of the scheme in this paper. With the help of our prediction scheme, the waste of bandwidth will be limited effectively and the network bandwidth allocation and renegotiation can be developed to be very dynamic and intelligent.

**Index Terms**—MPEG, video trace, forecast, time series, ARMA

## I. INTRODUCTION

Nowadays multimedia service is one of the major features of the present packet-switched and ATM networks, and video data is supposed to account for a large portion of the multimedia traffic. For transport over networks, video is typically encoded (i.e. compressed) to reduce the bandwidth requirements [1], [2]. Therefore, compressed video streams typically exhibit a highly VBR (Variable Bit Rates) property due to the spatial and temporal redundancy reduction produced in the compression. However, the IP-based internet is designed to offer real-time services for instantaneous users, in which environment the queuing delays and congestion losses brought by the VBR traffic characteristic cast severe challenges on the various stringent QoS (Quality of Services) requirements [6]–[8]. The dynamic bandwidth allocation as well as the bandwidth renegotiation during a connection's lifetime is a good way to achieve the balance between the bandwidth allocation and the QoS requirements [19]. To approach this, the prediction of future bandwidth requirements becomes the most significant problem that we have to solve first.

Extensive studies have been conducted to achieve these goals [9]–[26]. Some of these studies focus on off-line system modeling and simulation and theoretical performance analysis and evaluation based on large amounts of collected video traffic data [9]–[18]. On the other hand, other researches address the issues of on-line video traffic predictions [19]–[26]. In a word, two kinds of algorithms are mainly used to manage dynamic resources, one is based on parameter

measurements and the other is based on prediction [20]. However, there are several different problems brought by these proposals. For example, conventional traffic models based on special statistical parameters need prior knowledge of the traffic statistics [11], [13], which means a relatively larger system cache and longer delay, or a stationarity assumption is required [10], which means the scheme is not effective and accurate enough to enhance the QoS and improve network utilization. Another flaw that the mechanism suffers from is that the computational complexity of the algorithm is high and thus could not satisfy the time demand of real-time predictions [19]. Most MPEG prediction schemes separately differentiate and treat the I, P and B frames from the composite video traffic stream and predict them accordingly, which complicates the algorithms and increases the implementation complexity of the on-line video traffic predictor [22]–[24].

In this paper, we propose a composite dynamic VBR MPEG traffic prediction scheme based on a reversible preprocessing transformation and an ARMA fitting algorithm. The paper is organized as follows. In Section 2 the related work is reviewed and a brief introduction to MPEG GoP size trace is provided in Section 3. We abstract and analyze the problem of this paper in a view of time series in Section 4. In Section 5, we advance the transformation to the original video GoP sizes, design the ARMA fitting algorithm and take advantage of the multi-step forecast to perform a dynamic prediction. At last, the paper is summarized in Section 6.

## II. RELATED WORK

The importance and the hardship of the multimedia communications have led to extensive research on video traffic. One model was suggested in [12] in which video sources are approximated by a flow model (minisource) and stochastic multiplexing performance is estimated by an analytic technique. [14]–[17] suggested and conducted a series of studies on VBR video at ATM links by a continuous-time or discrete-time discrete-state space Markov chain source model. These studies measure the parameters of the model and subsequently compare the generated model mean and autocovariance to the mean and autocovariance that have been measured directly from the output of the video codec. There are three main unsatisfied conclusions from this work which have been listed in [10]. In [18] a train-car model is proposed by Jain, a

continuous-time discrete two-state model for data sources with parameters derived from measurements of the mean, coefficient of variation, and first lag of the autocovariance function. This requires much larger recorrelation lags to be considered [10]. Maglaris et al. [11] presented both a continuous-time discrete-state Markov model and a continuous state autoregressive model to model a CR codec with frame buffering as its output [10]. Although the continuous-time Markov process model facilitates queuing analysis, it is difficult to fit the model to general video source [19]. The AR (autoregressive) model and ARMA model are proposed to capture the statistical characteristics of the video traffic in [9], [10]. However, these methods for characterizing the VBR video traffic are just used for off-line applications. It is the capability of predicting future video traffic in a relatively short time period that is required for the dynamic bandwidth allocation [19].

Several prediction schemes have been proposed in the literature. In [22] an RLS (Recursive Least Square) method as well as a TDNN (Time Delay Neural Network) method was proposed to predict both JPEG and MPEG encoded video traffic. But in the case of MPEG traffic B frames can not be predicted [19]. Chang and Hu [24] used PRNN (Pipelined Recurrent Neural Network) combined with NARMA process (Nonlinear Autoregressive Moving Average) to adaptively predict MPEG video traffic. However, the explicit expression of the NARMA model is actually unknown. In [23] an adaptive linear prediction scheme based on LMS algorithm (Least Mean Square) was proposed by Adas and again in this scheme the I, P and B frames are treated separately. Zhao et al [25] approached the slow convergence problem of [23] by proposing a fast convergent algorithm. The work in [23] is extended to a composite MPEG video traffic prediction by [19] in which composite MPEG video traffic is predicted by a single predictor instead of 3 different predictors because of the differences between I, P and B frames. We can refer to [22] for more information about the algorithms both in time domain and wavelet domain for video traffic prediction. [21] even proposed both a time-domain and a wavelet-domain NLMS (Normalized Least Mean Square) based adaptive prediction scheme respectively. Also, an optimized adaptive method based on Kalman filter was proposed to model MPEG-4 video traffic in [26] and a robust video traffic prediction algorithm based on the  $H_\infty$  filtering approach was presented to predict the VBR traffic in [20].

Unlike the previous prediction schemes, our scheme does not just assume the GoP size series is stationary but to transform the data and make it stationary specifically before proceeding. Besides, this scheme focuses on the GoP aggregation level and thus deals with the data from the GoP size trace [2] because the curve of GoP size can represent the variable bit rate which stands for the bandwidth requirements approximately. We fit the transformed sequence with a time series model such as ARMA and use the projection casted in the close linear subspace composed of the former values as future forecast. These decisions help us achieve a more reliable accuracy with a lower implementation complexity.

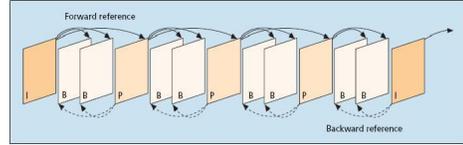


Fig. 1. Typical MPEG GoP pattern with references used for predictive coding of P and B frames

### III. MPEG GoP SIZE TRACE

#### A. MPEG Frame Types

The most widely used video encode standard is set by MPEG (Motion Picture Expert Group) [4]. The two main principles in MPEG video coding are intra-frame coding using the DCT (Discrete Cosine Transform), and inter-frame coding using motion estimation and compensation between successive video frames. In inter-frame coding, MPEG introduces 3 frame types: intra-coded frames (I) without reference to other frames, inter-coded predictive frames (P) with forward reference to a past I or P frame, and bidirectionally coded predictive frames (B) with forward reference to an immediate previous I or P frame as well as backward reference to an immediate future I or P frame [19]. These different frame types are organized into so called GoP (Groups of Pictures). GoPs constitute the MPEG video stream. The pattern that they make up a GoP is commonly referred to as GoP pattern or GoP structure. A typical GoP pattern with three P frames in a GoP and two B frames before and after each P frame (i.e. IBBPBBPBBPBB) is illustrated in Fig. 1 from [1]. A GoP is defined by its length which is the distance between I frames. And we refer to the sum of the sizes of the frames in a GoP as the GoP size (in byte) as expressed in (1).

$$Y_m = \sum_{n=mG}^{(m+1)G-1} F_n, \quad \text{for } m = 0, \dots, N/G - 1 \quad (1)$$

where  $Y_m$  stands for size of the m-th GoP,  $F_n$  represents size of the n-th frame,  $G$  is the length of the GoP and  $N$  is the total number of video frames [2].

#### B. Video Trace

Studies on the network transport of video use video traces instead of actual bit streams because of copyright issues [1]. A video trace gives predefined quantities typically in an ASCII file with one line per frame. Terse traces give only the frame sizes, while verbose traces give several of the defined quantities such as the frame number, cumulative display time, frame type, frame size and luminance quality. Single layer MPEG-1 encoded video traces have been available since the mid 1990s. More elaborate traces, containing both frame sizes and frame qualities, have become available for single-layer encoded video of different video formats and quality levels, as well as scalable encoded video [1], [2]. The video traces facilitate the research such as modeling, simulation and performance evaluation. In this paper, we focus on the GoP aggregation level and thus adopt the GoP size trace [2] to help

with our study because of the fact that the variable GoP sizes approximate the VBR. It is simpler than to use a frame size trace and could help us reduce the computational complexity of the predictor to be designed.

The video traces research group of Arizona State University [1] generates and provides a comprehensive trace library for research use. We pick up several MPEG-4 Part 2 GoP size traces for 3 different types of videos to expect a more comprehensive conclusion: (a) Tokyo Olympics with DVD as the source format; (b) Sony Demo with High Quality WM9 as source format; (c) NBC News with TV capture as source format. However, they share the same availability such as CIF  $352 \times 288$  30fps. We first focus on the single layer encoding for simplicity. Here are meanings of the denotations for the video traces by the video traces research group: a) GxBy means no. frames in a GoP is x while no. B frames in between I/P key pictures is y; b) quantization scales (M1)-(M9) stands for different encoding modes determined by the quantization parameters which we denote it by QP. We refer the interested readers to [1]–[4] for more details.

#### IV. ANALYSIS OF TIME SERIES

##### A. Abstract and Analysis

Since  $Y_m$  stands for size of the  $m$ -th GoP, the GoP size sequence  $\{Y_m\}$  can be regarded as a time series. What we want to do is to predict the sizes of future GoPs based on the knowledge of the sizes of acquired GoPs. For example, provided that we have got the sizes of the previous  $n$  GoPs, we would like to find a way to predict the  $(n+1)$ -th value of the GoP size sequence, or even the future 10, 20, 30, ... sizes. To constrain the implementation complexity of the predicting scheme,  $n$  should not be too big. An appropriate interval for the sample scale  $n$  is 100-500 [5]. In this paper, we adopt  $n = 200$ , i.e. we extract 200 values in the GoP size trace (e.g. from the 1-st to the 200-th which we denote it by source1-200).

However,  $\{Y_m\}$  is fluctuating obviously, so it is better to do some reversible transformations to the data and then get a new stationary time series  $\{X_n\}$  so that we can fit it by a time series model such as an ARMA( $p, q$ ) process [5]. After modeling the transformed time series, what we need to do next is to forecast  $\{X_n\}$  based on the established model. Once we get the forecast of  $\{X_n\}$ , we can predict the future GoP sizes based on the forecast because the transformation between  $\{Y_m\}$  and  $\{X_n\}$  is reversible. The total course of prediction can be shown as (2).  $\hat{X}$  is the forecast of  $X$  and  $\hat{Y}$  stands for the predicted value.

$$\{Y_m\} \xrightarrow{\text{transform}} \{X_n\} \xrightarrow{\text{forecast}} \{\hat{X}\} \xrightarrow{\text{predict}} \{\hat{Y}\} \quad (2)$$

Of course, several methods in the time series field can be applied directly to forecast the time series, e.g. the ARAR forecast and the Holt-Winters forecast. A comparison of forecast accuracy of different methods will be involved in future studies. In this paper, we apply the ARMA( $p, q$ ) (Autoregressive Moving Average) process model temporarily for demonstration.

##### B. Time Series

The whole process of ARMA modeling include the fitting of the orders  $p$  and  $q$ , the estimation of parameters, the analysis of residuals and the test of goodness of fit. During the process, the truncation effect of ACF (Autocorrelation Function) or PACF (Partial Autocorrelation Function) is important because it is an indication for an appropriate ARMA model. For example, the ACF of MA( $q$ ) follows (3). The truncation effect is especially indicative when a simple AR( $p$ ) or MA( $q$ ) process can fit the series well. More complex model can be found through preliminary estimation and subsequently by using MLE(Max Likelihood Estimation). The Durbin-Levinson recursive algorithm as well as the New-Info recursive algorithm plays a significant role in the estimation. Histogram, ACF and PACF plots of residuals and test of randomness can be used for residual analysis. And finally when we want to pick the most appropriate model, the AICC function is a good measure.

$$|\hat{\rho}_m| < 1.96n^{-\frac{1}{2}}, \quad \text{for all } m > q \quad (3)$$

where  $\rho_m$  indicates the sample ACF value of MA( $q$ ). The sample PACF of AR( $p$ ) follows a similar rule. In the sample ACF and PACF plot as will be shown in the following sections the bound  $\pm 1.96n^{-\frac{1}{2}}$  is illustrated by dashed lines.

Once we have an appropriate ARMA( $p, q$ ) model for the sequences, the projection theorem provides us a good forecast as shown in (4). In other words, we use the projection ( $\hat{x}$ ) casted in the close linear subspace ( $\mu$ ) composed of the former values in the series as the forecast of future values ( $x$ ). Therefore the forecast has the minimum *mean square distance* from the actual value which guarantees a high accuracy for us. We can apply Durbin-Levinson and New-Info recursive algorithms to calculate the forecast. More details about the modeling and forecast of time series can be found in [5].

$$\|x - \hat{x}\| = \inf_{y \in \mu} \|x - y\| \quad (4)$$

#### V. DATA ANALYSIS AND PREDICTION

Now we analyze the data source1-200 from GoP size trace of single layer MPEG-4 Part2 Tokyo Olympics G16B1 QP01 as an example. We use the ITSM PEST software [5] combined with MATLAB as tools for statistical analysis.

##### A. Initial Transformation

According to the typical structure of time series as shown in (5), a time series( $X_t$ ) is usually composed of trend ( $m_t$ ), seasonal( $s_t$ ) and noise components( $n_t$ ) [5]. Besides, the original data used to represent the GoP size is generally too large as illustrated in Fig. 2. As a result, we need to transform the original series to make it stationary before more proceedings. We plan to apply the natural logarithm function  $\ln Y$  to the source data first. The  $\ln Y$  function is in fact a Box-Cox Transformation using 0 as the parameter of  $\lambda$  so that it can meanwhile lower or eliminate the dependency of the variance ratio at some level if the dependency indeed exists [5]. After that, differencing at lag 1 can be introduced to eliminate the trend and seasonal components. Moreover, equation (6)

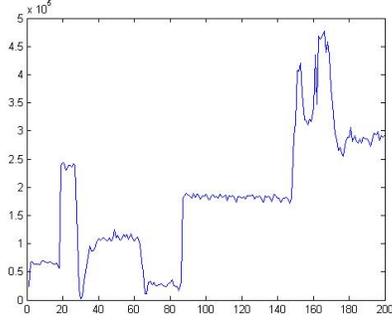


Fig. 2. plot of original data of source1-200 of single layer MPEG-4 Part2 Tokyo Olympics G16B1 QP01

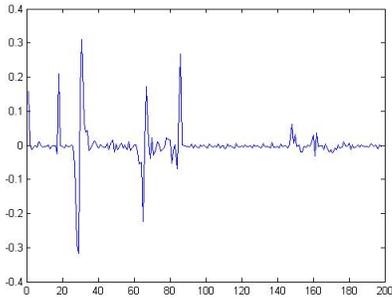


Fig. 3. plot of transformed data of single layer MPEG-4 Part2 Tokyo Olympics G16B1 QP01

brings us a good idea to do the transformation in (7) as it can effectively gives us a stationary series  $\{X_n\}$  plotted in Fig. 3 with its mean 0.6207 subtracted. Equation (8) is a generalized formation of (7) with  $\alpha$  as the parameter. We adopt  $\alpha = \frac{\sqrt{5}-1}{2}$  temporarily in this paper. In practice, in this experiment we do get  $\{X_n\}$  with most values around  $\frac{\sqrt{5}-1}{2} \approx 0.618$  which accords with the most ideal situation very closely. In future work, we will take other possible values of  $\alpha$  into consideration.

$$X_t = m_t + s_t + n_t \quad (5)$$

$$\frac{1 - \frac{\sqrt{5}-1}{2}}{\frac{\sqrt{5}-1}{2}} = \frac{\sqrt{5}-1}{2} \quad (6)$$

$$\frac{\ln Y_n - \frac{\sqrt{5}-1}{2} \ln Y_{n-1}}{\frac{\sqrt{5}-1}{2} \ln Y_{n-1}} = X_{n-1} \quad (7)$$

$$\frac{\ln Y_n - \alpha \ln Y_{n-1}}{\alpha \ln Y_{n-1}} = X_{n-1} \quad (8)$$

$$Y_n = Y_{n-1}^{\alpha(1+X_{n-1})} \quad (9)$$

Clearly  $\{X_n\}$  is the relative change of adjacent  $\{\ln Y\}$  and the time series  $\{X_n\}$  is much smoother than  $\{Y_m\}$ . Meanwhile, according to (9), the transformation is reversible

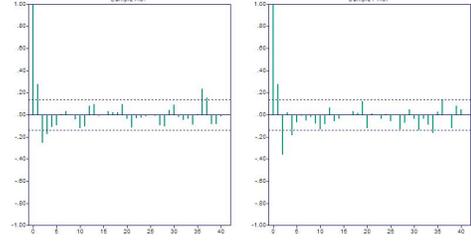


Fig. 4. sample ACF and PACF plots of transformed data of single layer MPEG-4 Part2 Tokyo Olympics G16B1 QP01

so that we can predict the source time series by modeling and forecasting the transformed sequence.

### B. Modeling

Fig. 4 shows the sample ACF and PACF plots of the stationary time series  $\{X_n\}$ . We find that they decrease rapidly. Therefore, we can employ the following algorithm to find an ARMA( $p,q$ ) model to fit  $\{X_n\}$ .

- 1: fit  $\{X_n\}$  with a simple AR or MA model based on ACF or PACF and calculate its AICC measure *aicc1*
- 2: **for**  $r = 1$  to  $\frac{n}{4}$  **do**
- 3: fit  $\{X_n\}$  with ARMA( $r,r$ ) using MLE method and calculate the AICC measure each time
- 4: **end for**
- 5: find  $r$  with the minimum AICC, make the preliminary estimation using ARMA( $r,r$ ) and compute the ratios of AR and MA coefficients to  $1.96 \times (\text{standard error})$
- 6: **while**  $|ratio| < 1$  **do**
- 7: set the corresponding coefficient to zero or not, fit  $\{X_n\}$  with the modified models using MLE method and calculate the AICC measures
- 8: **end while**
- 9: find the ARMA model with the minimum AICC *aicc2*, compare *aicc2* with *aicc1* and determine the model
- 10: residual analysis and test
- 11: **if** the residual is not a realization of white noise **then**
- 12: fit the residual sequence by an ARMA model and use it to modify the former one
- 13: goto 10
- 14: **else**
- 15: return the final ARMA model
- 16: **end if**

In this experiment, we finally get an ARMA(1,2) process after running the algorithm, i.e.  $X(t) = 0.7540X(t-1) + Z(t) - 0.3979Z(t-1) - 0.6078Z(t-2)$  with the AICC measure is  $-647.390199$ . And it has passed the residual analysis and test so that it can be regarded as the most appropriate ARMA model of  $\{X_n\}$ . Due to space constraints, we do not record the detailed in-between calculations and results here.

### C. Forecast and One-Step Prediction

According to (4), the forecast can be expressed as (10) and (11) [5]. Therefore, we subsequently run Durbin-Levinson and New-Info recursive algorithms to calculate the coefficients and

forecast several future values for  $\{X_n\}$  after we get the ARMA model. Then we use these forecast in (9) to predict the future GoP sizes for  $\{Y_m\}$ . We first study one-step prediction for simplicity. The first pair of points at x-coordinate 1 in Fig. 8 shows the comparison of the original and one-step predicted size of the 201-st GoP of single layer MPEG-4 Part2 Tokyo Olympics G16B1 QP01.

$$\hat{X}_{n+1} = \phi_{n1}X_n + \dots + \phi_{nn}X_1 \quad (10)$$

$$\hat{X}_{n+1} = \sum_{j=1}^n \theta_{nj}(X_{n+1-j} - \hat{X}_{n+1-j}) \quad (11)$$

Obviously we can find from the figure that the result of one-step prediction is not very accurate. That is because differencing at lag 1 could not reflect the trend of former data precisely. As a consequence, we need to enlarge the lag of differencing and generalize the transformation (8) furthermore.

#### D. Dynamic Prediction

As shown in (12) the  $k$ -step dynamic prediction is based on differencing at lag  $k$  instead of 1 as above.

$$\frac{\ln Y_n - \alpha \ln Y_{n-k}}{\alpha \ln Y_{n-k}} = X_{n-k} \quad (12)$$

Again, we temporarily adopt  $\alpha = \frac{\sqrt{5}-1}{2}$  here and experiment  $k = 30$ . To get a more comprehensive conclusion we experiment 3 videos of different source formats and extract resource samples randomly from the GoP size traces. Fig. 5, Fig. 6 and Fig. 7 respectively give the results. From the results, we can see that the scheme is especially effective as in Fig. 7 when dealing with videos that need a broad bandwidth in which situation it is very necessary to avoid a waste of resource. Meanwhile, the prediction scheme could basically approximate the trend and predict about 8-10 near future GoP sizes with a high accuracy. Moreover, we can infer from the result that the  $k$  value which represents the trend of former data to some extent could not be too large (as 30 in this test), in other words, there should be a limit of  $k$ . The reason is that GoPs separate too far away make no sense to each other. Besides the inherent dependency of video data, other parameters of the videos such as the video format, the encoding mode, the compression ratio and so on may all impact the variation of  $k$ . Even in the same movie maybe we should dynamically adjust  $k$  according to specific situation. More specific research about the dynamic estimation of  $k$  is expected.

With respect to a 200 sample-size 8-10 GoPs is acceptable, because this will help the dynamic bandwidth allocation a lot in practice. To improve the accuracy of prediction, based upon the scheme above we can add a rolling mechanism to the prediction suggested above. That is to use the new data we get as the movie goes to predict future data dynamically. For example, at some moment we use a  $k$ -step prediction to predict  $k$  future GoP sizes, however, after 1, 2,  $\dots$ , or  $k - 1$  GoP time we have already got new several GoP sizes so that

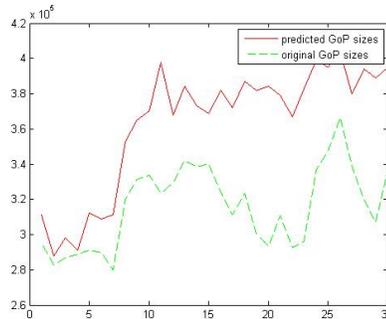


Fig. 5. comparison of original and 30-step predicted GoP sizes of source1-200 from single layer MPEG-4 Part2 Tokyo Olympics G16B1 QP01

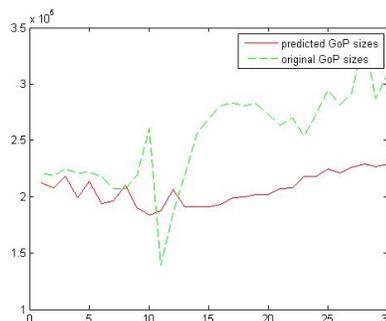


Fig. 6. comparison of original and 30-step predicted GoP sizes of source101-300 from single layer MPEG-4 Part2 Sony Demo G16B1 QP02

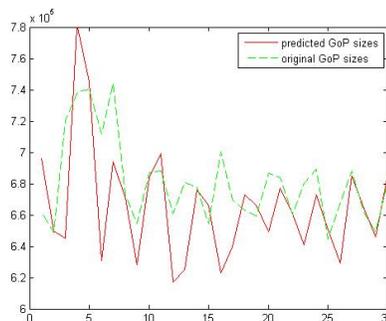


Fig. 7. comparison of original and 30-step predicted GoP sizes of source201-400 from single layer MPEG-4 Part2 NBC News G16B1 QP01

we can use these new sizes to predict repeatedly so as to achieve a more real-time and accurate result. Fig. 8 gives the result of the simplest 1-step rolling prediction (i.e. renew the data per 1 GoP time) of source1-200 from single layer MPEG-4 Part2 Tokyo Olympics G16B1 QP01. The 1-step rolling prediction is apparently of a much higher accuracy and meanwhile it means a high real-time demand. To conquer this problem and achieve better results, we can renew data every 2, 3,  $\dots$ , or  $k - 1$  GoP time, or even we can change the sample size. More experiments about the explicit rolling implementation will be involved in future studies. It is the

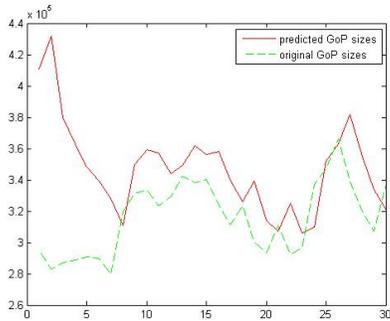


Fig. 8. comparison of original and one-step rolling predicted GoP sizes of source1-200 from single layer MPEG-4 Part2 Tokyo Olympics G16B1 QP01

rolling mechanism combined with the dynamic estimation of  $k$  advanced above that makes the whole prediction scheme more intelligent, accurate and dynamic.

## VI. CONCLUSION

A composite dynamic VBR MPEG prediction scheme based on a reversible transformation and an ARMA fitting algorithm is described in this paper. It has several advantages for online applications. One is that no stationarity assumption is required because of the initial transformation we have advanced. It doesn't need to separate I, P and B frames and hence leads to a lower complexity. Most importantly, it is dynamic and effective to avoid waste of bandwidth resource, especially when dealing with videos that require a broad bandwidth. With more explicit work in the future, the scheme can be developed to be very intelligent and dynamic.

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