Real-time Variable Bit Rate Video Traffic Using a Simple and Efficient Prediction Approach

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Abstract: The raising grandness of multimedia diligence has led to the increase in the usage of network resources. For assuring agreed Quality of Service (QoS) and for better network management, thorough analysis of traffic characteristics, modeling and prediction are crucial. In this process, a simple and effective traffic forecasting method which is suitable for time period prediction of MPEG encoded variable bit rate (VBR) video traffic. Our method is a variant of single exponential smoothing technique, which enhances prediction accuracy and in turn, enables better resource allocation and management. Results are compared with standard forecasting techniques like Single, Double exponential smoothing and Holt-winter’s. The proposed scheme attains relatively better prediction performance up-to 41%.

Key words: Exponential smoothing • VBR • MPEG • QoS • Traffic prediction

INTRODUCTION

Networked multimedia system diligences are imagination hungry and demand consistent QoS requirements throughout transit. Generally, the video compression process is used for reducing the bandwidth requirements for transport over networks. Due to the temporal and spatial superfluousness simplification in the compression, the MPEG encoded videos pours displays a highly VBR. The process of video compressing, the bandwidth require is predictably high. Therefore, traffic prediction plays a vital role in network control and management. The goal is to devise a simple and better prediction methodology that would forecast future traffic patterns as accurately as possible, based on observed past traffic behavior. First we have to solve the substantial problem of forecasting of bandwidth requirements.

Two main systems are predicting the above problem. First, offline system theoretical process, modeling and simulation based on more number of traffic data [9]. Second, on-line view traffic forecasting to predict the bandwidth requirements. These two algorithms are used to handle the bursty traffic. One class assumes that the trace traffic is known in advance and then a suitable statistical model is estimated. This model is expected to encapsulate the overall traffic characteristics. The other class assumes that traffic is not known in advance (a typical real time scenario) and prediction of few future frame sizes/traffic characteristics is performed based on the analysis of the past traffic.

“Single Exponential smoothing, Double Exponential smoothing and Holt-Winter’s” methods are discussed here, followed by the proposed methodology that is a modification of exponential smoothing technique called Modified smoothing method. Results are compared and analyzed for all of these methods by Mean Square Error (MSE).

Literature Survey: Aimin Sang et al proposed methods to control the network traffic by prediction. They used two metrics [1] in the prediction method. One of the
metrics used was, the traffic rate can be predicted for a future flow restraint and another was, check the minimum forecasting fault over a determined forecasting time interval. A wide variety of prediction methodologies have been reported in the literature among which Exponential smoothing is the simplest and efficient method. Dimce Risteski et al. discuss about the Single Exponential smoothing method [2] and they integrated Exponential method with neural network to produce better time series prediction. Exponential smoothing method uses a smoothing constant, whose empirical characteristics were studied by J. Morimoto et al. discuss about how to set the smoothing constant. They propose [3] an adaptive setting method of the smoothing constant by solving the problem of tuning the gain of the Kalman filter.

Joseph J et al. Work comparing the double exponential smoothing and predictive tracking algorithm based on kalman filter. The double exponential smoother run about 135 times faster with equivalent performance. Exponential smoothing method is not only used for bandwidth or network traffic prediction, it is also used for stock market, software reliability, air pollutant, etc. Yanyan Zheng et al. proposed an “adaptive exponential smoothing” method for software forecasting. The software failure data will be occurred as time series and to predict the software failure by this adaptive method. The adaptive model is better than traditional model. They prove that their model is better than the traditional Goel Okumoto model in these experiments [4]. M.G. Cortina-Januchs et al. works to forecast the “air pollution concentrations in Salamanca (Mexico) using smoothing exponential algorithm. The Mean Absolute Error (MAE) and Root Mean Square Error” (RMSE) are used for performance appraisal [5].

The Holt-Winters forecasting procedure is a variant of exponential smoothing, which is simple, yet generally works well in practice and is particularly suitable for producing short-term forecasts for sales or demand time-series data. Chris Chatfiel et al. discuss about the implementation of Holt-Winters method, normalization of seasonal indices, the choice of starting values and the choice of smoothing parameters [6]. They distinguish between an automatic and a non-automatic approach to forecasting and detailed suggestions are made for implementing Holt-Winters in both ways. In this process, a new algorithm which is a variation of single exponential method for predicting future traffic patterns and we compare our method with single, double exponential smoothing and Holt-Winter’s.

Existing Methodologies

**Single Exponential Smoothing:** Single exponential smoothing is the best method to predict the time series. The method uses a weighted linear combination of past time series data, with the weights chosen such that they are exponentially diminishing as the data gets older. In other words, older observation has lesser weights than the recent observation in forecasting. To calculate the prediction of single exponential smoothing formula is given below

\[
p_{t+1} = p_t + \alpha(z_t - p_t)
\]

where \( p_t \) represents forecast for time period \( t = 1,2,3,... \), \( z_t \) represents Actual value of the time-series in the prior period \( t = 1,2,3,... \), while \( \alpha \) represents smoothing parameter (lies between 0 and 1).

Equation (1) is the basic equation for single exponential smoothing. Moreover this methodology produces better results only when the time series data is devoid of trend or seasonality. However, single exponential smoothing is not suitable for trend data’s. Single coefficient \( \alpha \) may not produce better predictions results on particularly bursty VBR video traffic.

**Double Exponential Smoothing:** This method is used when the data shows a trend. Its works much like single exponential smoothing exclude the updating of two components in each period (trend and level). As well as, the simple smoothing work much like exponent smooth with a trend exclude the updating of two components in each period (trend and level). The specific formula for double exponential smoothing [4] is

\[
c_t = \alpha z_t + (1-\alpha)(c_{t-1} + d_{t-1})
\]

\[
d_t = \gamma (z_t - c_t) + (1-\gamma)d_{t-1}
\]

where represents time-series actual value in the prior period \( t = 1,2,3,... \), represents time period of forecast \( t = 1,2,3,... \) while \( \alpha, \gamma \) represents smoothing parameters whose value lies between 0 and 1.

**Initialization**

\[
c_1 = z_1
\]

\[
d_1 = z_2 - z_1
\]
The forecast value is calculated as below,

\[ p_t = c_t + d_t \]

**Triple Exponential Smoothing:** This method is preferred when the information depicts seasonality and trend. Seasonality aspect of the input data is handled by another parameter as shown in the expression (6) below. The new expression to handle seasonality along with the other expressions to handle trend and local level is collectively denoted to as “Holt-Winters” method. Multiplicative Seasonal Model and Additive Seasonal Model are two main HW models, depending on the type of seasonality.

**Multiplicative Seasonal Model:** Multiplicative seasonality is suitable for a time series in which the seasonal pattern amplitude is proportional to the average level of the series \[ [11] \].

\[ u_t = \alpha \frac{z_t}{g_{t-s}} + (1-\alpha)(u_{t-1} + d_{t-1}) \]  
\[ d_t = \beta(u_t - u_{t-1}) + (1-\beta)d_{t-1} \]  
\[ g_t = \gamma \frac{z_t}{u_t} + (1-\gamma)g_{t-s} \]  

where \( u_t \) is the local level of the series, \( d_t \) is the component of the trend and \( g_t \) is the relevant seasonal component, with \( s \) signifying the seasonal period, the integer \( l \) represents the forecasting horizon, while \( \alpha, \beta, \gamma \) represents smoothing parameter whose value lies between 0 and 1.

**Initialization:**

\[ u_0 = \frac{\sum_{t=1}^{s} z_t}{s} \]

\[ d_0 = \frac{\left\{ \sum_{t=1}^{s} z_t \right\} - \left\{ \sum_{t=s+1}^{s+k} z_t \right\}}{s} \]

\[ g_0 = \frac{z_k}{u_0} \]

where \( k=1,2,\ldots,s \)

In this method, the predicted value is calculated as below,

\[ p_{t+1} = (u_t + d_t)g_{t+s} \]

**Additive Seasonal Model:** Additive seasonality is understood to give better results for a time series, whose seasonal amplitude is independent of the series average level \[ [11] \].

\[ u_t = \alpha(z_t - g_t) + (1-\alpha)(u_{t-1} + d_{t-1}) \]  
\[ d_t = \beta(u_t - u_{t-1}) + (1-\beta)d_{t-1} \]  
\[ g_t = \gamma(z_t - u_t) + (1-\gamma)g_{t-s} \]  

where \( u_t \) is the local level of the series, \( d_t \) is the component of the trend and \( g_t \) is the relevant seasonal component, with \( s \) signifying the seasonal period, the integer \( l \) represents the forecasting horizon, while \( \alpha, \beta, \gamma \) represents smoothing parameter whose value lies between 0 and 1.

**Initialization:**

\[ u_0 = \frac{\sum_{t=1}^{s} z_t}{s} \]

\[ d_0 = \frac{\left\{ \sum_{t=1}^{s} z_t \right\} - \left\{ \sum_{t=s+1}^{s+k} z_t \right\}}{s} \]

\[ g_0 = \frac{z_k}{u_0} \]

where \( k=1,2,\ldots,s \)

In this method, the predicted value is calculated as below,

\[ p_{t+1} = (u_t + d_t)g_{t+s} \]

**Proposed Method:** A new method is proposed here called “Modified smoothing method”. This formula is obtained by solving the basic equation of Single Exponential smoothing method recursively and modifying it. The steps of solving the equation are given below.

**Recursive Smoothing Equation:** In equation (1), replace \( t = t-1 \)

\[ p_{t+1} = p_{t} + \alpha(z_t - p_t) \]  

Substitute equation (10) in (1),
\[ p_i = \alpha(z_{i-1} + (1-\alpha)p_{i-1}) + (1-\alpha)p_i \]  

where \( i \) represents time series, \( N \) represents total number of frames, \( Y_i \) represents actual or observed value \((1<i<N), X_i \) represents forecast value \((1<i<N)\).

Experimental Work: The input for this system is set of frame size values in bytes. Experiments are conducted on 5 minutes video traces of Star wars IV and NBC-news of different qualities that are encoded by H.264/SVC with 30 fps on G16B1 GOP pattern. The properties of the input videos are shown in the table below. The input video traces were obtained from [12]. Analysis of individual input video traces is shown in Table 1.

Results and Analysis: Exponential smoothing method of RMSE results are shown in Table 2. Last column shows the result obtained when our method is compared with the best in class. Exponential smoothing techniques perform well for time series data with low variability as is evident from the Table 2. Our method shows an improvement of up-to 41% over existing prediction techniques. Our method did not perform well when the variability in the traffic is unpredictably high which is evident from the results shown in the table 2 for high quality traces of Star

Table 1: Properties of Input Video Traces

<table>
<thead>
<tr>
<th>NAME</th>
<th>QUALITY</th>
<th>MEAN</th>
<th>STANDARD DEVIATION</th>
<th>BRUSTINESS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Star Wars IV</td>
<td>Low</td>
<td>591.03</td>
<td>917.81</td>
<td>22.5775</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>4565.6</td>
<td>7973.7</td>
<td>17.9936</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>64116.0</td>
<td>60110.0</td>
<td>5.5008</td>
</tr>
<tr>
<td>NBC-News</td>
<td>Low</td>
<td>1573.7</td>
<td>2282.3</td>
<td>9.9891</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>20798.0</td>
<td>23773.0</td>
<td>6.7333</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>2.6371E+5</td>
<td>88579.0</td>
<td>1.9498</td>
</tr>
</tbody>
</table>
**CONCLUSION**

In this method, a “Modified smoothing method” is used for VBR video traffic. We compare and analyses the proposed method with Single, Double Exponential smoothing and Holt-Winter’s method for Star war IV and NBC-news videos as input. The results indicate that prediction performance is improved. The proposed method is computationally simple and also takes into account the GOP structure as the basis, thus making it more suitable for real time traffic prediction.

**ACKNOWLEDGEMENT**

The authors are thankful to Mr. T Magesh Babu working at TCS, Chennai for giving Technical support while the research was being carried out.

**REFERENCES**