Prediction Algorithms for Real-Time Variable-Bit-Rate Video

Huabing Liu and Guoqiang Mao
School of Electrical and Information Engineering, The University of Sydney, Australia
Email: {hliu, guoqiang}@ee.usyd.edu.au

***Abstract*— Accurate prediction of variable bit rate (VBR) video traffic can be used to improve the network utilization efficiency while supporting guaranteed QoS requirements of VBR video. On-line prediction algorithms have been proposed in the literature to forecast real-time VBR video traffic for dynamic bandwidth allocation. In this paper, we survey a number of algorithms both in time domain and wavelet domain for video traffic prediction. The features of the existing algorithms are summarized, and on the basis of it we propose a time-domain and a wavelet-domain normalized least mean square (NLMS) based adaptive prediction scheme respectively. Our proposed time-domain scheme combines the separation and differential techniques in the literature to reduce short-term bit rate variation of VBR video traffic and smooth the data for more accurate perdition. Our proposed wavelet-domain prediction scheme uses the $\grave{a}\ trous$ wavelet transform instead of conventional decimated wavelet transform to improve the prediction accuracy by exploiting the redundant information in the wavelet transform coefficients. Simulations using three half-an-hour long full-motion Moving Picture Experts Group (MPEG) video traces show that our proposed methods can achieve better performance than those in the literature.**

I. Introduction

Real-time variable bit rate (VBR) video applications such as video conferencing and multimedia streaming are emerging as major applications over a variety of high-speed networks. The transmission of real-time VBR video traffic has put a stringent requirement on Quality of Service (QoS) such as guaranteed bandwidth, delay, jitter and packet loss. In order to satisfy the specified QoS requirements of video traffic during an entire transmission, the allocated bandwidth must meet the QoS requirements at peak rate. However, in addition to meeting the QoS requirements, the efficient use of network resources also needs to be considered. Therefore, a static bandwidth allocation scheme which allocates a bandwidth equal to the peak rate is not desirable because a significant amount of bandwidth may be wasted due to the bursty nature of the VBR video traffic. As such, it is desirable to allocate bandwidth dynamically according to the accurate prediction of future video frames. The statistical characteristics of VBR video traffic have been investigated in a number of researches [1], [2] and can be exploited to forecast the real-time VBR video traffic. A number of prediction algorithms have been proposed in the literature, which include neural network approach [3], Normalized Least Mean Square (NLMS) approach [4], [5] and wavelet decomposition approach [6]. The existing algorithms can be broadly classified into two categories: time-domain approaches and wavelet-domain approaches.

In time domain, two different NLMS-based methods exist in addition to the neural network approach. Traffic prediction based on the neural network approach can be quite complicated to implement. The accuracy and applicability of the neurula network approach to traffic prediction is limited [7]. Normalized Least Mean Square (NLMS) based prediction approaches are of particular interest due to its simplicity and relatively good performance. In addition, they do not require any prior knowledge of the video statistics, nor do they assume stationary [4]. Thus, they are suitable for on-line VBR video traffic prediction. However as I, P and B frames of MPEG-encoded video sequences are encoded with different degrees of compression and possess different statistical characteristics, which causes short-term bit rate variation, the video sequence is a highly fluctuating time-series in small timescale. In addition, there exists long-term bit rate variation caused by scene changes, which makes the situation even worse. Therefore, it is difficult to directly predict the VBR video frames using NLMS algorithm. Adas [4] proposed separating the MPEG-encoded video sequence into I, P and B subgroups and predicting video frames separately in each subgroup using NLMS algorithm. However the prediction error is increased when frequent scene changes occur. Xu and Qureshi [5] proposed a composite prediction method which smoothed the predicted data based on differential technique and predicts the relative size difference of the same frames in adjacent group of pictures (GOP). Since I, P and B frames are encoded with different schemes, the smoothed composite traffic is still highly fluctuating and thus the prediction is not effective. [4] used separation technique to reduce the short-term bit rate variation whereas [5] used differential technique to smooth the predicted video sequence for VBR video prediction.

A natural extension of their work would be to combine both the separation and differential techniques to reduce short-term bit rate variation and smooth the predicted video traffic. Based on the work of [4] and [5], we propose a method which first separates the original video sequence into I, P and B subgroups and then predicts the size difference between adjacent frames in each subgroup.

Due to the slow convergence property of time-domain NLMS algorithm [8] and complex scaling behaviors of VBR video traffic [9], a wavelet-domain NLMS based predictor was proposed in [6]. Instead of predicting the original video frames directly, this method first decomposes the traffic into wavelet coefficients and scaling coefficients at different timescales using the decimated Haar wavelet transform [10] and then predicts the coefficients independently at each scale using NLMS algorithm. The predicted values of the original video frames can be constructed based on the predicted coefficients. On the basis of [6], we propose a wavelet-domain NLMS prediction method based on the non-decimated $\grave{a}\ trous$ Haar wavelet transform [11] to exploit the redundant information in the wavelet transform coefficients for more accurate prediction. The predicted values of the original video frames can be reconstructed simply as a sum of predicted scaling and wavelet coefficients.

The rest of the paper is organized as follows. Section II briefly describes the characteristics of MPEG (Moving Picture Experts Group) video; in Section III, the NLMS algorithm is described and the time-domain NLMS methods in the literature are surveys; in section IV, we propose a new time-domain NLMS method; in Section V, the decimated and non-decimated wavelet transform is introduced and the wavelet-domain NLMS method is examined; in Section VI, we propose a new wavelet-domain NLMS method; Section VII provides the simulation results to compare the performance of each method and Section VIII concludes this paper.

II. Characteristic of MPEG Videos

In this section, we shall briefly introduce the characteristics of MPEG video. It is well known that MPEG [12] is one of the most widely used video encoding standards. MPEG encoder that compresses a video signal at a constant picture rate produces a coded stream with variable bit rate. Three types of frames are generated during compression, namely, I-frame (Intra-frame), P-frame (Predictive-frame) and B-frame (Bidirectional-Predictive-frame), each with different encoding methods. As a result of different compression rate of I, P and B frames, the MPEG video stream is a highly fluctuating time-series. Typically, I-frames have more bits than P-frames. B-frames have the least bits. After encoding, the frames are arranged in a deterministic periodic sequence called Group of Picture (GOP), e.g IBBPBBPBBPBB. Refer to [12] for details of MPEG encoding algorithm.

III. Least Mean Square Predictor

The k-step ahead LMS linear prediction involves the estimation of $x\,(n+k)$ through a linear combination of the current and past values of $x\,(n)$ [13]. A p^{th} order predictor can be expressed as in equation (1)

$$\hat{x}(n+k) = \sum_{l=0}^{p-1} w_n(l)x(n-l) = \mathbf{W}_n^T\mathbf{X}(n), \tag{1}$$

where $\mathbf{W}_n$ is the prediction coefficient vector which is time varying and updated by minimizing the mean square error ξ

$$\xi = \mathbf{E}[e^2(n)]. \tag{2}$$

$\mathbf{X}(n)$, $\mathbf{W}_n$ and $e(n)$ are defined in (3)-(6), where μ is the step size

$$\mathbf{X}(n) = [x(n), x(n-1), ..., x(n-p+1)]^T \tag{3}$$

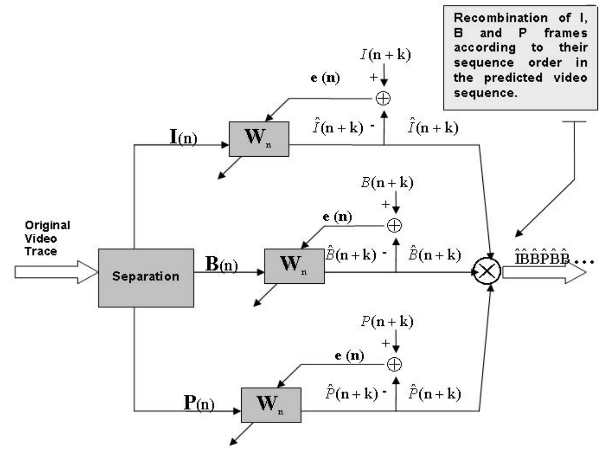

Fig. 1. Architecture of the separate NLMS prediction operation

$$\mathbf{W}_n = [w_n(0), w_n(1), ..., w_n(p-1)]^T \tag{4}$$

$$\mathbf{W}_{n+1} = \mathbf{W}_n + \mu e(n)\mathbf{X}(n) \tag{5}$$

$$e(n) = x(n+k) - \hat{x}(n+k). \tag{6}$$

The normalized LMS (NLMS) is a modification of LMS where $\mathbf{W}_{n+1}$ is updated as (7)

$$\mathbf{W}_{n+1} = \mathbf{W}_n + \frac{\mu e(n)\mathbf{X}(n)}{\|\mathbf{X}(n)\|^2}, \tag{7}$$

where $\|\mathbf{X}(n)\|^2 = \mathbf{X}(n)^T\mathbf{X}(n)$. Since at time n, the value of $x(n+k)$ is not available to compute $e(n)$, $e(n-k)$ is used instead [4].

A. Separate NLMS prediction

It is apparent that the prediction accuracy depends on the correlation between frames. In order to exploit the different correlation structures and statistical characteristics within I, P, B frames, Adas [4] proposed separating the MPEG encoded video sequence into I, P, B subgroups and forecasting each type of frames independently. The architecture of separate prediction operation is shown in Fig. 1. The separation technique makes the video traffic smoother, more correlated and thus easier to predict than the original one. However, the prediction error increases when frequent traffic variations caused by scene changes occur. In addition, the video traffic within each subgroup is still highly fluctuating even after separation. Due to the slow convergence characteristics of NLMS predictor [8], the prediction error is fairly large when the traffic is highly fluctuating.

B. Composite NLMS Prediction

Instead of separating video frames, the composite prediction method [5] tries to smooth the video traffic by predicting the relative size changes of the same frame in adjacent GOPs. Since I, P and B frame possess different statistical characteristics, the smoothed traffic is still highly bursty and later simulation results will show that it is not effective.

IV. Separate Differential NLMS Prediction

In this section, we shall introduce our proposed time-domain prediction scheme for VBR video traffic. Based on the work of [4] and [5], we propose a method which combines separation and differential techniques to reduce short-term bit rate variation and smooth the predicted data. Instead of predicting video frames directly, this method first separates video sequence into I, P and B subgroups and then predicts size difference between adjacent frames in each subgroup. Let $I(n)$ be the size of nth frame in the I subgroup. Let $D(n)$ be the size difference between adjacent I frames

$$D(n) = I(n) - I(n-1). \tag{8}$$

Once the difference $D(n+1)$ is predicted, the corresponding predicted values of $I(n+1)$ can be constructed as (10).

$$\hat{I}(n+1) = \hat{D}(n+1) + I(n+1-1) \tag{9}$$

B and P frames can be predicted in the same way. Since $D(n)$ is smoother and its values are small, it is easier to predict. Later simulation results will show that our proposed method performs better than those time-domain methods in the literature.

V. Wavelet Domain NLMS Prediction

Wavelet transform has been widely used for traffic analysis. Fundamentally, this is due to the non-trivial fact that the analyzing wavelet family itself possesses a scale invariant feature, a property not shared by other analysis methods. Quite different kinds of scaling features can be analyzed by the same technique. Wavelet transform when combined with adaptive prediction has shown advantages over its time-domain counterparts [14], [15]. Before delving into the details of wavelet-domain NLMS prediction algorithms, we shall introduce some fundamental knowledge of wavelet transform.

A. Discrete Wavelet Transformation

Wavelet analysis is based on the decomposition of a signal using orthogonal wavelet bases. There are many types of wavelet bases available [16] and among which, we are most interested in the orthogonal bases. Discrete wavelet transform (DWT) consists of a collection of coefficients, namely wavelet coefficients $D_J(k)$ and scaling coefficients $C_J(k)$ as in (10)

$$C_J(k) =< \mathbf{X}, \varphi_{Jk}(t) >, D_j(k) =< \mathbf{X}, \psi_{jk}(t) >, j, k \in Z, \tag{10}$$

where $< *, * >$ denotes the inner product; $\varphi_{Jk}(t) = \varphi_J(t-k)$ are constructed through time shifting operations of the mother scaling function $\varphi_J(t)$; $\psi_{jk}(t) = 2^{-j/2}\psi(2^{-j}t-k)$ are constructed through a time shifting and a dilation operations of the mother wavelet function $\psi(t)$. DWT decomposes a signal into a large timescale approximation and a collection of details at different scales and positions. The original signal can be reconstructed from the wavelet and scaling coefficients as (11)

$$\mathbf{X}(t) = \sum_k C_J(k)\varphi_{Jk}(t) + \sum_{j=1}^{J}\sum_k D_j(k)\psi_{jk}(t). \tag{11}$$

Theoretically, the scale j can span from $-\infty$ to $+\infty$. For practical signals, we limit the scale to [0, J] where J is the largest scale and 0 is the smallest scale. Details of wavelet transform can be found in [16], [17].

An efficient way to implement DWT is to represent the mother wavelet $\psi(t)$ and scaling function $\varphi(t)$ as a low-pass filter h and a high-pass filter g respectively [17]. The approximation at scale j, $C_j(t)$ is passed through the low-pass filter h and the high-pass filter g to produce the approximation $C_{j+1}(t)$ and the detail $D_{j+1}(t)$ at scale $j+1$. At each stage, the number of coefficients at scale $j+1$ is decimated into half of that at scale j, due to decimation. This decimation reduces the number of data points to be processed at the larger timescales and removes the redundancy information in the wavelet coefficients and the scaling coefficients. Thus it is desirable for some applications such as image processing to remove the redundant information. However, in the occasion of traffic prediction, it is not necessary to be implemented because in time series prediction, the redundant information can be used to improve the prediction accuracy. In addition, decimation has the undesirable effect that it prevents us from relating the information at a given time instant at different timescales in a simple manner.

Owing to the above drawbacks, we propose using a redundant wavelet transform, i.e. the $\grave{a}\ trous$ wavelet transform [11], to decompose the video frames. The $\grave{a}\ trous$ transform exploits the redundant information by eliminating the decimation effect to generate intact approximations and details. Using the $\grave{a}\ trous$ wavelet transform, the scaling coefficients at different scales can be obtained as

$$C_0(t) = x(t), \tag{12}$$

$$C_j(t) = \sum_{l=-\infty}^{\infty} h(l)C_{j-1}(t + 2^{j-1}l), \tag{13}$$

where $1 \leq j \leq J$ and h is a low pass filter with compact support. The wavelet coefficients at scale j can be obtained by taking the difference of the successive smoothed version of the signal as (14)

$$D_j(t) = C_{j-1}(t) - C_j(t). \tag{14}$$

The vector $[D_1, D_2, ..., D_J, C_J]$ represents the $\grave{a}\ trous$ wavelet transform of the signal up to resolution level J. The signal can be reconstructed as a linear combination of the wavelet and scaling coefficients

$$x(t) = C_J(t) + \sum_{j=1}^{J} D_j(t). \tag{15}$$

Many wavelet filters are available, such as Daubechies' family of wavelet filters, B3 spline filter, etc. Here we choose the Haar wavelet filter to implement the $\grave{a}\ trous$ wavelet transform. A major reason for choosing the Haar wavelet filter is that at any time instant t, the information after t never need to be used to calculate the scaling and wavelet coefficients, which is a very desirable feature in the time-series forecast. The Haar wavelet uses a simple filter $h = (1/2; 1/2)$. The scaling coefficients at the higher scale can be easily obtained from the scaling coefficients at the lower scale. In the following paragraphs, we designate the conventional and $\grave{a}\ trous$ wavelet transform as "decimated wavelet transform" and "non-decimated wavelet transform" respectively for description convenience.

B. Decimated Wavelet-domain NLMS Prediction

The NLMS prediction, when combined with wavelet transform, allows us to exploit the correlation structure at different timescales, which may not be easily examined in the time-domain. [6] proposed a wavelet NLMS prediction method which decomposes the video frames into wavelet and scaling coefficients at three timescales using decimated Haar wavelet transform [10]. Instead of predicting the original video traffic directly, this method predicts the scaling coefficients and wavelet coefficients independently at different scales. The predicted values of original frames can be constructed based on predicted wavelet and scaling coefficients.

VI. Non-decimated Wavelet-domain NLMS Prediction

In this section, we propose a non-decimated wavelet-domain NLMS prediction scheme which first separates the video frames into I, P and B subgroups and decomposes each subgroup into different scales using the $\grave{a}\ trous$ Haar wavelet transform. Then we predict the wavelet coefficients and the scaling coefficients independently at each scale. Finally, the predicted values of the original frames can be constructed as a sum of the predicted wavelet and scaling coefficients. The prediction of coefficients can be expressed as

$$\widehat{C_J}(t+p) = f(C_J(t), C_J(t-1), ...C_J(t-k+1)) \quad (16)$$

$$\widehat{D_j}(t+p) = f(D_j(t), D_j(t-1), ...D_j(t-k+1)), \quad (17)$$

where f represents the NLMS predictor and k is the length of the NLMS predictor. Fig. 2 shows the complete architecture of wavelet decomposition and coefficients predictions using our proposed method.

VII. Simulation Results

In this section, simulations using three half-an-hour long video traces are conducted to compare the performance of all the methods aforementioned. The data sets are frame-size traces generated from UC Berkeley MPEG-1 encoder software. They represent a variety of video scenes such as action movies, TV sports events and TV shows. The GOP pattern of all the three video traces are IBBPBBPBBPBB (12 frames). More information about the encoder parameters and video trace files can be found in [18].

For performance comparison of each method, we use four metrics. The first is normalized mean square error (NMSE)

$$NMSE = \frac{\frac{1}{N}\sum_{n=1}^{N}(x(n)-\hat{x}(n))^2}{var(x(n))}, \quad (18)$$

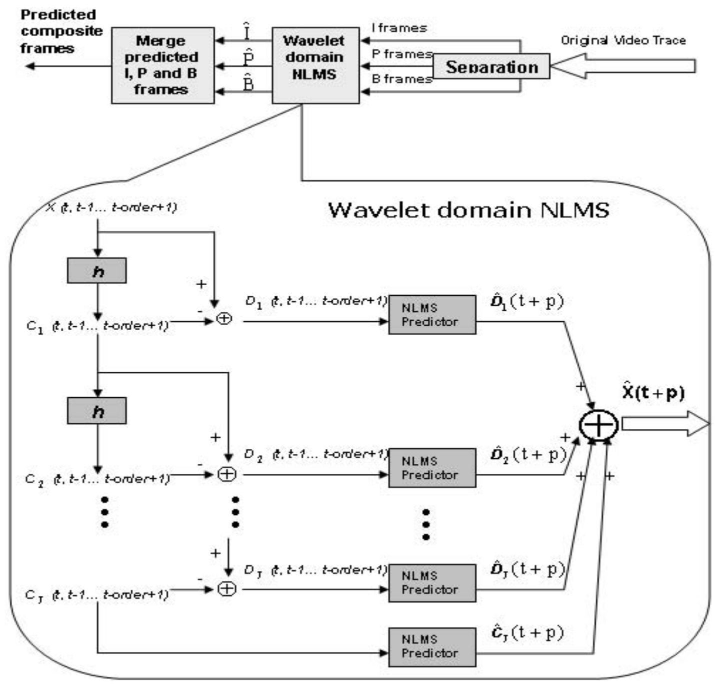

Fig. 2. Architecture of the wavelet-domain separate NLMS predictor

TABLE I
Prediction performance on "Star War"

Prediction method	NMSE	MAE	MARE	SNR^{-1}
Separate NLMS	0.12516	1927.4	0.21836	0.08192
Composite NLMS	0.17202	2483.7	0.26415	0.1131
Proposed NLMS	0.11664	1663.2	0.18261	0.07669
Non-decimated NLMS	0.1101	1918.5	0.20455	0.07246

where $\hat{x}(n)$ is the predicted value of $x(n)$ and $var(x(n))$ is the variance of $x(n)$. The second is mean absolute error (MAE)

$$MAE = \frac{1}{N}\sum_{n=1}^{N} \mid x(n) - \hat{x}(n) \mid . \quad (19)$$

The third is mean absolute relative error (MARE)

$$MARE = \frac{1}{N}\sum_{n=1}^{N} \left| \frac{x(n)-\hat{x}(n)}{x(n)} \right|. \quad (20)$$

The final one is the reciprocal of signal noise ratio

$$SNR^{-1} = \frac{\sum e(n)^2}{\sum x(n)^2}. \quad (21)$$

In our simulation, the $\grave{a}\ trous$ Haar wavelet transform with a decomposition level of three is used. Both time-domain and wavelet-domain algorithms use one-step-head prediction. Multi-step prediction can be easily achieved with the proposed scheme.

Tables I-III show the performance of our proposed methods and those in the literature both in time domain and wavelet domain. In time domain, it is readily seen that our proposed time-domain method outperforms the other two conventional

TABLE II

PREDICTION PERFORMANCE ON "JURASSIC PARK"

Prediction method	NMSE	MAE	MARE	SNR^{-1}
Separate NLMS	0.09169	2130.9	0.17844	0.05146
Composite NLMS	0.11384	2421.3	0.20219	0.06431
Proposed NLMS	0.06877	1584.8	0.13618	0.03859
Non-decimated WT	0.06733	1726.7	0.14527	0.03778

TABLE III

PREDICTION PERFORMANCE ON "SOCCER GAME"

Prediction method	NMSE	MAE	MARE	SNR^{-1}
Separate NLMS	0.11781	3485.2	0.14247	0.048773
Composite NLMS	0.19971	5000.2	0.19143	0.082684
Proposed NLMS	0.10072	3040.8	0.12479	0.041908
Non-decimated WT	0.0986	3170.9	0.13454	0.04040

ones in terms of NMSE, MAE, MARE and SNR^{-1} values. In wavelet domain, the SNR^{-1} values of decimated WT method in table IV was obtained from [6]. Table IV shows our proposed non-decimated method performs better than the decimated one in terms of SNR^{-1} for I, P and B frames. In addition, it performs the best in terms of SNR^{-1} among all the time-domain and wavelet-domain methods. Besides, the computation complexity of our proposed wavelet-domain is lower than the decimated wavelet transform due to the fact that the scaling and wavelet coefficients at time t uses information before t only and the scaling coefficients at higher scale can be easily obtained from the scaling coefficients in the lower scale.

VIII. CONCLUSION

In this paper, we examined time-domain and wavelet-domain NLMS based predictors for the prediction of VBR MPEG video traffic. Furthermore, we proposed a time-domain predictor and a wavelet-domain predictor respectively to improve the prediction accuracy. In time domain, our proposed method performed better than those in the literature due to its capability of reducing short-term bit rate variation and smoothing data through combining the separation and differential operations. In wavelet domain, our proposed non-decimated prediction scheme clearly outperformed the decimated one in the literature and performed the best among all the methods due to its unique capability of diagnosing the correlation structure of the complex time-scaling input VBR video traffic and eliminating the decimation effect.

The proposed methods and the methods in the literature were applied to the real full-motion video traffic. The performance of each method was compared with each other. Simulation results showed that the proposed time-domain method outperformed the conventional ones in the literature and gave more accurate prediction. The proposed wavelet-domain method performed best among all the methods.

TABLE IV

COMPARISON OF THE SNR^{-1} OF DECIMATED AND NON-DECIMATED PREDICTION ON I, P AND B FRAMES

Sequence	Frame Type	Decimated WT	Non-decimated WT
Star War	I	0.0126	0.0063
	P	0.2209	0.1142
	B	0.0661	0.0348
Jurassic Park	I	0.0113	0.0027
	P	0.1148	0.0499
	B	0.0490	0.0120
Soccer	I	0.0264	0.0074
	P	0.0341	0.0192
	B	0.0443	0.0218

REFERENCES

[1] J. Beran, R. Sherman, M. Taqqu, and W. Willinger, "Long-range dependence in variable-bit-rate video traffic," *IEEE Transactions on Communications*, vol. 43, no. 234, pp. 1566–1579, 1995.
[2] M. W. Garrett and W. Willinger, "Analysis, modeling and generation of self-similar vbr video traffic," *SIGCOMM Comput. Commun. Rev.*, vol. 24, no. 4, pp. 269–280, 1994.
[3] Y. Liang, "Real-time vbr video traffic prediction for dynamic bandwidth allocation," *Part C, IEEE Transactions on Systems, Man and Cybernetics*, vol. 34, no. 1, pp. 32–47, 2004.
[4] A. Adas, "Using adaptive linear prediction to support real-time vbr video under rcbr network service model," *IEEE/ACM Transactions on Networking*, vol. 6, no. 5, pp. 635–644, 1998.
[5] W. Xu and A. Qureshi, "Adaptive linear prediction of mpeg video traffic," in *Signal Processing and Its Applications, 1999. ISSPA '99. Proceedings of the Fifth International Symposium on*, vol. 1, 1999, pp. 67–70 vol.1.
[6] X. Wang, S. Jung, and J. Meditch, "Dynamic bandwidth allocation for vbr video traffic using adaptive wavelet prediction," in *ICC 98. Conference Record.1998 IEEE International Conference on Communications, 1998.*, vol. 1, 1998, pp. 549–553 vol.1.
[7] J. Hall and P. Mars, "Limitations of artificial neural networks for traffic prediction in broadband networks," *Communications, IEE Proceedings-*, vol. 147, no. 2, pp. 114–118, 2000.
[8] S. Feng and R. Sankar, "Limitation of and improvement to linear prediction and smoothing-based bandwidth allocation for vbr traffic," in *Global Telecommunications Conference, 1999. GLOBECOM '99*, vol. 1A, 1999, pp. 209–213 vol.1a.
[9] M. K. Tripathi and S. K., "Scene-based characteristics of vbr mpeg-coded video traffic," *Univ. Maryland*, vol. CS-TR-3573, 1997.
[10] J. K. Martin Vetterli, *Wavelets and Subband Coding*. Prentice Hall, 1995.
[11] M. Shensa, "The discrete wavelet transform: wedding the a trous and mallat algorithms," *IEEE Transactions on Signal Processing[see also IEEE Transactions on Acoustics, Speech, and Signal Processing]*, vol. 40, no. 10, pp. 2464–2482, 1992.
[12] D. L. Gall, "Mpeg: a video compression standard for multimedia applications," *Commun. ACM*, vol. 34, no. 4, pp. 46–58, 1991.
[13] S. Haykin, *Adaptive Filter Theory*, 4th ed. Upper Saddle River, N.J.: Prentice Hall, 2002.
[14] M. Doroslovacki and H. Fan, "Wavelet-based linear system modeling and adaptive filtering," *IEEE Transactions on Signal Processing[see also IEEE Transactions on Acoustics, Speech, and Signal Processing]*, vol. 44, no. 5, pp. 1156–1167, 1996.
[15] N. Erdol and F. Basbug, "Wavelet transform based adaptive filters: analysis and new results," *IEEE Transactions on Signal Processing [see also IEEE Transactions on Acoustics, Speech, and Signal Processing]*, vol. 44, no. 9, pp. 2163–2171, 1996.
[16] I. Daubechies, *Ten Lectures on Wavelets*. Society for Industrial and Applied Mathematics, 1992.
[17] G. S. Nguyen and Truong, *Wavelets and Filter Banks*. Wellesley-Cambridge Press, 1996.
[18] 2005. [Online]. Available: http://www3.informatik.uni-wuerzburg.de/˜rose/files/MPEGtraces.zip