QoE-driven Adaptation Scheme for Video Applications over Wireless Networks

Asiya Khan, Lingfen Sun, Emmanuel Jammeh and Emmanuel Ifeachor

Centre for Signal Processing and Multimedia Communication

School of Computing, Communications and Electronics

University of Plymouth, Plymouth PL4 8AA, UK.

Email: asiya.khan,l.sun,emmanuel.jammeh,e.ifeachor@plymouth.ac.uk

ABSTRACT

User's perceived Quality of Service or Quality of experience (QoE) is likely to be the major determining factor in the success of new multimedia applications over wireless/mobile networks. The primary aim of this paper is to present an adaptation scheme that is QoE-driven for optimizing content provisioning and network resource utilization for video applications over wireless networks. The proposed scheme encompasses the application of a QoE-driven model for optimizing content provisioning and network resource utilization. The content provisioning is optimized by the determination of initial content quality by adapting the video Sender Bitrate (SBR) according to users' Quality of Experience (QoE) requirement. By finding the impact of the QoS parameters on end-to-end perceptual video quality, the optimum trade-off between SBR and frame rate is found and the benefits to network providers in maximizing existing network resources is demonstrated. The QoE is measured in terms of the Mean Opinion Score (MOS). The proposed scheme makes it possible for content providers to achieve optimum streaming (with an appropriate sender bitrate) suitable for the network and content type for a requested QoE. The scheme is also beneficial for network providers for network resource provision and planning and therefore, maximizing existing network infrastructure by providing service differentiation.

Keywords— QoE, QoS, MOS, SBR, video applications

I. INTRODUCTION

Content-aware networks have the potential to intelligently and resourcefully link hundreds and thousands of content sources to millions of viewers. It offers service providers a strong service differentiation tool as compared to traditional networks and it can dramatically increase service revenue while increasing user's Quality of Experience (QoE). QoE requirements under wireless environments have been gaining importance. QoE or the perceived quality of streamed videos is likely to be the major determining factor in the success of the new multimedia applications. It is therefore important to choose and adapt both the application level i.e. the compression parameters as well as network settings so that they maximize end-user quality. The prime criterion for quality evaluation of multimedia applications is the user's perception of service quality [1]. The most widely used metric is the Mean Opinion Score (MOS). Among the various encoding parameters that play a significant role in QoE, the sender bitrate and the content dynamics such as the spatial and temporal activity are critical for the final perceptual outcome. The inter-relationships between adapting the video sender bitrate, the activity of the content and QoE are not well understood and relatively less researched. With limited network resources both content providers and network providers looking to maximize existing network resources and provide service differentiation to the end customer. Holistically, to provide service differentiation on existing network infrastructure and provide premium service to end users it is important to define the user requirement (measured in MOS) for any adaptation to take place. That is the motivation of our study.

A QoE-driven adaptation scheme for optimizing content provisioning and network planning for video applications over wireless networks is proposed in this paper. Two major research questions for video bitstream adaptation subject to low-bitrate constraints transmitted over error prone and bandwidth restricted wireless/mobile network environment have been looked at:

(1) How can content providers optimally match the initial video content quality according to the user's QoE requirement?

(2) How can network providers best utilize existing network resources according to user's QoE requirement?

The first question is addressed by adapting the SBR according to a QoE prediction model given by the authors in [2]. This ensures a maximization of users' QoE. The second question is addressed by finding the impact of application level parameters of SBR and Frame Rate (FR) and network level parameters of Packet Error Rate (PER) on delivered QoE in order to maintain acceptable quality. The main contribution of this paper is to present an adaptation scheme that is QoE-driven for video applications over wireless networks and encompasses the following:

- Application of QoE-driven model in the determination of initial content quality provision by adapting the SBR
- Application of QoE-driven model in network planning and optimization by finding the impact of QoS parameters on end-to-end perceptual quality.

This consequently enable content providers to select optimal SBR and network providers to dimension network resources such as bandwidth requirements efficiently. This will ensure an improved user experience, by making the content network-aware and the network content- aware.

The paper is organized as follows. Section II presents an overview of previous studies related to sender bitrate adaptation schemes for the optimization of users' perception of service quality. In section III the proposed QoE-driven adaptation scheme is introduced and section IV outlines the simulation set-up. In section V, the impact of QoS parameters on video quality is given and section VI demonstrates the applications of the proposed adaptation scheme. Section VII concludes the paper and highlights areas of future work.

II. BACKGROUND

The provision of optimized QoE is crucial for wireless/mobile multimedia design and delivery. With limited resources and bandwidth constraints video adaptation have become one of the most important and challenging issues in wireless/mobile multimedia applications. Perceived QoS or QoE is crucial in the service uptake by users and hence in the full utilization of the potential services offered by the recent advances in wireless and multimedia technologies. Users' demand for quality of video applications is very much content dependent and streaming video quality for example, is dependent on the intrinsic attribute of the content. There are many aspects to QoS provisioning, and these include Network-level QoS (NQoS), Application-level QoS (AQoS) and ultimately End-user QoS. NQoS is concerned with the reliable delivery of multimedia data over the wireless technologies. AQoS on the other hand is concerned with the quality of the multimedia content encoding, delivery, adaptation, decoding and play-out on the client device. Authors in [3] proposed a content-based video adaptation scheme where a machine learning method is applied to extract content features from compressed video streams. The content features are then used in the adaptation operation. Authors in [4] proposed a content-based adaptation scheme using an optimum adaptation trajectory, whereas in [5] an end-to-end theoretical framework is proposed for video quality prediction. The proposed framework is dependent on the content dynamics and the send bitrate of the codec. Authors in [6] proposed video adaptation based on utility function obtained from content characteristics. They propose a model based on utility functions in trms of the send bitrate and frame rate for each video sequence. In [7] authors have proposed context-aware computing to adapt video content accessed by users with differing device capabilities. Authors in [8] have carried out video adaptation to a suitable three dimension combination based on spatial and temporal feature combinations. In [9] authors measured the impact of temporal artifacts on video quality and characterized the influence of content motion on perceived quality. A QoE management method is proposed in [10], where network resources are preserved in a way that minimizes the impact on the QoE. In [10] authors show a practical demonstration on how to control application QoS parameters for QoE management. Most of these work consider adaptation of video sender bitrate to maximize end user quality i.e. Application QoS parameters, but they do not however consider the impact of network or how to maximize network resources.

A GAP model is proposed in [11] where user's QoE is measured from network impairments of bandwidth, delay, jitter and loss.. In [12] the problem of optimizing the delivery of multimedia services is given by assuming that the network provides two distinct classes of service to users based on their QoS requirement such as premium or economy. Based on that they presented a filtering strategy that adaptively controlled the allocated bandwidth and the transfer delay of traffic flows downloaded from content servers to mobile users. In [13] the authors have proposed a bitrate control scheme based on congestion feedback over the Internet. In [14],[15],[16] authors presented adaptation based on network state and congestion control over UMTS transport channels. Authors in [17] have presented an adaptive bandwidth allocation scheme based on the queue length and the packet loss probability. Most of these schemes maximize network resources without considering the impact of content. Traditional QoS adaptation schemes do not take into account the video content even though video content dynamics is critical for the final perceptual outcome. In addition, the main aim of most of these schemes is to minimize the end-to-end packet loss/delay. This optimization is based mainly on Network Quality of Service parameters without taking the Application QoS parameters in to account.

In existing literature of video quality prediction and adaptation, work is either focused on AQoS or NQoS. There is very little work that aims to combine parameters in both levels as both AQos and NQoS parameters impact on the end user QoS. This was shown by the authors in [2], where they proposed a model that combined both application and network level parameters over wireless networks for predicting the quality of video. The proposed model is QoE-driven and has been used in this paper (See section III) in the proposed adaptation scheme. Therefore, the main contribution of this paper is to propose an adaptation scheme which optimizes the network resources and content provision and show a practical demonstration of the proposed scheme. The novelty of the scheme is that it uses a combination of application and network level parameters in the QoE-driven model and finds the impact of both application and network level parameters on end-to-end quality.

III. PROPOSED QOE-DRIVEN ADAPTATION SCHEME FOR VIDEO APPLICATIONS

The conceptual diagram for video SBR adaptation from QoE prediction models is given in Fig. 1. The adaptation can be either at the sender side, such as adapting the sender bitrate or at the receiver side to achieve an optimized end-to-end QoE. At the top of Fig. 1, intrusive video quality measurement block is used to measure video quality at different network QoS conditions (e.g. different packet loss, jitter and delay) or different application QoS settings (e.g. different codec type, content type, sender bitrate, frame rate, resolution). The measurement is based on comparing the reference and the degraded video signals. Peak Signal to Noise Ratio (PSNR) is used for measuring video quality in the paper to prove the concept. The MOS values are obtained from PSNR to MOS conversion mapping from Evalvid [22]. The mapping is given in Table I.

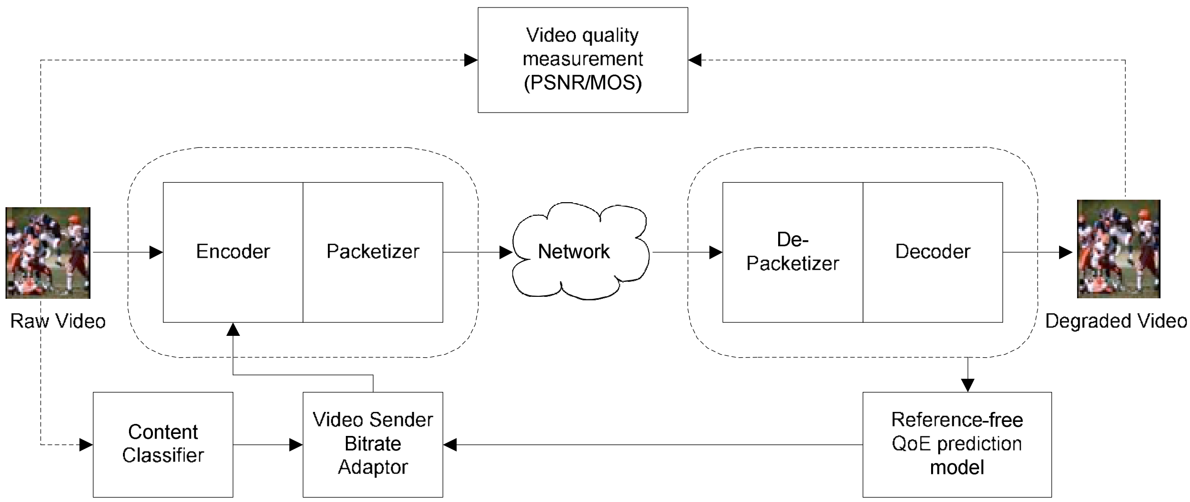

Fig. 1 Conceptual diagram of QoE-driven scheme for video adaptation

The video quality measurements based on the MOS values achieved objectively are used to derive non-intrusive QoE prediction model and/or rate adaptive control mechanism based on non-linear regression methods. The derived QoE prediction model can predict video quality (in terms of MOS) from network QoS parameters of packet error rate and application QoS parameters of content type, SBR and frame rate. The predicted QoE metrics along with network QoS parameters are used in QoE-driven adaptation scheme. Feedback information can be sent through extended RTCP report.

TABLE I

PSNR TO MOS CONVERSION

PSNR (dB)	MOS
>37	5
31 – 36.9	4
25 – 30.9	3
20 – 24.9	2
< 19.9	1

A. Content classifier

The video content classification is carried out from raw video at the sender side by extracting the spatial and temporal features using a well known multivariate statistical analysis called cluster analysis [18]. This technique is used as it groups samples that have various characteristics into similar groups. Cluster analysis is carried out on the twelve video sequences ranging from slow movement to fast moving video clips based on the temporal and spatial feature extraction. The design of the content classification method is given in Fig. 2 [2].

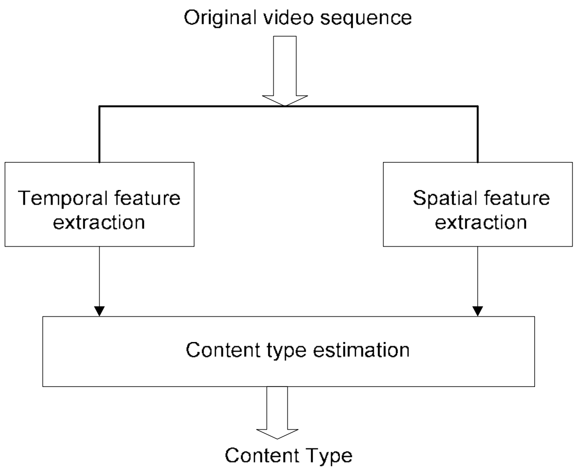

Figure. 2 Content classification design

Temporal feature extraction

The movement in a video clip given by the SAD value (Sum of Absolute Difference). The SAD values are computed as the pixel wise sum of the absolute differences between the two frames being compared and is given by (1):

$$SAD_{n,m} = \sum_{i=1}^{N} \sum_{j=1}^{M} |B_n(i,j) - B_m(i,j)| \quad (1)$$

Where B_n and B_m are the two frames of size $N X M$, and i and j denote pixel coordinates.

Spatial feature extraction

The spatial features extracted were the edge blocks, blurriness and the brightness between current and previous frames. Brightness (B_r) is calculated as the modulus of difference between average brightness values of previous and current frames and is given by eq. (2).

$$Br_{n,}=\sum_{i=1}^{N}\sum_{j=1}^{M}\left|Br_{av(n)}(i,j)-Br_{\mathrm{av(n-1)}}(i,j)\right| \quad (2)$$

Where $Br_{av(n)}$ is the average brightness of n-th frame of size $N\,X\,M$, and i and j denote pixel coordinates.

The spatio-temporal metrics have quite low complexity and thus can be extracted from videos in real time. For the data Euclidean distances in 4 dimensional space between the SAD, edge block, brightness and blurriness measurements are calculated and hierarchical cluster analysis conducted. Fig. 3 shows the obtained dendrogram (tree diagram) where the video sequences are grouped together on the basis of their mutual distances (nearest Euclid distance).

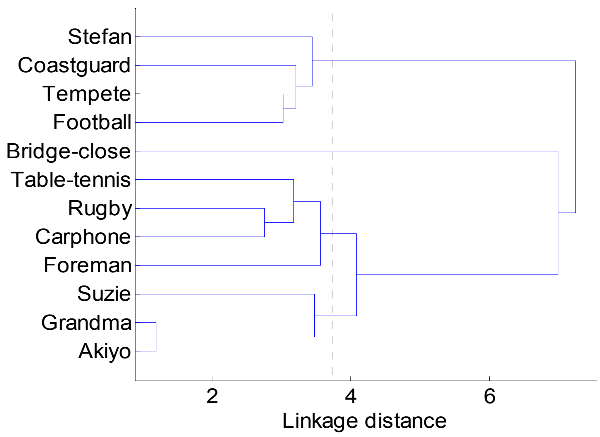

Figure. 3 Tree diagram based on cluster analysis

The test sequences were divided at 38% from the maximum of Euclid distance into three groups as the data contains a clear ‘structure’ in terms of clusters that are similar to each other at that point (see the dotted line on Fig. 3). The cophenetic correlation coefficient, c, is used to measure the distortion of classification of data given by cluster analysis. It indicates how readily the data fits into the structure suggested by the classification. The value of c for our classification was 80% indicating a good classification result.

Group 1 (sequences Grandma, Suzie and Akiyo) as shown in Fig. 4a are classified as ‘Slight Movement’ (SM). This group includes sequences with a small moving region of interest (face) on a static background.

Fig. 4a Snapshots of typical ‘SM’ content

Group 2 (sequences Carphone, Foreman, Table-tennis and Rugby) are classified as ‘Gentle Walking’ (GW). They include wide-angled clips in which both background and content is moving as shown in Fig. 4b

Fig. 4b Snapshots of typical ‘GW’ content

Group3 (sequences Stefan and Football) are classified as ‘Rapid Movement’ (RM). They include sports type of video clips as shown in Fig. 4c.

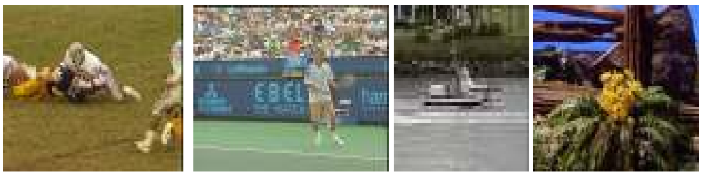

Fig. 4c Snapshots of typical ‘RM’ content

Therefore, video clips in one cluster have similar content complexity. Hence, our content classifier takes the content features as input observations, while content category as the output. For larger video clips or movies the input will be segmented by segment analysis of the extracted content features. Consequently, within one movie clip there will be a combination of all three content types. This is best explained by the flow diagram of the proposed QoE-driven adaptation scheme which is depicted in Fig. 5. From Fig. 5 the video application is first defined based on the content features (e.g. SM, GW or RM). Then from the QoE prediction model the process of optimization of content provisioning and network resources takes place based on either adapting the SBR or finding the impact of QoS parameters.

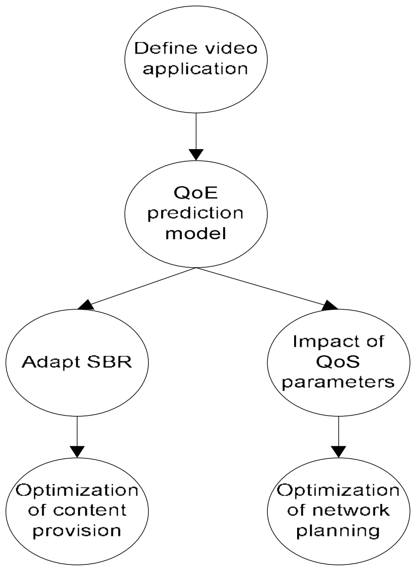

TABLE II

COEFFICIENTS OF METRIC MODELS FOR ALL CONTENT TYPES OVER WLAN

Coeff	SM	GW	RM
a1	2.797	2.273	-0.0228
a2	-0.0065	-0.0022	-0.0065
a3	0.2498	0.3322	0.6582
a4	2.2073	2.4984	10.0437
a5	7.1773	-3.7433	0.6865
R^2	90.27%	90.99%	99.57%

Fig. 5 Flow diagram of the proposed QoE-driven adaptation scheme

B. QoE-driven prediction model

The reference-free QoE models depicted in Fig. 1 over wireless network was developed in a previous work [2], where video quality in terms of the MOS is predicted from a combination of network and application parameters of Sender Bitrate (SBR), Frame Rate (FR) and Packet Error Rate (PER) for three different video applications classified earlier as SM for video conferencing application, GW representing a typical video call and RM representative of video streaming. The video codec for these applications was MPEG4. The prediction model is obtained by nonlinear regression analysis of the QoS parameters both in the application and network level and is given as below in eq. (3).

$$MOS = \frac{\mathrm{a}_1 + \mathrm{a}_2\mathrm{FR} + \mathrm{a}_3\ln(\mathrm{SBR})}{1 + \mathrm{a}_4\mathrm{PER} + \mathrm{a}_5(\mathrm{PER})^2} \qquad (3)$$

The metric coefficients were obtained by a non-linear regression of the prediction model with our training set (MOS values). The re-fitted metric coefficients a_1, a_2, a_3, a_4 and a_5 along with R^2 showing the goodness of fit for all three video applications over WLAN networks are given in Table I. The model was trained with three video sequences of akiyo, foreman and stefan in the three categories of SM, GW and RM, whereas the model is verified with three different video sequences of suzie, carphone and football in the three corresponding content categories. MATLAB™ function *nlintool* has been used to carry out the nonlinear regression analysis. R^2 indicates the goodness of fit of the fitted coefficients of the three models.

The predicted QoE metrics are then used in the QoE-driven adaptation scheme to adapt the video sender bitrate as shown in Fig. 1.

In order to establish the initial encoding sender bitrate for the three content types, the variables of FR and PER are fixed in eq. (3). The FR was fixed at 10fps and PER as 0 assuming that there are no network losses. The SBR versus MOS curve is shown in Fig. 6 for the three content types. The purpose of Fig. 6 is to show the maximum and minimum SBR achieve able highlighting the initial encoding requirement. Therefore, it shows the relationship of MOS with application QoS parameter of SBR. For details see [19],[20]. From Fig. 6 it is observed that there is a minimum sender bitrate for acceptable quality (MOS>3.5) for all content types. A MOS of 4 is considered "good" for streaming applications [21] where most users are satisfied. There is also a maximum sender bitrate for the three content types that gives maximum quality (MOS ~ 4.2). For example for the content category of SM, sender bitrate of 100kbps gives a maximum of 4.2. However, in RM higher sender bitrates are required for maximum quality i.e. > 500kb/s. From Fig. 3 it can be derived that when the sender bitrate drops below a certain threshold, which is dependent on the video content, then the quality practically collapses. Moreover, the quality improvement is not significant for sender bitrates higher than a specific threshold, which is also dependent on the spatial and temporal activity of the clip. This is useful when applying adaptation to SBR as it defines the initial encoding bitrates for all content types.

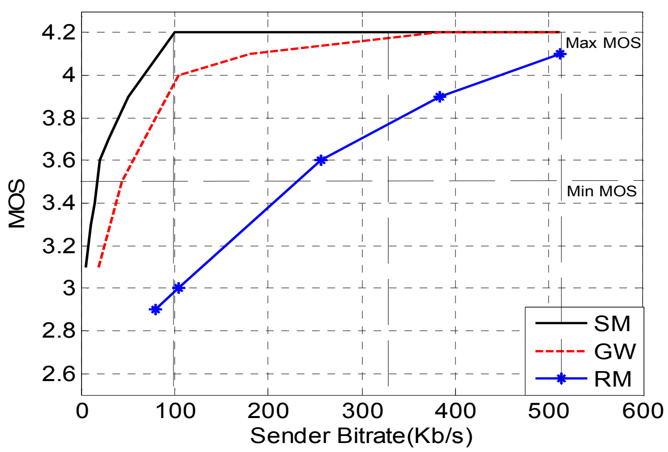

Fig. 6 MOS Vs Sender Bitrate for the three content types

IV. SIMULATION SET-UP

The experimental set up is given in Fig 4. There are two sender nodes as CBR background traffic and MPEG4 video source. MPEG4 and H26X are recommended codecs for mobile/wireless environments. Future work will focus on H264 codec. Both the links pass traffic at 10Mbps, 1ms delay over the internet. The router is connected to a wireless access point at 10Mbps, 1ms and further transmits this traffic to a mobile node at a transmission rate of 11Mbps 802.11b WLAN. The simulation set-up is configured so that no congestion occurs in the wired segment of the video delivered path from source to destination. The maximum transmission packet size is 1024 bytes. The video packets are delivered with a random uniform error model. The CBR rate is fixed to 1Mbps to give a more realistic scenario. The packet error rate is set in the range of 0.01 to 0.2 with 0.05 intervals. To account for different packet loss patterns, 10 different initial seeds for random number generation were chosen for each packet error rate. All results generated were obtained by averaging over these 10 runs.

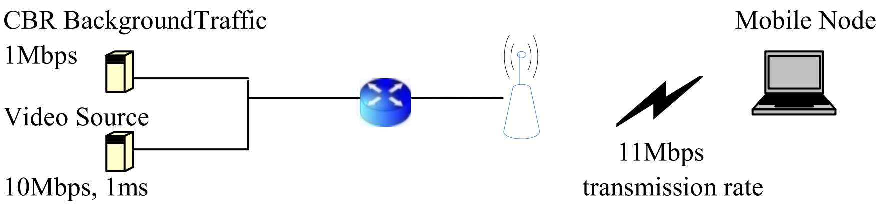

Fig. 7 Simulation setup

All simulations were carried out using open source network simulator NS2 [22] integrated with Evalvid [23]. Video quality is measured by taking the average PSNR over all the decoded frames. PSNR given by (2) computes the maximum possible signal energy to noise energy. PSNR measures the difference between the reconstructed video file and the original video file.

$$PSNR(s,d) = 20\log\frac{MAX}{\sqrt{MSE(s,d)}} \tag{4}$$

where MAX is the maximum pixel value of the image, which is 255 for 8 bit samples. Mean Square Error (MSE) is the cumulative square between compressed and the original image. The computed PSNR is used to obtain MOS using conversion mapping from Evalvid [23].

For the tests twelve different video sequences were selected of QCIF resolution (176x144) and encoded in MPEG4 format with an open source ffmpeg [24] encoder/decoder with a Group of Pictures (GOP) pattern of IBBPBBPBB. Each GOP contains three types of frames - Intra (I) frames are encoded independently of any other type of frames, Predicted (P) frames are encoded using predictions from preceding I or P frames and Bi-directionally (B) frames are encoded using predictions from the preceding and succeeding I or P frames.

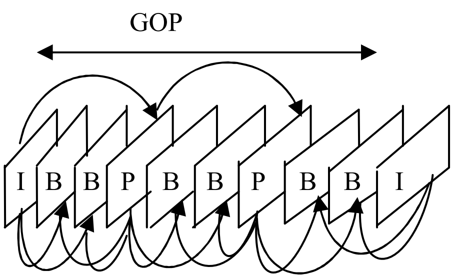

Fig. 8 A sample of MPEG4 GOP (N=9, M=3)

A GOP pattern is characterized by two parameters, GOP(N,M) – where N is the I-to-I frame distance and M is the I-to-P frame distance as shown in Fig. 8.

V. IMPACT OF QOS PARAMETERS

In this section the impact of QoS parameters in the application and network level is found. Statistical tools of principal component analysis and ANOVA are used to find the impact of QoS parameters and their influence on end-to-end perceived quality.

A. QoS Parameters

The following quality affecting parameters both in the application level and the network level have been considered as follows:

Application level parameters: Frame Rate (FR) was used as the application level parameter, and it was configured to take one of three values as 10, 15 and 30 frames per second (fps). The Sender Bitrate (SBR): the rate of the encoders output, which is chosen to take 18, 44, 80, 104 and 512kb/s. These values are typical for video applications in wireless/mobile environments.

Network Level Parameters: Packet Error Rate (PER) was used as the network level parameter, and it was configured to take one of five values as 1, 5, 10, 15 and 20% using a random uniform error model. It is widely accepted that a loss rate higher than 20% will drastically reduce the video quality.

The simulation parameters are given in Table III.

TABLE III

SIMULATION PARAMETERS

Video sequences	Frame rate (fps)	Sender bitrate	Packet error rate
Akiyo, suzie, grandma, carphone, foreman, bridge-close, table tennis, rugby	10, 15, 30	18, 44, 80	0.01, 0.05, 0.1, 0.15, 0.2
Stefan, football, tempete, coastguard		80, 104, 512	

B. Distribution of Quality Ratings

The distribution of the PSNR to MOS scores obtained from experiments objectively for all the contents is given in Fig. 6 which shows that the distribution of quality was balanced across the rating scale. The median quality for our data range was around 2.8 (shown by the dotted line in Fig. 6). The different colours represent MOS scores obtained by the different test conditions of the QoS parameters – both in the application and network levels for the twelve content types chosen.

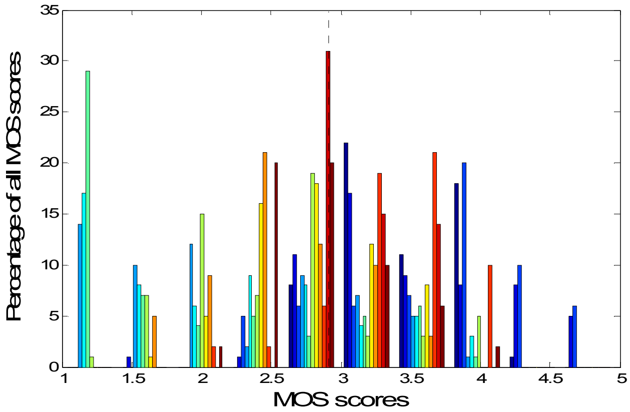

Fig. 9 Histogram of objective quality ratings

C. *PCA Analysis*

To find the impact of each QoS parameter statistical analysis of Principal Component Analysis (PCA) [18] was carried out. PCA is a method to reduce the dimensionality of a data set, in which there are a large number of inter-related variables. PCA uses a covariance matrix in the case where the same data has the same set of variables or correlation matrix in the case where data has a different set of variables. In this paper, a covariance matrix was used because of the same data set. The objective of principal component analysis is to reduce the dimensionality (number of variables) of the dataset but retain most of the original variability in the data. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. Fig. 10 shows the variance of the six principal components for our data. 83% of the variability is explained by the first two principal components of which a total variation by first principal component was 72.7% and 10% by the second component. Consequently, only scores from the first component were chosen.

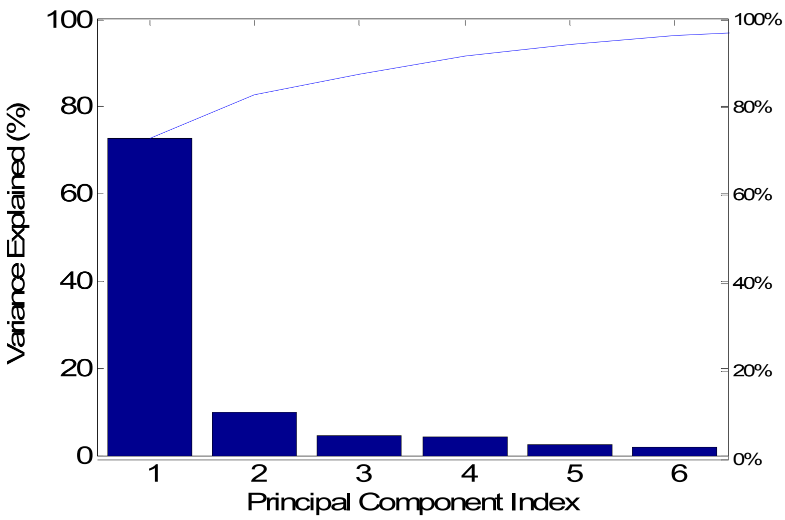

Fig. 10 Eigen values of the six principal components

TABLE IV

PRINCIPAL COMPONENT SCORE TABLE

Content type	Content	Scores	SBR	FR	PER
SM	Akiyo	0.212	0.57	-0.58	-0.58
	Suzie	0.313	0.66	0.25	-0.71
	Grandma	0.147	-0.76	0.64	-0.05
	Bridge-close	0.092	0.41	-0.22	-0.89
GW	Table Tennis	0.287	0.08	-0.99	0.11
	Carphone	0.154	0.35	-0.93	0.10
	Foreman	0.204	0.56	0.45	-0.69
	Rugby	0.454	0.65	-0.59	0.48
RM	Tempete	0.231	0.25	-0.46	-0.85
	Coastguard	0.221	0.62	-0.60	0.51
	Stefan	0.413	0.40	-0.72	0.58
	Football	0.448	0.62	-0.57	0.55

The principal component scores for each content are shown in Table IV. Table IV shows the influence of each QoS parameter on video quality. The PCA scores of each QoS parameter in Table IV is given under the columns of SBR, FR and PER. The higher the value e.g. for the video sequence of Akiyo in the category of SM SBR=0.57, whereas, FR and PER=-0.58. This shows that for Akiyo the parameter of SBR has a greater impact on quality compared to that of PER and FR as the value of SBR is the highest. Similarly, for the video sequence of carphone, the impact of PER is slightly higher than SBR, whereas FR is least important. To summarize, scores for sports video contents are higher than those of news type videos. Also in the category of RM higher packet loss have a greater impact on video quality compared to that of SBR and FR. Similarly, for SM content type PER does not have a bigger impact on video quality.

From Table IV the main QoS parameters that impact on end-to-end quality for the three content types are summarized below:

- The main factors degrading objective SM video quality are frame rate and send bitrate. However, for the sequence of Grandma SBR is a bigger degrading factor compared to frame rate. However, for most sequences in this category the requirements of frame rate are higher than of send bitrate.
- The main factors degrading objective GW video quality are the send bitrate and packet error rate. In this category packet loss has a much higher impact on quality compared to SM.
- The main factor degrading the RM video quality are send bitrate and packet error rate. A video coded at low send bitrate and/ with high packet losses is very annoying for most users'. This is because the initial encoding requirement of fast moving video is greater than slow moving video. This is shown in

Fig. 6 previously, where for content type of SM minimum MOS is achieved for a sender bitrate of 220kbps compared to that of SM of around 30kbps. Also if packet losses are high, that results in partial/total loss of I-frames thus reducing the overall end-to-end quality.

D. *ANOVA Analysis*

In order to thoroughly study the impact of the QoS parameters on MOS, ANOVA (analysis of variance) [18] was performed on the MOS data set. A three-way repeated measurement analysis of variance (ANOVA) on the MOS data set given by the 3 QoS parameters differ when grouped by multiple factors (i.e. the impact of all the factors combined) is given in Table V and supports our observations concerning the impact of the QoS parameters of SBR, FR and PER. Table V shows the results, where the first column is the Degrees of Freedom associated with the model, the second column shows the F statistic and the third column gives the p-value, which is derived from the cumulative distribution function (cdf) of F [18]. The small p-values ($p \leq 0.01$) indicate that the MOS is substantially affected by at least one parameter. The results of ANOVA reported in Table V indicate the main effects of SBR (p-value=0.002). The FR and PER, on the other hand, are not as significant as SBR. There were interactions between each pair of factors. Specifically, the p-value ($p=0.0013$) for the two way interaction between frame rate and sender bitrate indicates that the impact of frame rate reduction for some content types is dependent on the sender bitrate. Hence, it is important to achieve an optimal SBR-FR trade-off for acceptable quality.

TABLE V

ANOVA RESULTS FOR MAIN AND INTERACTION EFFECTS

Source	df	F-value	p-value
Send Bitrate (SBR)	8	20.82	0.002
Frame Rate (FR)	8	3.81	0.0855
Packet Error Rate (PER)	14	3.25	0.0744
SBR * FR	17	8.4	0.0013
SBR * PER	17	3.32	0.0409
FR * PER	17	1.81	0.185
SBR * FR * PER	26	2.82	0.0322

The impact of the three QoS parameters on the three content types is given by the box and whiskers plot shown in Fig. 11, which shows the influence of each QoS parameter both in the application and network level on video quality for the three content types. The whiskers shows the extent of the rest of the data, and for SM, PER is not as important as for GW and RM. As the range of MOS value for SM is less for the QoS parameter of FR compared to that of SBR and PER. This shows the FR has a bigger impact on QoS compared to SBR and PER for content type of SM. Similarly, PER has bigger impact than SBR and FR and degrades quality for content type of GW, whereas, for RM, SBR has bigger impact on quality. FR has a bigger range with the same median as PER.

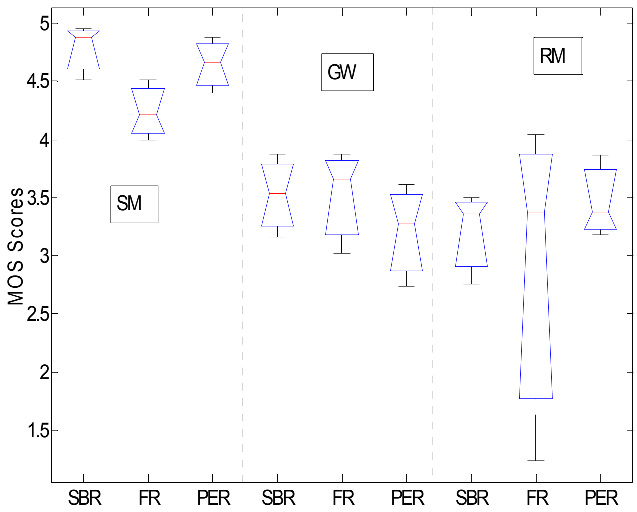

Fig. 11 Significant effects of SBR, FR and PER

VI. APPLICATIONS OF THE PROPOSED QOE-DRIVEN ADAPTATION SCHEME

In this section, two cases are demonstrated to show how the proposed QoE-driven adaptation scheme benefits both the provisioning of content and optimization of existing network resources. The implementation of our scheme is fairly straightforward. The optimization of the content is carried out by applying the QoE-driven model [2] at the receiver end in real time. The optimization of the network resources is dependent on finding the impact of QoS parameters on end-to-end quality for each type of video application. Through statistical analysis of ANOVA and PCA the QoS parameters have been identified for each video application, hence enabling in the optimization of existing network resources.

A. Optimization of content provision

The MOS value is specified by the content provider to achieve specific quality level to meet the end customers' requirement. In today's network infrastructure the motivation for service providers' to provide new services to customers is reduced due to low revenue margins. Therefore, it makes sense to optimize existing network infrastructure and provide service differentiation to customer in terms of premium and tailor-made services according to customer's requirement. Hence, the motivation to use MOS as an input in our model as QoS is best captured in the MOS value. The video application is either video-conferencing, video call or video streaming. The Frame Rate (FR) is decided based on the service and application provider. In this paper, the application is wireless/mobile environment and hence the FR was fixed at 10f/s. The PER information can be provided from the network statistics and it is assumed no packet loss conditions for concept proofing and simplicity.

The QoE-driven model (given in Section III) is used to obtain the SBR as shown in Fig. 12. Therefore, equation 1 can be re-written as equations 5, 6 and 7.

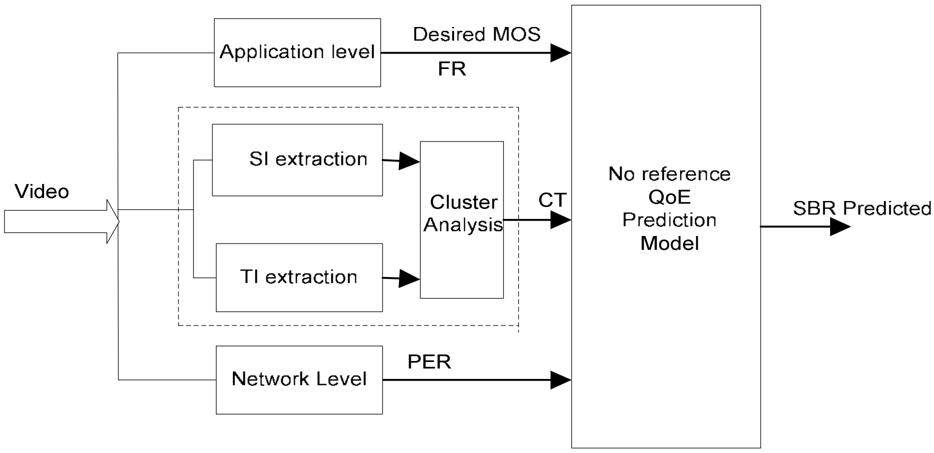

Fig. 12 Method to calculate the SBR

$SBR_{SM}= e^{(MOS- 2.797+ 0.0065FR)/0.2498}$ (5)

$SBR_{GW}= e^{(MOS- 2.273+0.0022FR)/0.3322}$ (6)

$SBR_{RM}= e^{(MOS+0.0228+0.0065FR)/0.6582}$ (7)

According to [21] for video applications MOS between 3.7- 4.2 is considered 'acceptable to good' for most people. Based on [21] and from the basic MOS requirement of 3.5, and from Equations (5)-(7) SBR adaptation is illustrated from content providers point of view in Table VI for the three content types for a quality range of 3.5 - 4.2. Hence the content provider is able to identify the SBR that corresponds to a given QoS (in terms of MOS) level by simply using equations (3)-(5) (i.e. QoE-prediction model).

TABLE VI

PREDICTED SEND BITRATE VALUES FOR SPECIFIC QUALITY LEVELS

MOS	FR	SBR_{SM}	SBR_{GW}	SBR_{RM}
3.5	10	21	43	233
3.7	10	48	78	315
3.9	10	107	143	428
4.1	10	237	261	578
4.2	10	354	353	675

B. Optimization of network resources

The results taken from Table IV were used to illustrate how to maximize the utilization of network resources and hence provide different levels of service quality.

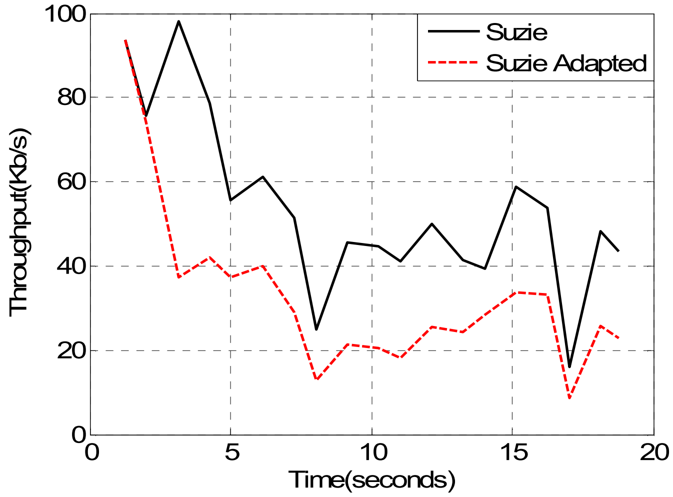

Fig. 13 Network throughput utilization for SM

The video sequence of 'Suzie' from the content type of SM is encoded at 10f/s with send bitrate of 40kb/s. It is known from Table IV that the send bitrate can be reduced while maintaining the same quality. The send bitrate was reduced to 20kb/s. The network throughput utilization is depicted in Fig. 13. Approximately 16% gains of network resources are achieved. Similarly, Fig. 14 shows a very small gain of 6-8% for the content type of RM by increasing the SBR from 384kb/s to 512kb/s and reducing the frame rate from 30f/s to 10f/s and hence the optimum trade-off to maintain QoS. The increase in SBR actually increases the network bandwidth utilization. However, this is compensated by reducing the frame rate. Therefore, as a result there is no net gain on network resources in this case compared to the previous one shown in Fig. 13.

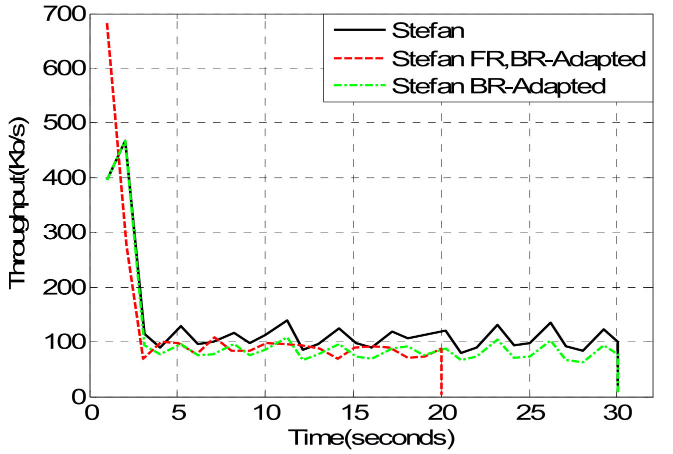

Fig. 14 Network throughput utilization for RM

It has been shown from Figs. 13 and 14 that user's QoE can be maximized while preserving network resources. The results from Table IV allows network operators to allocate network resources according to user's QoE requirements.

C. Comparison to existing work

Recent studies in [8] have proposed video adaptation to suitable three dimension combination based on spatial and temporal feature combination. Whereas, work in [10] proposed a QoE management methodology aimed at maximizing user's QoE and in [12] authors propose an optimization function that adapts the bitrate of each application, e.g. voice or video, data, etc. that share the same QoS requirement and hence optimizes the network throughput for the delivery of multimedia services with different QoS requirement. Scheme in [8] focuses on the application level parameters only for adaptation. In [12] authors main focus is adapt the network bandwidth according to requirement of the user, e.g. premium or economy. Scheme in [12] focuses mainly on the network level. Whereas in [10] authors propose a QoE-aware management system that maximizes existing network resources. Authors in [10] have demonstrated how AQoS can be used to maximize network resources. Compared to these schemes, our proposed scheme addresses the optimization in both application and network level by optimizing both content provisioning and network resources. The scheme is driven by user's QoE by the proposed prediction model as given in [2] that uses a combination of application and network level parameters. In the application level the proposed scheme demonstrates the application of the QoE model in maximizing content provisioning by adapting the SBR. In the network level the proposed scheme demonstrates the utilization of existing network resources by finding the impact of QoS parameters (both AQoS and NQoS) and finding an optimal trade-off between them. The proposed scheme enables a content provider to estimate the delivered video considering specific encoding parameters and network requirements. In addition, it also enables the network provider depending on the impact of QoS parameters to allocate network resources intelligently.

VII. CONCLUSIONS

This paper proposed a QoE adaptation scheme for video applications that maximizes content provisioning and network resources according to user's QoE requirement over resource constraint wireless/mobile networks.

The QoE-prediction model from a previous work [2] has been applied to obtain sender bitrate adaptation and the impact of QoS parameters was found by statistical analysis of PCA and ANOVA. Our proposed adaptation scheme enables content providers to identify the video sender bitrates that correspond to various quality levels and hence provide high-quality video services over wireless/mobile networks. It also enables network providers to optimize existing network resources by finding the impact of QoS parameters and hence the trade-off between them.

Future work will focus on including network statistics information such as periodic RTCP reports. The network bandwidth utilization will be studied in order to allocate bandwidth resources according to user's QoE requirements. The work will also be extended to H.264/AVC codec and UMTS access networks. In addition, extensive subjective tests will be conducted to verify our adaptation scheme.

ACKNOWLEDGMENT

The work reported here is supported in part by the EU FP7 ADAMANTIUM project (contract No. 214751).

REFERENCES

[1] ITU-T. Rec P.800, "Methods for subjective determination of transmission quality," 1996.

[2] A. Khan, L. Sun and E. Ifeachor, "Content clustering based video quality prediction model for MPEG4 video streaming over wireless networks", *IEEE ICC Conference,* Dresden, Germany, 14-18 June 2009.

[3] Y. Wang, M. Schaar and A. Loui, "Classification-based multidimensional adaptation prediction for scalable video coding using subjective quality evaluation", *IEEE transactions on circuits and systems for video technology*, Vol. 15, No. 10, Oct. 2005.

[4] N. Cranley, L. Murphy and P. Perry, "Content-based adaptation of streamed multimedia*, IEEE Int. Conf. on management of multimedia networks and services,* No. 7, San Diego, CA, 3-6 Oct 2004.

[5] H. Koumaras, A. Kourtis, C. Lin and C. Shieh, "End-to-end prediction model of video quality and decodable frame rate for MPEG broadcasting services", Int. Journal on Advances in Networks and Services, Vol. 1, No.1, 2008.

[6] O. Onur and A. Alatan, "video adaptation based on content characteristics and hardware capabilities", *Second International workshop on semantic media adaptation and personalization*, IEEE computer society press, 2007.

[7] M. Manzato and R. Goularter, "Live video adaptation: a context-aware approach", *ACM proceedings on the 11th Brazillian symposium on multimedia and the web*, 2005.

[8] G. Zhai, J. Cai, W. Lin, X. Yang and W. Zhang, "Three dimensional scalable video adaptation via user-end perceptual quality assessment", *IEEE Trans. on Broadcasting*, special issue on Quality Issues in Multimedia Broadcasting, vol. 54, no. 3, pp. 719-727, Sept. 2008.

[9] Q. Huynh-Thu and M. Ghanbari, "Temporal aspect of perceived quality in mobile video broadcasting", IEEE Transaction on broadcasting, Vol. 54, No.3, Sept. 2008.

[10] F. Agboma and A. Liotta, "QoE-aware QoS management", 6th Int. Conf. on Advances in Mobile computing and Multimedia, 24-26 Nov. 2008.

[11] P. Calyam, E. Ekicio, C. Lee, M. Haffner and N. Howes, "A gap-model based framework for online VVoIP QoE measurement", *Journal of Communications and Networks*, Vol. 9, No.4, Dec. 2007, pp. 446-56.

[12] F. Angelis, I. Habib, F. Davide and M. Naghshineh, "Intelligent content aware services in 3G wireless networks", IEEE Journal on Selected Areas in Communications", Vol. 23, No.2, Feb. 2005.

[13] P. Papadimitriou and V. Tsaoussidis, "A rate control scheme for adaptive video streaming over the internet", IEEE ICC 2007.

[14] A. alexiou, C. Bouras, V. Igglesis, "A decision feedback scheme for multimedia transmission over 3G mobile networks", *WOCN,* 2005, Dubai, UAE.

[15] H. Garudadri, H. Chung, N. Srinivasamurthy and P. Sagetong, "Rate adaptation for video telephony in 3G networks", *Packet Video*, 12-13 Nov. 2007.

[16] A. Alexiou, D. Antonellis and C. Bouras, "Adaptive and reliable video transmission over UMTS for enhanced performance", *Int. Journal of Commun. Syst*. 20:65-81, 2007.

[17] D. Kim and K. Jun, "Dynamic bandwidth allocation scheme for video streaming in wireless cellular networks", *IEICE Trans. Commun*., Vol.E89-B, No.2 Feb. 2006.

[18] W. J. Krzanowski, "Principles of multivariate analysis", Clarendon press, Oxford, 1988.

[19] A. Khan, L. Sun and E. Ifeachor, "Impact of video content on video quality for video over wireless networks", 5th ICAS, 20-25 April, Valencia, Spain, 2009.

[20] A. Khan, L. Sun and E. Ifeachor, "Content classification based and QoE-driven video send bitrate adaptation scheme", 5th Int. Mobimedia Conference, 7-9 Sept., London, UK, 2009.

[21] Telchemy application notes, "Understanding of video quality metrics", Telchemy, Feb. 2008. http://www.telchemy.co.uk

[22] NS2, http://www.isi.edu/nsnam/ns/

[23] J. Klaue, B. Tathke, and A. Wolisz, "Evalvid – A framework for video transmission and quality evaluation", *In Proc. Of the 13th International Conference on Modelling Techniques and Tools for Computer Performance Evaluation,* Urbana, Illinois, USA, 2003, pp. 255-272.

[24] Ffmpeg, http://sourceforge.net/projects/ffmpeg