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Classification of Video Content and Qualilty Prediction using Cluster Analysis and Multiple Linear Regression over LTE Networks

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***Abstract*— Classification of video content has a high impact on video quality as perceived by the user (Quality of Experience). The most common methods for classification of video content are based on spatial and temporal feature extraction. However, little research has been done to classify video content over Long Term Evolution (LTE) networks. The aim of this study is to classify video content according to the influence of video content on video quality in streaming H264 video over LTE networks using a statistical tool known as 'cluster analysis'. The degree of impact of each of the quality of service (QoS) parameters on video quality is then determined by analysing the relationship between video content and those parameters. Thereafter, our video classification is compared to other methods that based on spatio-temporal dynamics of the video content. Our simulation results show that out of multiple linear regression models, which are used to determine the relationship between video quality prediction and its content based on QoS parameters, the regression-based model provides excellent performance with respect to the root mean square error (RMSE) and the correlation coefficient. This study can potentially aid in developing non-intrusive video prediction models and QoS control methods for video streaming over LTE networks.**

Keywords*— *Video content classification; Video Quality; QoE; QoS; LTE

I. Introduction

With the increasing demand for video-based applications, video quality assessment is becoming a very challenging task. Transmission of video content by wireless communication is increasing exponentially and gaining popularity. Video content has the capacity to play an important role in future data traffic with multimedia applications over the Internet. A recent study conducted by Cisco [1] indicated that global mobile data traffic grew by 81% in 2013, and mobile data traffic will grow at a compound annual growth rate (CAGR) of 61% between 2013 and 2018. Two-thirds of the world's mobile data traffic will be video by 2018. This increase in video traffic is one of the key drivers of the evolution towards new QoE frameworks. A QoE framework is an essential element of fourth-generation (4G) wireless technologies (LTE) to achieve acceptable service delivery of evolving Internet applications to customers, and management of network resources. Most mobile Internet applications, such as video calls, video streams, and IPTV have different traffic characteristics, and thus require a variety of QoS methods. The reliable assessment of video quality is the main contributor to potentially meet the QoS and improve the end user's QoE.

End users' viewing habits are changing according to the difference of video contents, therefore, users' requests quality and price of video in accordance with the requirements of the viewing. For instance, users prefer low video quality to understanding information, like news, while they prefer high video quality for content such as a live football match or movie. Thus, it is important to define the relationship between the physical properties of video content and users' perception of quality toward improving the service to the end user. A recent study conducted by Telecoms [2] indicates that operators see video content streaming as one of the most lucrative LTE services. The Telecoms Intelligence Annual Industry Survey 2015 has showed approximately (75%) of respondents identified video content as one of the highest services enabled by LTE with the most revenue-generating potential. Consequently, we take video content and users' preferences of video quality into account to design video prediction models in order to provide high-quality video transmission over LTE networks. This work explores the relationship between perceived video quality and video content. This is done by classifying video content through the impact of QoS parameters in the network; application and LTE-related layers. The purpose of content classification is to make new groups with similar attributes. The most important parameters that cause distortions on video quality are the network access and the encoder technique. However, the influence of those distortions depends greatly on video content. Therefore, video content becomes a priority when designing video prediction models.

The importance of video content to predict video quality has been shown in several types of research. The method most commonly used to classify video content is the feature extraction of temporal (i.e. movement, direction) and spatial (i.e. colours, brightness, edges) characteristics. The authors in [3-5] are classified video content according to the spatial-temporal feature extraction, which is then used with other related parameters to predict video quality. The limitation of using this method is that it is based only on the formal features, and does not express the semantic scene importance. Work presented in [6, 7] explore the impact of spatial and temporal features on video quality prediction. However, this work does not include any application layer parameters related to video quality thus making it a limiting factor. Recent studies in [8, 9] classify video content using principal component analysis (PCA) [10] and cluster analysis [11]. This classification is based on content characteristics obtained from users' subjective evaluations. In [12, 13] a mixture of spatial-temporal feature extraction and PCA are used to classify video content. In [14]

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video content was classified on the basis of objective video quality evaluation, which was then used to predict video quality with other parameters of network and application layers. However, this work is limited to three parameters: send bitrate (SBR), frame rate (FR), and packet error rate (PER). These limited numbers of features cannot satisfy the network requirements, especially when network development becomes complex as in 4G technologies (LTE). To the best of our knowledge, the classification of video content for video quality prediction over LTE networks has not been considered in the recent literature.

With this background our aim to identify the most popular video content types, then classify them into clusters according to the impact of video content on video quality. Video quality evaluation can be measured in terms of the Peak Signal-to-Noise Ratio (PSNR). The PSNR scores are obtained from QoS parameters in the network and application layers; such as packet loss rate (PLR), send bitrate (SBR), frame rate (FR), and resolution (RES), and from the scheduling algorithm in the LTE layer. The cluster analysis method is used with selected parameters which affect video quality as input to classify the video clips into clusters based on their attributes. The proposed work is based on open source simulator for LTE networks known as LTE-Sim [15] with an integrated tool Evalvid [16]. The EvalVid (Video Quality Evaluation Tool-set) is open source software for assessment of the video quality streamed over simulated or real wireless networks. This framework is designed to be used in scientific research with a view to contributing in the development of communication networks in terms of user perceived video quality. The use of LTE-Sim and EvalVid simulation software offers a lot of flexibility to assess a variety of topologies and adjust the parameter to different values instead of the high-cost real networks. This work can potentially contribute in the development of non-intrusive video prediction models and adaptive control methods for high-quality video streaming over LTE networks.

The main contributions of this paper are: (i) a simulation-based investigation of the combined effects of application and network parameters on end-to-end perceived video quality over 4G networks for four distinct content types; (ii) the classification of video content types into four main classes based on most frequently used objective video quality evaluation metric, using a well-known analytical tool cluster analysis. This is a new classification model and more specific than previous research; and (iii) developing a new regression-based model for video quality estimation for the new classification content types. This model gives it more accuracy than previous models reported in the literature. This model predicts quality for video streaming over 4G networks.

The rest of the paper is organized as follows. Section II presents the fundamentals of LTE, data set generation and simulation set-up. Section III discusses the impact of quality parameters on video quality, classifies the video content using cluster analysis and finds the degree of influence of quality parameters. Section IV proposes a regression-based model to evaluate video quality over LTE. Section V concludes our work in this paper and outlines the future directions of the research.

II. THE SYSTEM MODEL

A more detailed description of the LTE system and the classification model will be provided in the following subsections: (A) the LTE system, (B) the generation of datasets used to develop the model, and (C) Experiments.

A. *The LTE System*

Long-Term Evolution (LTE) was identified by the 3rd generation partnership project (3GPP) as the preliminary version of the 4G wireless networks. The goal of this new technology (LTE) is to provide higher radio access data rates, low latency, achieve great capacity and a reliable high speed of mobile telephone networks. Furthermore, LTE guarantees enhanced spectrum flexibility and compatibility with other 3GPP radio access technologies. The LTE uses a completely different radio technology than 3G. LTE uses multiple input multiple output (MIMO) operation and orthogonal frequency division multiplexing (OFDM) instead of CDMA over 3G. Applying MIMO and OFDM supported data rate up to 100 Mb/s download and 50 Mb/s upload. The Quality of Service (QOS) support is an important feature of the 4G over 3G. QoS varies the priority levels for different data streams and usually VoIP is given the highest priority followed by video stream than other data. Also, the overall network architecture, the so-called system architecture evolution (SAE), has been improved. The LTE radio access provides a highly flexible bandwidth from 1.4 MHz up to 20 MHz based on orthogonal frequency division multiplexing (OFDM). It supports both time-division duplex (TDD) and frequency division duplex (FDD) multiple access techniques [17]. These significant differences make 4G about 10 times faster than 3G, therefore, prediction models of 3G are not practical to apply over 4G networks. Although the presence of numerous protocols supports QoS, applying it in live LTE networks remains challenging due to channel characteristics, handoff support among a variety of networks, changing bit rates, bandwidth allocation propagation conditions and application types [18].

B. *Data Set Generation*

The most effective parameters of video quality related to video applications in LTE networks need to be identified and chosen. The video clips detailed in Table I are available in Video Trace Library [18] and were used for the model comparison. The video clips were classified into different classes, according to the spatial and temporal activity. Each clip was coded in H.264 in four send bitrates (128 kb/s, 242 kb/s, 440 kb/s and 880 kb/s), in three frame rates (10 fps, 20 fps and 30 fps) and in two different display sizes (QCIF and CIF). Transmission impairment was performed with the percentage of packet loss between 0% and 2%.

Table I. Simulation Scenarios

Clip Name	**Tennis**	**Suzie**	**Football**	**Tempete**	**Foreman**
Frames	150	150	260	260	300
Clip Name	**Akiyo**	**Coast**	**Stefan**	**News**	**Carphone**
Frames	300	300	300	300	382
FR	10, 20 and 30 f/s			**RES**	QCIF and CIF
SBR	128, 242, 440 and 880 kb/s			**PLR**	0, 1 and 2 %

In order to evaluate the performance of a model that takes into account different sets of parameters, including SBR, FR, RES, and PLR, a very large set of tests should be performed. The best way to evaluate the performance of a model is by contrasting the model results obtained using an objective test approach against the results obtained with subjective tests. This is because subjective tests are difficult to implement, and consume considerable time; for this reason, we have used an objective test.

C. *Experiments*

In order to create a degraded video database consisting of sequences corresponding to several configurations of related parameters, the simulation scenario shown in Figure 1 was used. An LTE-Sim [15] simulator was used to generate a video distortion database as follows: a realistic single-cell scenario was made, which had a radius of 1 km and the cell itself had one eNodeB and a between 5 and 20 UEs. The UEs' movement travelling cell with one video flow was elaborated with the random walk mobility model with a speed of 0 to 30 km/h. There are two sender nodes, video source and background traffic (CBR), as illustrated in Figure 1. The video traffic used is known as a trace-based application, which delivers packets that are based on the realistic video trace files. The simulation parameters are summarized in Table II. Three simulations were run for each number of users using three different scheduling algorithms; proportional fair (PF), modified largest weighted delay first (M-LWDF), and exponential/proportional fair (EXP/PF) to calculate the average packet loss ratio.

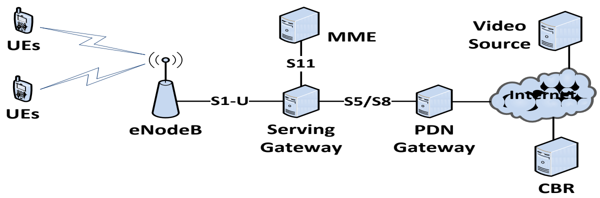

Fig. 1. LTE Network Topology

While the simulation begins to transmit video stream over LTE network topology, every configuration with its defined input data should be mapped into the system composed of the network, the source, and the receiver. The destination stores the corresponding values of the parameters of the transmitted video sequence. Then, by running the simulation several times, we generated and stored a set of distorted video sequences with corresponding parameter values.

Table II. Simulation Parameters

Parameter	Value
Simulation length	60 s
Number of cells	1 eNodeB
Physical details	Carrier frequency: 2 GHz; Downlink bandwidth: 5 MHz; Modulation scheme: QPSK, 16QAM, and 64QAM; eNodeB: Power trans = 43 dBm;
Cell layout	Radius: 1 KM
Number of users	5, 10, 15, 20
User speed	0, 3, and 30 KM/H
Traffic model	Real-time video flows type: H.264, and background traffic (CBR)

After completing the distorted database the open source framework Evalvid [16] was used to compare the original and distorted video sequences. PSNR metric [20] which measures the quality by simple pixel to pixel comparisons was chosen as an objective quality assessment parameter; because it is the most commonly used and represents a high degree of correlation with perceived video quality of the end user [21]. Then a set of PSNR values were obtained by comparing the original (transmitted) and distorted (received) video sequences. The corresponding MOS values were extracted as shown in Table III. The PSNR and MOS values with the corresponding parameters' values related to network and application layers were stored in a second database called the quality database.

Table III. Possible PSNR to MOS conversion [16]

PSNR [dB]	MOS	Quality
> 37	5	Excellent
31 - 37	4	Good
25 - 31	3	Fair
20 - 25	2	Poor
< 20	1	Bad

III. The Relationship Between The Objective Quality Assessments of Video and its Content

Based on the quality database introduced above, the relationship between objective video quality and video contents was analysed as follows: firstly, the degree of impact of each quality parameter on video quality was found; then video content was classified on the basis of an objective video quality evaluation (PSNR scores), and finally our classified contents were compared to the spatial and temporal dynamics classification.

A. Impact of Quality Parameters on Video Quality

In this section, the effect of video content type on video quality has been studied by analysis its impact with the selected quality parameters (SBR, FR, RES and PLR). In order to have a clear and easy analysis, we selected a set of 3D figures in which we varied one parameter with all available content types and kept the other three fixed. The PSNR scores were computed as a function of the values of the aforementioned four parameters.

1. PSNR vs Send Bitrate vs Video Content

Figure 2 shows the PSNR scores: the video quality increases when the send bitrate (SBR) increases from 128 kb/s up to 880 kb/s. We observed that with a higher SBR, the video quality was excellent (PSNR ≥ 50 dB in news videos); however, the quality fades (to PSNR < 27 dB) with decreased SBR, which was not an acceptable value to meet communication quality requirements.

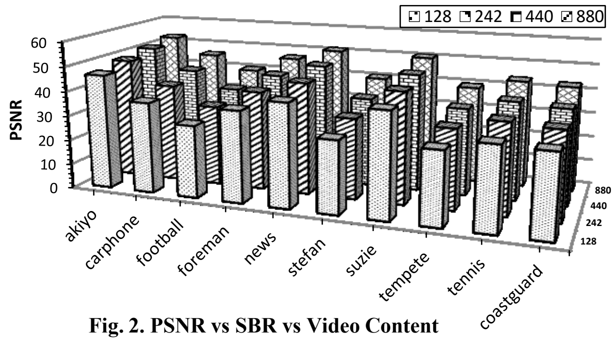

Fig. 2. PSNR vs SBR vs Video Content

2. PSNR vs Packet Loss Rate vs Video Content

Figure 3 shows the PSNR scores: the video quality decreases when the packet loss rate (PLR) increases from 0% up to 2%. We observed that with a lower PLR, the video quality was very good (PSNR up to 49 dB); however, the quality fades rapidly (to PSNR < 25 dB) with increased PLR, which was not an acceptable value to meet communication quality requirements.

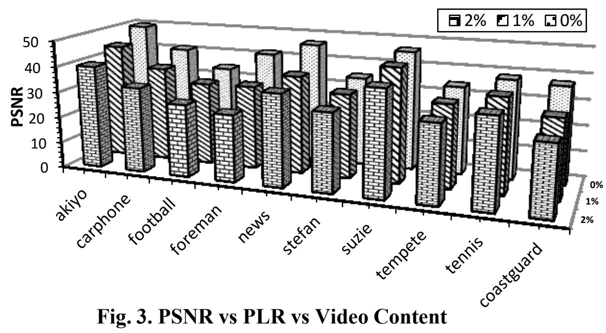

Fig. 3. PSNR vs PLR vs Video Content

3. PSNR vs Frame Rate vs Video Content

Figure 4 shows the PSNR scores: the video quality increases when the frame rate (FR) decreases from 30 f/s to 10 f/s. We observed that with a lower FR, the video quality was very good (PSNR up to 50 dB); however, the quality fades (to PSNR up to 30 dB) with increased FR, which is an acceptable value to meet communication quality requirements.

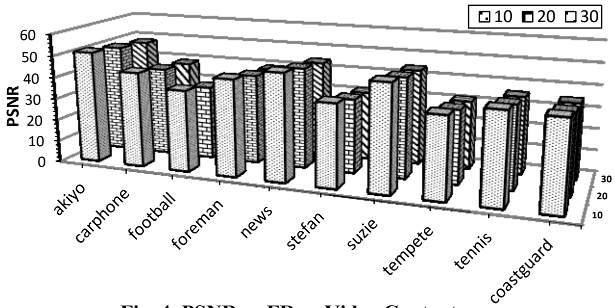

Fig. 4. PSNR vs FR vs Video Content

4. PSNR vs Resolution vs Video Content

Figure 5 shows the PSNR scores: the video quality decreases when the resolution (RES) increases from QCIF to CIF. We observed that with a lower revaluation, the video quality was very good (PSNR up to 50 dB); however, the quality fades (to PSNR up to 30 dB) with increased RES, which is an acceptable value to meet communication quality requirements.

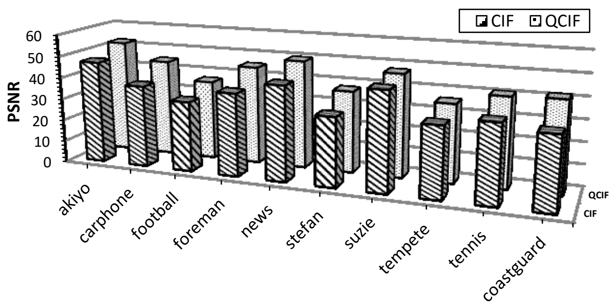

Fig. 5. PSNR vs RES vs Video Content

5. PSNR vs Send Bitrate vs Packet Loss Rate

Figure 6 shows the PSNR scores: the video quality increases dramatically when the send bitrate (SBR) increases from 128 kb/s up to 880 kb/s, but the absolute increase of the quality depends also on a decrease of BLR. We observed that with a higher SBR and no packet loss, the video quality was very good (PSNR > 40 dB); however, the quality fades rapidly (to PSNR < 27 dB) with increasing packet loss and decreased SBR, which is not an acceptable value to meet communication quality.

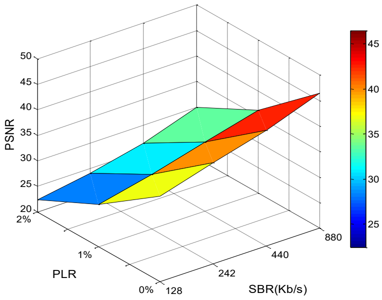

Fig. 6. PSNR vs SBR vs PLR

6. PSNR vs Send Bitrate vs Frame Rate

Figure 7 demonstrations that frame rate (FR) is less significant than send bitrate (SBR). Furthermore, we noted that the improvement in video quality was achieved by (FR = 10 f/s) and (SBR = 880 kb/s) which confirms that high SBR and low FR gives better video quality (PSNR > 45 dB).

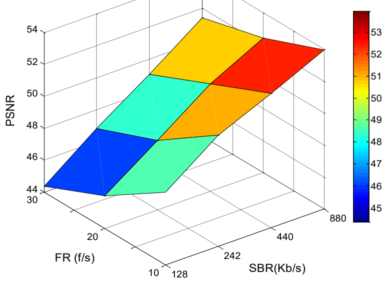

Fig. 7. PSNR vs SBR vs FR

7. PSNR vs Send Bitrate vs Resolution

From Figure 8, we found that Resolution (RES) is not significant as Send Bitrate (SBR). Also, we noted that the improvement in video quality was achieved by (SBR = 880 kb/s) and (RES = QCIF) which confirms that low SBR and high RES gives worse video quality.

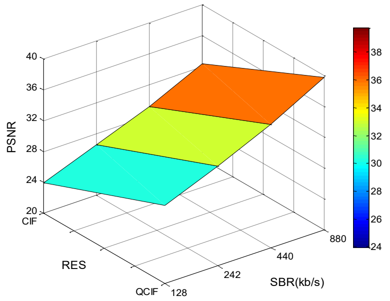

Fig. 8. PSNR vs SBR vs RES

In conclusion, we can confirm that the SBR effect is important and comparable to that of PLR. When the SBR increases, the quality increases too, particularly in the case of poor conditions (i.e. lower values of SBR or higher values of PLR), while decreasing FR and RES improve video quality, especially in good conditions (high SBR and low PLR).

B. Content Classification Model

Video contents were classified according to the PSNR scores obtained from the SBR, FR and RES parameters in the application layer, from PLR in the network layer and from the scheduling algorithm in the LTE layer. Cluster analysis [10] is one of the most common methods of a multivariate statistical analysis was applied to classify the video contents as shown in Figure 9. This technique lays groups' samples that have similar characteristics into the same group (cluster). The objective quality scores (PSNR) that obtained from video quality evaluation from the QoS parameters listed above addition to LTE scheduling algorithm were applied as an input to the cluster analysis tool that classifies the video content into four types.

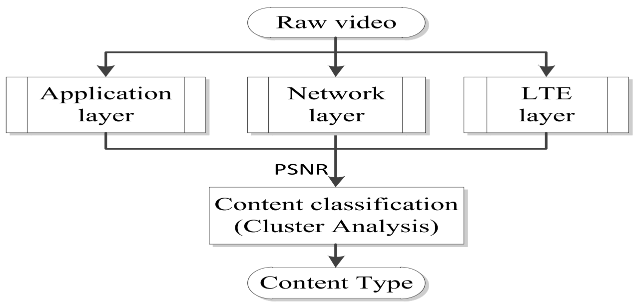

Fig. 9. Content Classification Model

The hierarchical cluster analysis was used to classify our data so the video clips that have the nearest Euclid distance are grouped together in the same cluster as shown in Figure 10 (dendrogram). Based on Sturge's rule ($k = 1 + 3.3 \, Log \, N$) [22], where (N) is the number of video clips. If we apply this equation to our data, k = 4, we will have four groups. As shown in Figure 10, the data contains a clear structure in terms of clusters that have similar attributes with a slight difference in the degree of similarity between the elements of each cluster as indicated by the dotted line. The Hierarchical cluster analysis figure illustrated that the selected video clips were grouped into four clusters according to content type: Low Motion (LM), Medium Motion (MM), High Motion (HM) and Rapid Motion (RM). The correlation coefficient (cophenet) was used to determine the defacement of our data classification given by cluster analysis method. The value of the cophenet should be very close to 100% for a high-quality solution which shows how readily the data fit into the structure proposed by classification methods. In our classification, the cophenet was (84.96%), which indicates an excellent classification result.

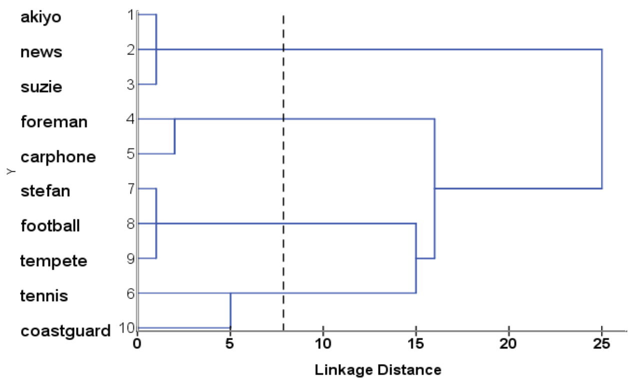

Fig. 10. Hierarchical Cluster Analysis

The classification used in this study is exclusive to this research and it encompasses four of the most frequently used contents for video transmitted over wireless networks which are classified as below:

1. First type – Low Motion (LM): contains video clips which have a slight moving region of interest (face and shoulder with a static background), e.g. news type (sequences Akiyo, News and Suzie).
2. Second type – Medium Motion (MM): contains video clips which have contiguous scenes unstable in the background (face and shoulder with a dynamic background), e.g. video call (sequences Foreman and Carphone).
3. Third type – High Motion (HM): contains video clips which have a wide-angle sequence where the motion includes most parts of the picture, e.g. individual sports (sequences Tennis and Coastguard).
4. Fourth type – Rapid Motion (RM): contains video clips which have a professional wide-angle sequence where the motion includes the entire picture parts uniformly, e.g. team sports (sequences Football, Stefan and Tempete).

C. Evaluation with other common methods

The most common method to classify video clips is according to their spatio-temporal features [21]. Therefore, to classify video clips based on this method and its intricacy of content, the spatio-temporal grid divides each video clip into four varieties based on its spatial and temporal features, as shown in Figure 11. When we compared our content classification based on PSNR scores with correlation (84.96%) and the classification in [14] based on the MOS scores with correlation (73.29%) to the common method of classification by spatio-temporal grid based on feature extraction in [24] with correlation (88.1%) we found a significant correlation between our classification and the spatio-temporal grid.

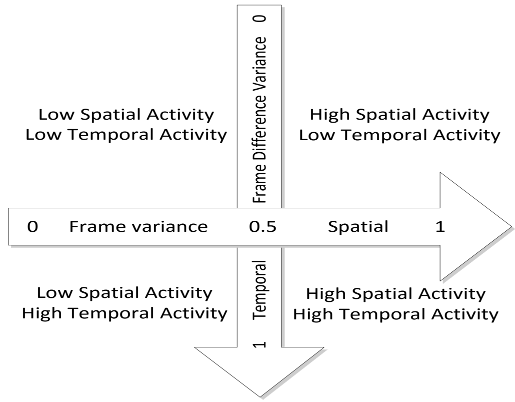

Fig. 11. The Spatio-Temporal Grid

D. Degree of Influence of Quality Parameters

Principal component analysis (PCA) was implemented to determine the degree of impact of each video quality parameter that used to classify video content. PCA is a method of data decrease aimed at obtaining a small set of derived variables which can be used instead of the larger set of original variables to simplify subsequent analysis of the data. There are two types of PCA: a covariance matrix used in the case where the same data share a single set of variables, and a correlation matrix used in the case where the data has different sets of variables. In this work, the type of a covariance matrix was used because our data has the same set. PCA was carried out to identify the relationship between video quality assessments (PSNR/MOS) and related parameters. The PCA was performed for the four video content types of LM, MM, HM and RM separately. The PSNR correlation coefficient (r) matrix of the four content types is shown in Table IV.

Table IV. PSNR Correlation Coefficient Matrix

Content Type	Clip Name	FR	SBR	RES	PLR
LM	Akiyo	-0.257	0.439	-0.387	-0.711
	Suzie	-0.429	0.647	-0.261	-0.506
	News	-0.417	0.429	-0.381	-0.640
MM	Foreman	-0.179	0.343	-0.507	-0.724
	Carphone	-0.246	0.512	-0.527	-0.568
HM	Tennis	-0.434	0.659	-0.489	-0.299
	Coastguard	-0.370	0.454	-0.465	-0.606
RM	Football	-0.475	0.596	-0.335	-0.479
	Stefan	-0.410	0.644	-0.514	-0.295
	Tempete	-0.462	0.728	-0.331	-0.327

The value of the correlation coefficient is such that $-1 < r < +1$. The (+) and (–) signs are used for positive linear correlations and negative linear correlations, respectively. The PCA scores of each quality parameter are given in the columns in Table IV. A higher score value, regardless of the sign (+) or (–), means that the parameter has a higher impact. Table IV demonstrates the impact of each quality parameter on video quality. This can be seen all the values of SBR are positive and the values of PLR, FR and RES are negative. This means that the SBR has a positive impact (when the value of SBR increases, the quality increases too), while the other variables have the opposite effect (when the values of PLR, FR and RES increase, the quality decreases). These findings confirm the results obtained in the section IV-A.

Another interesting finding in the PCA scores is that SBR and PLR parameters for video contents have a higher impact than FR and RES parameters for video contents. Moreover, in the LM category, higher PLR had a greater impact on video quality than SBR, FR and RES. In contrast, in the RM category, SBR had a bigger impact on video quality than other parameters. The findings of this work could be used to help in understanding the behaviour of video streaming over LTE networks. It can contribute to the design of accurate models to predict the video quality and to develop control schemes allowing to achieve the best quality for the video streaming over LTE networks.

IV. Video Quality Prediction Model

In order to apply the results obtained from section III, we investigated the quantitative relationship between video quality assessment and video contents. Multiple linear regression analysis for the four video content types (LM, MM, HM and RM) was carried out using video quality related parameters (SBR, FR, RES and PLR). Equation 1 shows the multiple regression models while Table V show the coefficient of multiple linear regression, RMSE and R^2. Since all the R^2 are greater than (90%), these estimations are done with high accuracy and give the goodness of fit of the proposed mathematical models. The estimated equations have been derived in terms of the PSNR for the four video content types and can be switched to the MOS according to Table III. The mathematical models can predict the users' perception of video quality based on the QoS related parameters as explained in equation (1):

$$PSNR_{CT} = a + b * FR + c * SBR + d * RES + e * PLR \qquad (1)$$

Table V. Coefficients of Multiple Linear Regression Models

CT	*a*	*b*	*c*	*d*	*e*	RMSE	R^2
LM	*50.449*	*- 0.245*	*0.01*	*- 2.445*	*- 2.897*	1.308	92.7%
MM	*53.971*	*- 0.195*	*0.01*	*- 9.029*	*- 7.888*	2.397	93.2%
HM	*48.4*	*- 0.325*	*0.011*	*- 6.669*	*- 5.325*	1.284	95.1%
RM	*44.276*	*- 0.307*	*0.013*	*- 6.3*	*- 2.211*	1.644	93.3%

V. Conclusion

In this study, the relationship between objective video quality and video contents was analysed. The degree of influence of each of the quality parameters on video was investigated using PCA and the relationship between video quality and video contents were established using multiple linear regression analysis. Video contents streaming over LTE networks were classified into four groups based on objective quality assessment acquired from quality parameters in the network, application and LTE layers, with obvious and appropriate clusters. In addition, when we matched our new classification to the conventional method of the spatio-temporal feature extraction, a close relationship between them was found. The outputs from regression-based model correlate well and also performed better in terms of the cophenet and the RMSE. Our results have also an approximate 12% increase in the correlation coefficient, compared to that of the previous model reported in the literature. This leads us to conclude with confidence that our models are more accurate and useful for real-time measurements then previous models. Applying the results to rate control methods based on content types is potentially one direction for the future research in this area. Another possible route is to develop a new scheduling algorithm for real-time video streaming over LTE networks based on a Random Neural Network (RNN), as it combines the advantages of an RNN applied to the four content types.

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