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Using Factor Analysis Techniques to Find Out Objective Video Quality Metrics for Live Video Streaming over Cloud Mobile Media Services

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Abstract

The increased adoption of smartphones, the access to mobile broadband networks and the availability of public Clouds allow new multimedia services, called Cloud Mobile Media Services. Under this new architecture the proliferation of live video streaming applications and the Quality of Experience (QoE) given by the final user are an issue, due to the higher and variable delay, as result of the virtualization methods used in the Clouds. Thus in this paradigm new challenges appear related to keep and estimate a good QoE in terms of a standardized subjective video quality called Mean Opinion Score (MOS). In this paper, we propose several objective video quality metrics to estimate the subjective MOS based on Factor Analysis techniques both using Full Reference and Non Reference approaches. We compare the performance of the estimated MOS against publicly available video quality algorithms.

Keywords: Live video streaming, cloud computing, quality of experience, objective video quality metric, factor analysis

1 Introduction

Big companies like Google, Cisco Systems, Apple and Microsoft predict that by 2018, more than 90% of Internet traffic will be multimedia content (images, 3D images, ultra high definition video and audio, etc.) [1]. In addition, three recent developments: a) increased adoption of smart phones and tablets, b) increased access to mobile broadband networks, and c) availability of public Clouds are aligning to possibly enable a new generation of truly ubiquitous multimedia services on mobile devices, called Cloud Mobile Media (CMM) services [2] [3]. These new infrastructures are replacing the traditional Content Delivery Networks (CDN) [4]. Among the various multimedia applications, video content delivery applications dominate the usage of mobile data.

In this new paradigm, it is challenging to accurately assess a service in this context and hence the term Quality of Experience (QoE) [5] has been coined to differentiate between user perceived quality and Quality of Service (QoS) [6] . This strictly user-centric focus of QoE is also reflected in its definition as "*overall acceptability of an application or service, as perceived subjectively by the end user*" [7]. Notice that new challenges appear related to the QoE management [8] over these cloud based infrastructures, in particular with live video streaming, due to the additional delay and jitter introduced because the virtualization processes and increase of network distance between end-user and service.

Thus, developing accurate, perceptual-based quality metrics is a key requirement for these CMM services. As QoE is purely related to end-users, we consider in this paper the effect of both core networks and cloud networks as a whole to find out expressions in a robust manner. However, subjective testing is time-consuming, expensive and it requires special assessment facilities to produce reliable and reproducible test results. A standardized process for a subjective video quality metric is given by Mean Opinion Score (MOS) [9] [10]. In this paper we consider the QoE metric for live video streaming in terms of MOS.

Our goal is to find out an objective video quality metric to estimate or predict the Mean Opinion Score (MOS), denoted by $\widehat{MOS}$. As many factors are affecting QoE in live streaming video as a CMM service, we collect extensive statistics and variables for various system parameters and apply an statistical method called Factor Analysis (FA) [11] to process all of them, due to its advantage of parsing a large parameter set into a lower number of statistically independent parameters required to estimate $\widehat{MOS}$. We evaluate different approaches such as Full Reference (FR) criteria (it requires information of the original video) as well as Non Reference (NR) [12] (it requires only the received video data) by measuring variables such as Quality of Service (QoS), bit stream and video quality related metrics. This paper is an extended and revised version of a preliminary conference paper [13].

Finally, in order to evaluate the accuracy of the proposed metrics ($\widehat{MOS}$) for the different approaches, we have measured the subjective MOS through surveys following the recommendations given by ITU-R (BT.500-13 [9], P.910 [10]) and have analyzed the quality metrics for the different approaches following the recommendations given by [14].

The rest of the paper is structured as follows. Section 2 discusses the related work. Section 3 characterizes the delay and jitter in cloud infrastructures. Section 4 describes the methodology, both the statistical method based on FA and the subjective video quality measurements by video quality surveys. Section 5 explains the network infrastructure and test bench, defining the observable variables related with QoS, bit stream and basic video quality metrics. Section 6 details the different expressions to estimate the $\widehat{MOS}$ for different approaches. Section 7 analyzes and compares the performance of the different approaches to define a metric against well known video quality metrics. Finally, Section 8 concludes the paper.

2 Related Work

New applications in the field of health, aged care, surveillance and education will contribute significantly to increase multimedia traffic and their requirements (encoding, transcoding, storing, streaming and indexing). In this kind of scenarios, hundreds of petabytes of multimedia content are generated in real time, as well as off-line, and they require to be processed efficiently (storing, streaming and indexing with an outline and proper semantics). These techniques should be done without compromising the QoS [6] and the end-user QoE [5] in terms of availability, delay, content quality, etc. Moreover, the information retrieved will be consumed and processed in many places at the same time and under various conditions. Notice that content delivery in the Internet is commonly facilitated by CDNs [4], that act as a cache memory, close to the user, to avoid having to transfer massive amounts of data through the Internet, but fail in this new scenarios, such as in live streaming video applications, live TV, etc. Thus, the emergence of cloud computing [15] sheds new alternatives. A cloud platform offers reliable, elastic and cost-effective resource provisioning, which has been changing the way of enabling scalable and dynamic network services.

Cloud computing infrastructures together with fast and wireless communication infrastructures may be the perfect solution for coding, storing and streaming multimedia content (Multimedia Cloud Computing [16][2]). These new networks are classified as Cloud Mobile Media (CMM) [3]. Nevertheless for these applications in CMM new challenges appear, related to the Quality of Experience (QoE) management [8].

In the literature we can find several works related to live video streaming over cloud infrastructures. In [17] the authors propose a solution for providing scalable, seamless, live video streams service using cloud infrastructures and software defined networks to provide alternative paths to meet with the user demands. In [18] it is proposed a cloud-based media processing platform for enabling elastic live broadcasting on the processing of a large number of streams to adapt the user requirements, trying to minimize the use of cloud resources without affecting the quality of streams. The authors in [19] propose an algorithm to allocate the machines to host servers in a cloud infrastructure, for load balancing and task scheduling (in particular for transcoding) to deliver live content to meet the user demand, trying to minimize the use of resources (number of servers) and costs. From previous [17] [18][19] references, we can see that the main research is focused on the performance of the cloud, but not in the end user itself. It is worth mentioning that in [20] although it does not address live video streaming, the authors show a content distribution algorithm within CDNs using cloud infrastructures, taking into account not only on QoS but also on the QoE in terms of MOS, estimated using neural networks. In [3] is shown a survey the existing research, reflections and outlooks, in cloud infrastructures for media content accessed through wireless broadband networks, called Cloud Mobile Media services. The authors consider different aspects related to the management and control of the infrastructures, strategies to deploy new media services and new challenges associated with scalability, usability, heterogeneity, security and reliability issues. In addition, it is worth mentioning the work carried out in [21], where the authors define a new framework based on multiple agents allowing secure and reliable communication among open clouds.

Regarding to the QoE estimation, we find also different techniques in the literature. On the one hand, based on Machine learning techniques such as Naive Bayes (NB), Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Tree (DT), Random Forest (RF) and Neural Networks (NNet), the authors in [22] and [23] estimate QoE. They take measurements first by means of test setup that reflects real-time network and obtain different metrics such as delay, jitter, packet loss and video types. From these metrics, MOS is evaluated. WEKA tools are used to analyze these machine learning algorithms and a network emulator is used to introduce artificial delay, jitter and packet loss in the experiments in order to check the consistency. On the other hand, another recent approach to estimate QoE for video streaming over wireless network is based on artificial neural networks [24], where the authors use a NR QoE estimation model, based on Radial Basis Function Networks (RBFN) for video streaming. RBFN is a type of supervised learning method which consists of both training and testing process. In addition,

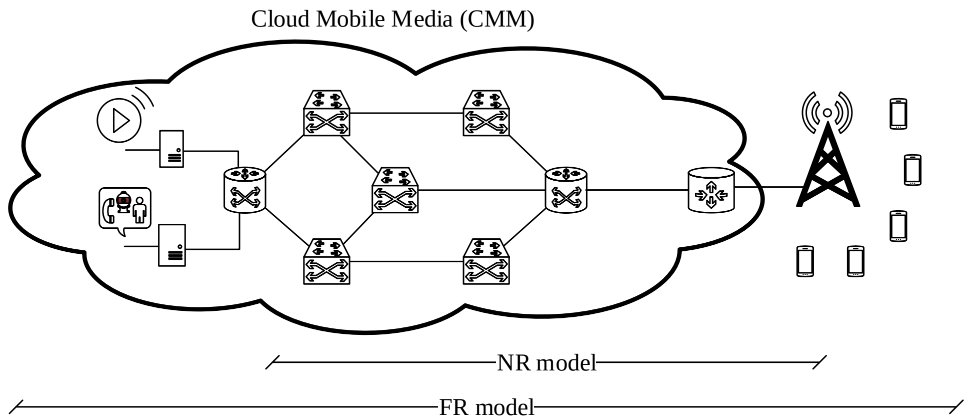


Figure 1: Cloud Mobile Media architecture. Detail of the different approaches (FR and NR) to estimate MOS.

computational complexities of the different neural methods are characterized. In [25] and [26], Back Propagation Neural Network (BPNN) methods are used. These are a type of supervised algorithms where data sets are trained before conducting experiments. They involve forward and feedback propagation of training patterns and allow to rectify errors. However, they take a long time to converge and may not be viable in practice.

Finally, we also have related papers in terms of QoE estimation with different applications. The authors in [27] analyze and define a delay-aware packet dropping scheme for Voice over IP (VoIP) by a user-level quality assessment. In the same direction, in [28] it is proposed the integration of machine learning techniques to adapt protocols for QoS-enabled distributed real-time applications.

In summary, there are certain limitations in all of them. Machine learning techniques require large number of datasets while neural networks based are extremely time consuming and computationally intensive. To overcome these limitations, we have chosen in this paper a statistical method called Factor Analysis (FA).

3 Cloud Mobile Media features

According to [8] in CMM infrastructures for live video streaming applications, the main inconvenient arises due to the additional delay and jitter mainly introduced by the virtualization processes and increase of network distance between end-user and service. A global scheme of a complete CMM architecture is shown in Fig 1, where it is given the detail for the different approaches, FR and NR. Thus, in order to validate this statement, we have performed several experiments to measure the delay and jitter in three different scenarios. The testbed has been deployed in four physical nodes. Each node has the following hardware: 32 GB RAM, 2 Intel XEON CPU E5-2630 v3 @ 2.40 GHz with 8 cores with hyper threading, 2 TB Hard Disk, and 1Gbps NICs. In all physical nodes was installed Ubuntu 14.04 Server (Trusty Tahr).

Notice that the most noteworthy virtual bridging solutions mainly used inside the cloud infrastructures adopted by hypervisors (or Virtual Machine (VM) manager [29]) running on Linux systems are: a) Linux Bridge (LB), the native kernel bridging module [30], and b) Open vSwitch (OVS), a distributed OpenFlow-enabled software-based switching facility capable of

Table 1: Average Round Trip Time and jitter in ms for three scenarios with different virtualization techniques between physical and virtual machines (PM and VM).

Scenario	RTT [ms]	Jitter [ms]
PM-PM	*0.121*	*0.008*
PM-VM	*0.339*	*0.012*
VM-VM	*0.536*	*0.032*

reaching kernel-level performance [31].

Thus, the scenarios selected to measure the virtualization effect are as follows. In the first scenario, we have measured these time properties between two physical machines (PM) connected via a physical switch Cisco Catalyst WS-C2960-24TC-L. In the second scenario, the communication is between a PM and a VM. The VM is connected to a LB and this bridge is connected to the Ethernet interface. In the last scenario, the communications are done between two VMs in a real deployment of OpenStack [32]. The VM is connected to a LB, this LB is connected to a OVS switch (known as integration bridge), that is finally connected to another OVS switch attached to the physical interface. The hypervisor used in all cases is KVM [33] and it has been optimized to use `vhost-net` networking mode, that bypasses the hypervisor and directly connects with the kernel.

We have used `ping` to measure the Round Trip Time (RTT) and `iperf` to obtain the jitter in all the scenarios. Table 1 summarizes these results. As we can see, the delay and the jitter increase as more virtualization layers are added, even four times more approximately. Notice that the values are small because all the machines (virtual and physical) belong to the same infrastructure (intracloud) and there is not extra background traffic.

4 Factor Analysis technique

Factor Analysis (FA) is a statistical method, which parses a large set of variable (most of them are uncorrelated) into a small set of uncorrelated variables called factors (denoted as F_i where i is the factor identifier) [11]. In turn, FA searches for any hidden patterns and expresses observed variables as a linear combination of the potential factors and error terms. The interdependencies between observed variables are used to reduce in our case the set of variables to measure the QoE in terms of MOS. FA is encompassed of principal component analysis where a reduced set of component is obtained by analyzing the correlation matrix of the different variables. After that, we obtain an orthogonal set by applying a rotation via Varimax algorithm and Kaiser normalization [34]. At the end, we estimate $\widehat{MOS}$ in the following form:

$$\begin{aligned} F_i &= constant_i + \sum_{j=1} \alpha_j \cdot variable_j; \\ \widehat{MOS} &= constant + \sum_{i=1} \beta_i \cdot F_i; \end{aligned} \tag{1}$$

where α_j and β_i are coefficients of the linear regressions. Notice that in this paper we find out $\widehat{MOS}$ using different approaches: FR and NR. Because FA is based on the correlation between the different variables, for each measurable variable we will consider the first four standardized moments of the measured variables: *mean*, *standard deviation*, *skewness* and *kurtosis*. All these variables are analyzed through the study of different cases, as shown in Section 6.

In order to perform the regression for the $\widehat{MOS}$ expression over the different calculated factors, it is necessary to get at the same time real MOS values for the different received videos in live video streaming. From the subjective tests defined at ITU-R BT.500-13 [9] and P.910 [10] we chose the Absolute Category Rating (ACR) that is a single stimulus method with both the original reference and the processed video being shown to the evaluators in a random sequence. The evaluators are unaware of its presence or its location in the displayed video set. The evaluators provide one rating for the overall video quality using a discrete five-level scale ranging from Bad (1) to Excellent (5). The study was conducted over two sessions, each lasting less than half an hour, as per recommendations in [9] in order to minimize evaluator fatigue. The evaluators' pool consisted of 35 under-graduate students of different ages (in average 21 years old) from our university. They are students (male and female) with a male majority, of the last course of Multimedia Engineering and they have enough knowledge about multimedia streaming.

5 Test bed

In order to evaluate the live video streaming as a CMM service, we have implemented a video client and a streaming server in different VMs, using the scenario with more virtualized processes as described in Section 3, from a VM to a VM. The detail of the architecture was shown in Fig 1, where we see both the cloud media and the wireless infrastructure. Besides, for the wireless access according to [35], we have selected a Guaranteed Bit Rate scenario, QoS Class Identifier (QCI=4). Overall, we have a mean end to end delay of 300 ms and 10% of jitter and a packet loss rate of 10^{-6}, following the arguments given in [8] and [35]. To adjust these parameters we use `iproute2` Linux utilities, in order to analyze the effect of both the core, cloud and access network as a whole.

The tool used to stream the video has been VideoTester [37] that allows video transmission with RTP over UDP unicast. VideoTester is furnished with a rich set of offline analysis capabilities, allowing us to extract the different variables, as shown in Table 2, related to the QoS, bit stream and basic video quality parameters. All these variables are processed in Section 6 using FA. In order to emulate the live video streaming, the client requests a precoded video stream.

For the video streaming, a set of 12 video sequences have been used. As shown in Fig. 2, the first 6 videos are used to define the proposed models: *akiyo*, *bride-far*, *football*, *foreman*, *mobile* and *news*. The next 6 videos are used for testing purpose: *coastguard*, *flower*, *hall*, *paris*, *silent* and *tempete*. These videos span a wide range of content types in terms of video mobility, type of images, colours, etc. in order to generalize the different video streams, to find out a MOS model ($\widehat{MOS}$) independent of the type of video. All these videos are available at [38].

These videos have a CIF (Common Intermediate Format, 352x288) resolution and have been coded with 3 different bit rates according to the different scenarios (256 kbps, 512 kbps and 768 kbps) using the codec H.264/AVC with the following coding options: 25 frames per second, profile Main@L1.3 and a GOP size of 50 frames. Notice that although we have other coding options, such as Scalable Video Coding (SVC) and other adaptive video streaming

Table 2: Explanation of the measured variables related with QoS, bitstream and video quality parameters.

Name [unit]	Description
	QoS
Latency (L) [ms]	End to end delay
Delta (D) [ms]	Packet inter-arrival time measured per RTP packet
Jitter (J) [ms]	Delay variation
Skew (S) [ms]	Clock skew between sender and receiver from RTP timestamp
BandWidth (BW) [kbps]	Binary rate of video
	Bit stream
PLR [%]	Packet Loss Rate, ratio between number of lost and sent packets
PLD	Packet Loss Distribution measured by PLR per time
StreamEye (SE) [Byte/frame]	Visualization of the video stream framing structure at the receiver end, probably impaired with frame losses
GOP [size]	Group of Pictures or frames with inter dependences for decoding
IFLR [%]	I-Frame Loss Rate between number of I-frames lost and sent
	Video Quality
PSNR [dB]	Peak Signal to Noise Ratio in Y component
SSIM [index/frame]	Structural Similarity Index in Y component that measures the image degradation as perceived changes in structural information [36]
ITU-T G.1070	Opinion model for video applications based on coefficients in video quality estimation function with respect to coding and packet-loss degradations
DIV [%]	Distortion in Interval, maximum percentage of frames with a PSNR worse than original

Figure 2: Video sequences. The first 6 videos are used to define the proposed models: *akiyo*, *bride-far*, *football*, *foreman*, *mobile* and *news*. The next 6 videos are used for testing purpose: *coastguard*, *flower*, *hall*, *paris*, *silent* and *tempete*.

techniques, H.264/AVC is still most currently used in Internet and has attracted a lot of attention from industry and has been adopted by various application standards.

6 Objective video quality metrics

As described previously in Section 4, now we go into detail to perform FA with the variables obtained measuring them over the scenario described in previous section. We have used *SPSS* [39] software package for statistical analysis and Matlab [40]. As described in Section 4, in order to analyze potential hidden relations of the measured variables, we compare the information contributed by the first four standardized moments of the measured variables: *mean*, *standard deviation*, *skewness* and *kurtosis*, denoted by $\mathrm{mean}()$, $\mathrm{var}()$, $\beta()$ and $\kappa()$ respectively. From the variables described in Table 2, for the FR approach we work with all the variables (14 variables in total) and for the NR approach we work only with the variables related to QoS. Notice that for the NR approach we work only with the variables related with QoS, that can be monitored within the service provider. We define different cases based on the number of statistical moments considered in the analysis: *Case I* considers only mean, *Case II* considers only mean and variance, *Case III* considers mean, variance and skewness of data set and finally *Case IV* considers mean, variance, skewness and kurtosis of data sets.

6.1 Full Reference approach

FR metrics require both the original and the distorted videos to compute the quality scores. These metrics are typically used for benchmarking image and video processing algorithms such as lossy encoding or watermarking techniques, as well as media distribution networks during the testing phases. Next, we show the different expressions for factors and $\widehat{MOS}$ expressions in each case.

- **Case I:** By applying FA to data set, we obtain 3 factors that corresponds to eigenvalues greater than 1 and explaining a cumulative statistical variance of 83.607%. In this case we have used linear regression to compute $\{F_i\}_{i=1}^{3}$ and which in turn we used to estimate $\widehat{MOS}$.

$$\begin{aligned}
F_1 &= -2.379 + 0.003\,\mathrm{mean(BW)} + 0.494\,\mathrm{mean(G.1070)} \\
&\quad - 0.047\,\mathrm{mean(D)} \\
F_2 &= -1.419 - 0.019\,\mathrm{mean(DIV)} + 0.022\,\mathrm{mean(PSNR)} \\
&\quad 1.907\,\mathrm{mean(SSIM)} \\
F_3 &= -61.764 + 0.067\,\mathrm{mean(GOP)} + 0.030\,\mathrm{mean(J)} \\
&\quad 0.365\,\mathrm{mean(L)}
\end{aligned}$$

The Pearson's squared coefficient R^2 is 0.999, 0.989 and 0.989 for F_1, F_2 and F_3 respectively. Next, using the above factors we obtain by linear regression $\widehat{MOS}$ as follows:

$$\widehat{MOS} = 3.166 + 0.013F_1 + 0.921F_2 + 0.088F_3 \tag{2}$$

with $R^2 = 0.957$ for $\widehat{MOS}$.

- **Case II:** By applying FA to the data set, we obtain 4 factors that corresponds to eigenvalues greater than 1 and explaining a cumulative statistical variance of 88.255%. The expressions for factor $\{F_i\}_{i=1}^{4}$ are:

$$\begin{aligned}
F1 &= -1.497 + 0.002\,\mathrm{mean(BW)} + 0.228\,\mathrm{mean(G.1070)} \\
&\quad + 8.109 \times 10^{-5}\,\mathrm{mean(SE)} - 0.054\,\mathrm{mean(D)} \\
&\quad + 9.872 \times 10^{-6}\,\mathrm{var(BW)} + 7.739 \times 10^{-8}\,\mathrm{var(SE)} \\
F2 &= -4.587 + 0.077\,\mathrm{mean(PSNR)} + 2.808\,\mathrm{mean(SSIM)} \\
&\quad + 2.184\mathrm{var(SSIM)} \\
F3 &= -4.185 + 0.067\,\mathrm{mean(GOP)} - 0.006\,\mathrm{mean(J)} \\
&\quad - 0.030\,\mathrm{mean(DIV)} + 7.003 \times 10^{-5}\mathrm{var(D)} + 0.023\,\mathrm{var(J)} \\
&\quad + 0.001\,\mathrm{var(DIV)} \\
F_4 &= 30.018 - 0.182\,\mathrm{mean(L)} + 0.002\,\mathrm{mean(S)} \\
&\quad + 1.096 \times 10^{-6}\,\mathrm{var(S)}
\end{aligned}$$

where R^2 is 0.997, 0.954, 0.981 and 0.975 for F_1, F_2, F_3 and F_4, respectively. By plugging the above factors into the following expression, we obtain by linear regression:

$$\widehat{MOS} = 3.166 + 0.026F_1 + 0.856F_2 - 0.268F_3 - 0.256F_4 \tag{3}$$

with $R^2 = 0.974$ for $\widehat{MOS}$.

- **Case III:** In this case, we obtain 5 factors that corresponds to eigenvalues greater than 1 and explaining a cumulative statistical variance of 91.770%. The expressions for factors

$\{F_i\}_{i=1}^5$ are:

$$\begin{aligned}
F_1 &= -1.271 + 0.019\,\text{mean}(\text{GOP}) + 0.003\,\text{mean}(\text{J})\\
&\quad - 0.298\,\beta(\text{J}) - 0.058\beta(\text{DIV}) + 0.149\beta(\text{PSNR})\\
&\quad + 0.137\,\beta(\text{SE}) + 4.091\,\beta(\text{S}) - 0.018\,\beta(\text{SSIM})\\
F_2 &= -3.558 + 0.002\,\text{mean}(\text{BW}) + 0.478\,\text{mean}(\text{G.1070})\\
&\quad + 0.025\,\text{mean}(\text{D}) + 1.190^{-5}\,\text{var}(\text{BW}) + 6.196^{-8}\,\text{var}(\text{SE})\\
F_3 &= -3.422 + 0.067\,\text{mean}(\text{PSNR}) + 1.463\,\text{mean}(\text{SSIM})\\
&\quad + 0.001\,\text{var}(\text{D}) + 0.001\,\text{var}(\text{PSNR}) - 2.470\,\text{var}(\text{SSIM})\\
&\quad - 0.110\,\beta(\text{D})\\
F_4 &= -0.371 - 0.017\,\text{mean}(\text{DIV}) - 0.003\,\text{mean}(\text{S})\\
&\quad + 0.001\text{var}(\text{DIV}) - 3.891^{-6}\,\text{var}(\text{S})\\
F_5 &= -219.743 + 1.378\,\text{mean}(\text{L}) + 0.040\,\text{var}(\text{J})
\end{aligned}$$

where R^2 is 0.995, 0.997, 0.995, 0.955 and 0.754 for $\{F_i\}_{i=1}^5$ respectively. Then, we obtain by linear regression:

$$\begin{aligned}
\widehat{MOS} &= 3.166 - 0.251F_1 + 0.024F_2 + 0.832F_3 - 0.347F_4\\
&\quad + 0.015F_5
\end{aligned} \tag{4}$$

with $R^2 = 0.979$ for $\widehat{MOS}$.

- **Case IV:** In this case, we obtain 6 factors that corresponds to eigenvalues greater than 1 and explaining a cumulative statistical variance of 93.323%. The expressions for factors $\{F_i\}_{i=1}^6$ are:

$$\begin{aligned}
F_1 &= 0.132 + 1.851\,\beta(\text{S}) + 0.056\,\text{mean}(\text{GOP}) + 0.314\,\beta(\text{SSIM})\\
&\quad + 0.106\,\beta(\text{DIV}) - 1.417\,\kappa(\text{S}) - 0.026\,\kappa(\text{DIV})\\
&\quad + 0.341\,\beta(\text{J}) + 0.006\,\text{mean}(\text{J}) + 0.118\,\kappa(\text{J})\\
&\quad - 0.126\,\beta(\text{PSNR})\\
F_2 &= 8.043 - 0.462\,\text{mean}(\text{D}) - 0.518\,\text{mean}(\text{G.1070})\\
&\quad - 0.002\,\text{mean}(\text{BW}) + 1.484 \times 10^{-5}\,\text{var}(\text{BW})\\
&\quad + 1.845 \times 10^{-7}\,\text{var}(\text{SE})\\
F_3 &= -5.930 + 5.937\,\text{mean}(\text{SSIM}) + 0.024\,\text{mean}(\text{PSNR})\\
&\quad + 13.897\,\text{var}(\text{SSIM}) - 0.941\beta(\text{D}) + 0.210\kappa(\text{D}) + 0.001\text{var}(\text{D})\\
F_4 &= -1.545 - 0.023\,\kappa(\text{SSIM}) - 3.614 \times 10^{-6}\text{var}(\text{S})\\
&\quad + 0.008\,\text{mean}(\text{DIV}) - 0.003\,\text{mean}(\text{S}) + 0.037\,\text{var}(\text{J})\\
F_5 &= 2.456 + 0.001\,\kappa(\text{BW}) + 2.455\beta(\text{BW}) - 1.721\beta(\text{SE})\\
&\quad + 0.269\kappa(\text{SE})\\
F_6 &= -223.062 + \text{mean}(\text{L}) + 0.120\,\kappa(\text{PSNR})
\end{aligned}$$

where R^2 is 0.997, 0.987, 0.960, 0.972, 0.862 and 0.738 for $\{F_i\}_{i=1}^6$ respectively, and $\widehat{MOS}$ is calculated by linear regression as:

$$\begin{aligned}
\widehat{MOS} &= 3.166 - 0.192F_1 + 0.022F_2 + 0.803F_3\\
&\quad - 0.449F_4 + 0.007F_5 + 0.049F_6
\end{aligned} \tag{5}$$

with $R^2 = 0.991$ for $\widehat{MOS}$.

6.2 Non Reference approach

NR approach requires only the received video data. In this approach we follow the same previous procedure, but using only the five variables given by the QoS section in Table 2.

- **Case I:** By applying FA to this set of variables, we obtain 2 factors that corresponds to eigenvalues greater than 1 and explaining a cumulative statistical variance of 78.265%. In this case we have used linear regression to compute $\{F_i\}_{i=1}^{2}$ and which in turn we used to estimate $\widehat{MOS}$.

$$F_1 = -0.710 - 0.003\,\mathrm{mean(BW)} + 0.156\,\mathrm{mean(D)}$$

$$F_2 = -122.63 - 0.001\,\mathrm{mean(S)} + 0.040\,\mathrm{mean(J)}$$
$$0.765\,\mathrm{mean(L)}$$

with R^2 is 0.981 and 0.985 for F_1 and F_2 respectively. Next using the above factors, we obtain by linear regression $\widehat{MOS}$ as follows:

$$\widehat{MOS} = 3.166 - 0.051F_1 + 0.334F_2 \tag{6}$$

with $R^2 = 0.128$ for $\widehat{MOS}$.

- **Case II:** By applying FA to the data set, we obtain 3 factors that corresponds to eigenvalues greater than 1 and explaining a cumulative statistical variance of 82.563%. The expressions for factor $\{F_i\}_{i=1}^{3}$ are:

$$\begin{aligned}F1 &= -2.745 + 0.004\,\mathrm{mean(BW)} + 0.040\,\mathrm{mean(D)}\\ &\quad + 3.139\times10^{-5}\,\mathrm{var(BW)}\\ F2 &= -49.233 + 0.305\,\mathrm{mean(L)} - 0.001\,\mathrm{mean(S)}\\ &\quad - 4.539\times10^{-7}\,\mathrm{var(S)}\\ F3 &= -2.714 - 0.001\,\mathrm{mean(J)} + 0.002\,\mathrm{var(D)}\\ &\quad + 0.052\,\mathrm{var(J)}\end{aligned}$$

where R^2 is 0.936, 0.994 and 0.906 for F_1, F_2 and F_3 respectively. By plugging the above factors into the following expressions, we obtain by linear regression $\widehat{MOS}$ as follows:

$$\widehat{MOS} = 3.011 + 0.120F_1 + 0.365F_2 + 0.172F_3 \tag{7}$$

with $R^2 = 0.198$ for $\widehat{MOS}$.

- **Case III:** In this case, we obtain 4 factors that corresponds to eigenvalues greater than 1 and explaining a cumulative statistical variance of $88.361\ \%$. The expressions for factor $\{F_i\}_{i=1}^4$ are:

$$\begin{aligned} F_1 &= 0.355 - 0.015\,\mathrm{mean(J)} + 0.001\,\mathrm{var(D)} \\ &\quad + 0.794\,\beta(\mathrm{BW}) - 0.127\,\beta(\mathrm{J}) + 4.857\,\beta(\mathrm{S}) \\ F_2 &= -1.621 + 0.002\,\mathrm{mean(BW)} - 0.061\,\mathrm{mean(D)} \\ &\quad + 1.979 \times 10^{-5}\,\mathrm{var(BW)} + 0.436\,\beta(\mathrm{D}) \\ F_3 &= -0.228 + 0.001\,\mathrm{mean(S)} + 1.894 \times 10^{-6}\,\mathrm{var(S)} \\ F_4 &= -0.228 + 0.001\,\mathrm{mean(L)} + 0.057\,\mathrm{var(J)} \end{aligned}$$

where R^2 is 0.971, 0.993, 0.949 and 0.897 for $\{F_i\}_{i=1}^4$, respectively. We obtain by linear regression:

$$\widehat{MOS} = 3.166 + 0.036F_1 + 0.119F_2 + 0.932F_3 + 0.183F_4 \tag{8}$$

with $R^2 = 0.151$ for $\widehat{MOS}$.

- **Case IV:** Finally in this case, we obtain 5 factors that corresponds to eigenvalues greater than 1 and explaining a cumulative statistical variance of $93.047\ \%$. The expressions for factors $\{F_i\}_{i=1}^5$ are:

$$\begin{aligned} F_1 &= 9.184 - 0.060\,\mathrm{mean(J)} + 0.097\,\beta(\mathrm{J}) \\ &\quad + 8.004\,\beta(\mathrm{S}) + 0.326\,\kappa(\mathrm{J}) - 4.705\,\kappa(\mathrm{S}) \\ F_2 &= -1.341 - 0.091\,\mathrm{mean(D)} + 2.63 \times 10^{-5}\,\mathrm{var(D)} \\ &\quad + 0.690\,\beta(\mathrm{D}) + 0.053\,\kappa(\mathrm{S}) \\ F_3 &= 0.414 + 0.002\,\mathrm{var(D)} + 0.028\,\beta(\mathrm{BW}) \\ &\quad - 0.327\,\kappa(\mathrm{BW}) \\ F_4 &= -0.166 + 0.002\,\mathrm{mean(S)} + 3.178 \times 10^{-6}\,\mathrm{var(S)} \\ F_5 &= -136.946\,\mathrm{mean(L)} + 0.077\,\mathrm{var(J)} \end{aligned}$$

where R^2 is 0.947, 0.997, 0.915, 0.956 and 0.933 for $\{F_i\}_{i=1}^5$, respectively, we obtain by linear regression $\widehat{MOS}$ as follows:

$$\begin{aligned} \widehat{MOS} = 3.166 - 0.476F_1 + 0.329F_2 + 0.447F_3 + 0.518F_4 \\ + 0.125F_5 \end{aligned} \tag{9}$$

with $R^2 = 0.151$ for $\widehat{MOS}$.

7 Evaluation of the approaches

In this section, we will analyze the FA performance with different approaches and cases, comparing the cumulative % of variance explained. Also, we will compare the average error when estimating MOS values, using the set of videos for this purpose. Finally, we will compare the quality metric of the estimations against well known video quality metrics.

Table 3: Cumulative % of variance in for FR and NR approaches corresponding to $(\#)$ number of factors.

Case $(\#)$	I $(\#)$	II $(\#)$	III $(\#)$	IV $(\#)$
FR	83.60% (3)	88.25% (4)	91.77% (5)	93.32% (6)
NR	78.26% (2)	82.56% (3)	88.36% (4)	93.04% (5)

Table 4: R^2 coefficients achieved to estimate $\widehat{MOS}$ with FR and NR approaches and different cases

Case	I	II	III	IV
FR	0.957	0.974	0.979	0.991
NR	0.128	0.198	0.015	0.15

7.1 Cumulative % of variance explained and accuracy of the models

Table 3 shows the cumulative % of variance for different cases with FR and NR approaches, with $(\#)$ representing number of factors obtained in the FA, that correspond in each case to eigenvalues greater than 1 as explained in Section 6.

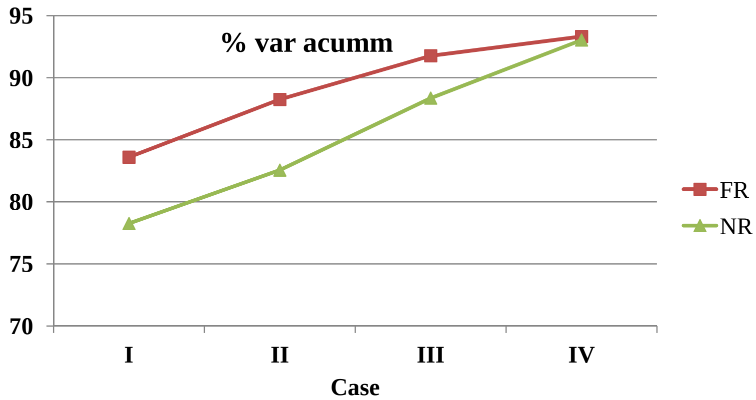
Table 4 shows the R^2 coefficients achieved by the different regressions to estimate $\widehat{MOS}$ with FR and NR approaches, for the different cases. Notice that in NR models the R^2 coefficients are very low (less than 0.2). In Fig. 3 we compare the cumulative % of variance in the different cases with FR and NR approaches as well as we show the number of factors that correspond to eigenvalues greater than 1 as explained in Section 6. We have seen that the number of factors increase linearly with the number of statistics included in both approaches, while the cumulative % of variance explained tends to a maximum with FR and even keeps growing linearly with NR. The main reason for this, is because with FR we add 14 new variables in each case, while in NR we only add 5 of them. In both approaches, the cumulative % of variance explained is always above 78%.

7.2 Average estimation error

From previous $\widehat{MOS}$ expressions ((2)-(5) for FR and (6)-(9) for NR), in Table 5 we compare the percentages of the average error estimating the real subjective MOS. In order to estimate the average error, we consider the set of videos for testing purpose as explained in Section 5, in particular: *coastguard*, *flower*, *hall*, *paris*, *silent* and *tempete*. We see that the FR approach is accurate for the different cases, with an average error less than 10% and a minimum average of 3%. Nevertheless with the NR approach, things are very different, where we have a minimum average error of 41.91% (*case II*) and a maximum of 182% (*case III*). With the NR approach, notice that we have a R^2 coefficient very low (less than 0.2) for all cases, as shown in Table 4. Thus, with there results we discard the NR approach for further evaluation.

7.3 Quality metric evaluation

Finally, in order to evaluate the accuracy and quality of the FR metric, we follow the recommendations given by VQEG [14]. This process consists of adjusting the scatter plot of the estimated MOS vs. measured MOS values, using in this case a nonlinear monotonic regression



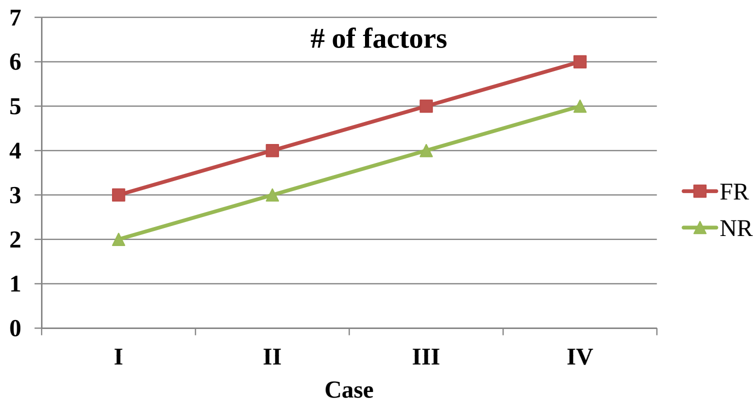


Figure 3: Cumulative % of variance (top) and number of factors (bottom) in the different cases with FR and NR approaches

Table 5: Average errors in % estimating real MOS values for different cases using FR and NR approaches

Case	FR	NR
I	0.035	0.664
II	0.099	0.419
III	0.062	1.821
IV	0.033	0.567

Table 6: Objective video quality metrics.

Metric	Description
PSNR	Peak Signal-to-Noise Ratio is a numerical measurement based on the mean square error calculated for each frame (Y component only)
VQM [41]	Video Quality Metric is DCT-based metric which exploits the property of visual perception and it is contained in ITU-T recommendation J.144 [42]
3SSIM [43]	3SSIM is based on region division (edges, textures and smooth regions) of source frames. Notice that the human eye can see difference on textured or edge regions precisely than on smooth regions. The result metric is calculated as weighted average of Structural SIMilarity (SSIM) metric for those regions.
MSSSIM [44]	MultiScale SSIM based on SSIM metric of several downscaled levels of original images. Result is weighted average of those metrics. MSSSIM accounts for the multiscale nature of both natural images and human visual system

with a 4-parameter cubic polynomial fitted to the data with the best fit in a least squares sense. The functional form of the nonlinear regression is not critical as specified in [14]. In particular, we are going to evaluate the proposed metric given by (3) using only mean and variance (*case II*) in the FR approach, because it is the best option as a tradeoff between complexity and accuracy (estimation error). We have compared it with well known publicly available objective video quality algorithms, described in Table 6. These video quality metrics are implemented in the MSU video measurement tool [45]. Fig. 4 shows the nonlinear regressions and the scatter plots for the proposed FR approach (estimated MOS), as well as the available objective video quality algorithms (see Table 6). Once we have plotted the objective metrics vs the subjective MOS, we perform the statistical analysis, described in [14], to show the evaluation metrics relating to: a) prediction of accuracy, by the Pearson Correlation Coefficient (PCC or R [46]) and Root Mean Square Error (RMSE), b) monotonicity by Spearman Rank Order Correlation coefficient (SROCC), and c) consistency (Outlier Ratio). More detail for these evaluation metrics can be found in [12]. The fidelity of an objective quality assessment metric to the subjective assessment is considered high if PCC and SROCC are close to 1, as well as OR and RMSE are low, close to 0.

As shown in Table 7, on the one hand, we can see that PCC and SROCC for all the metrics, except for MSSSIM, are above 0.93, which are good results for video. On the other hand RMSE and OR are smaller than 0.3 for for all the metrics, which means that most of the MOS computed by the metrics are within the grades given by the evaluators. It is worth mentioning that PSNR, although it does not follow the human visual criteria, it has a good performance due to the packet loss rate of 10^{-6}, as detailed in Section 5.

8 Conclusion

Because QoE is highly subjective in nature and several factors influence on it, we have applied a statistical method called Factor Analysis to find out a robust video quality metric, considering all types of variables gathered in live video streaming applications. These variables are

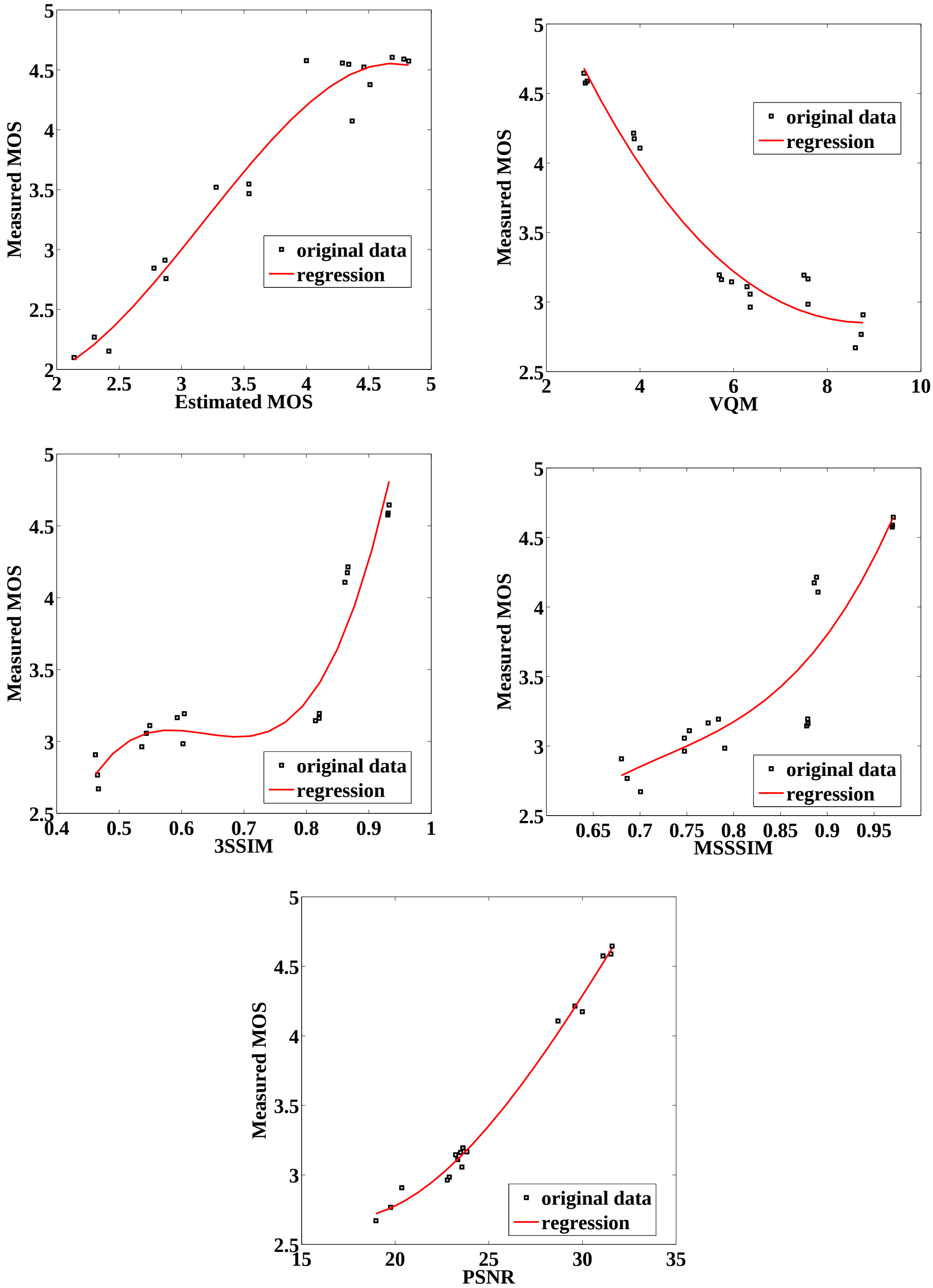


Figure 4: Scatter plots: objective metrics vs. measured MOS. From left to right, top to down: $FR\ case\ II3$, VQM, 3SSIM, MSSSIM and PSNR.

Table 7: Evaluation metrics to compare the performance of the different ($\widehat{MOS}$) expressions with different approaches against other video quality algorithms.

algorithm:	**PCC**	**SROCC**	**RMSE**	**OR**
FR case II (3)	0.98	0.89	0.19	0.27
VQM	-0.98	-0.96	0.15	0.20
3SSIM	0.94	0.94	0.26	0.06
MSSSIM	0.92	0.91	0.30	0.09
PSNR	0.99	0.97	0.12	0.07

tied with QoS, bit stream and video, including also their first four standardized moments. We have expressed the QoE for live video streaming applications in terms of MOS and have found several expressions to estimate it ($\widehat{MOS}$) with different approaches, FR and NR. We have defined these approaches by combining different measured variables as well as their statistics though different cases. In particular, FR requires information of the original video to measure QoS, bit stream and video related variables, while NR requires only QoS related variables.

From the Factor Analysis process, we have seen that the number of factors, though the different cases, increase linearly with the number of statistics included in both approaches for the variables. Nevertheless, the cumulative % of variance explained tends to a maximum with FR while keeps growing with NR. In both approaches, the cumulative % of variance explained is always above 78%.

At the end, we have found out using the FR approach an accuracy of the MOS estimation around 93% in the worst case. In particular for the NR approach, although it seems to explain well the variance of the set of variables (more than 78%) with few factors (less than in FR approach), the number of variables used (only the ones related to QoS) are not enough to give an acceptable estimation error; the minimum average error is above 41%. This result agrees with very low values of R^2 coefficient, less than 0.2.

In summary, it should be noticed that the cumulative % of variance for the factors in each approach and case, it is not enough as a criteria for a good estimation model, but the average estimation error and the process to asses the video quality metrics given by VQEG [14]. As it is explained in Section 7.3, this assessment process is done by means of scatter plots against well-known available objective video quality algorithms.

Also, in the estimation process, it is observed that considering as many as statistical moments yields high accuracy in the estimation as well as reveals hidden parameters, but as we stated previously, this is not sufficient to meet the requirements for a good video quality metric. It is worth mentioning, that in our models, we have variables such as GOP, IFLR, PLD, and PLR which remains constant, mainly due to the packet loss rate of 10^{-6} as detailed in Section 5. Then, to analyze the behavior of the variables in an initial step is important, because these variables could be eliminated to reduce computational complexity.

As future work, the proposed approach could be extended including additional variables both from the Service Provider (e.g. inner variables to the system) and the customer (e.g. resources of the mobile devices) point of view, as well as considering just noticeable differences on these variables. Also, we could consider advanced regression techniques to improve our model.

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