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Estimation techniques to measure subjective quality on live video streaming in Cloud Mobile Media services

Miguel Garcia-Pineda, Jaume Segura-Garcia, Santiago Felici-Castell*

Departament de Informàtica, ETSE, Universitat de València, Avd. de la Universidad S/N, 46100 Burjassot, (Valencia), Spain

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ABSTRACT

The adoption of smart phones, the increased access to mobile broadband networks and the availability of public cloud infrastructures are aligning to the next generation of truly ubiquitous multimedia services, known as Cloud Mobile Media (CMM) services offering mobile video. Nevertheless, due to an inherent higher and variable end to end delay mainly as a result of the virtualization process, new challenges appear. One challenge is given by live video streaming applications when trying to keep a good Quality of Experience of the delivered video, measured in terms of a subjective video quality metric, named Mean Opinion Score (MOS). Our goal is to estimate and predict this subjective metric in a holistic manner using different estimation techniques, such as Artificial Neural Networks, Factor Analysis and Multinomial Linear Regression, with Full Reference and Non Reference approaches. For this, we have analyzed and measured different variables related to Quality of Service, bit stream and basic video quality metrics, throughout the CMM infrastructure. With these variables, we apply the mentioned techniques which allows us to estimate MOS of the delivered video in a robust and reliable way, achieving an average estimation error between 0.46 and 15.94% depending on the technique used. The real MOS has been evaluated through surveys. Finally, we compare the accuracy of the estimated MOS against well known publicly available video quality algorithms, following the recommendations given by Video Quality Experts Group.

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1. Introduction

Big companies like Google, Cisco Systems, Apple and Microsoft predict that by 2020, 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]. These infrastructures are replacing the traditional Content Delivery Networks (CDN) [3] because they are expensive solutions and indeed are designed mainly for static content (not optimized for applications such as live video streaming) and fail when requiring intensive processing and when the content cannot be stored ahead of time, as well as other issues related to scalability, heterogeneity and usability [2].

In this new context, content providers strive to offer the best Quality of Experience (QoE) for customers linked to their different

Quality of Service (QoS) solutions. Therefore, developing accurate, perceptual-based quality metrics is a key requirement for these CMM multimedia services. As QoE is purely related to end-users, we analyze the effect of both core networks and cloud networks as a whole. In addition, subjective testing is time-consuming, expensive and requires special assessment facilities to produce reliable and reproducible test results. However, new challenges appear related to the QoE management [4] over these cloud based infrastructures, in particular with live video streaming, due to the additional delay and jitter introduced by the virtualization processes.

Usually, QoE in video services is measured in terms of subjective Mean Opinion Score (MOS) [5]. In practice, this subjective estimation is carried out using objective video quality metrics. But most of these metrics fail or are not sufficiently accurate, or require extra information that it is unavailable in practice, such as the original video sequence. Thus, to define a reliable, robust and holistic video quality metric, we measure and analyze different variables monitored throughout the whole system, from the streaming server to the end user.

As many factors and variables are affecting QoE in these cloud mobile networks, our goal is to process these measured variables using different techniques such as Factor Analysis (FA) [6], Multinomial Linear Regression (MLR) and Artificial Neural Networks

* Corresponding author.

E-mail addresses: migarpi@uv.es (M. Garcia-Pineda), jsegura@uv.es (J. Segura-Garcia), felici@uv.es (S. Felici-Castell).

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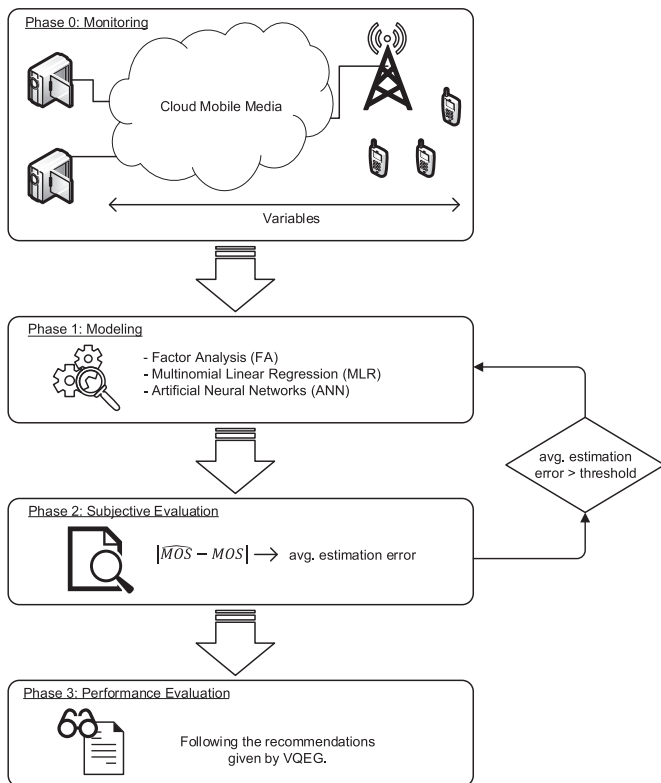


Fig. 1. Flow chart of the global process and phases to find out objective video quality metrics.

(ANN) [7] in order to estimate MOS (denoted by $\widehat{MOS}$), comparing their results with well-known objective video quality metrics. It is worth mentioning that we apply these techniques at different time scales and with two approaches, Full Reference (FR) and Non Reference (NR) [8]. FR approaches require access to the original (or reference) and received video while with NR approaches we do not. In particular, NR metrics are more interesting from a practical point of view of a Service Provider (SP) in order to implement corrective actions. In addition, for the NR approach, we consider two different approaches, the customer (called NR_{cu}) and the SP (called NR_{sp}), where the difference is that in NR_{cu} we include three variables related to the bit-stream measured at the customer site.

Thus, to have a global vision of the different phases carried out in this paper, in Fig. 1 we show the flow chart used in this paper: a) the monitoring process where we gather the different variables throughout the system (phase 0), b) the modeling using the selected techniques FA, MLR and ANN (phase 1), c) the subjective evaluation to measure the capability to estimate the subjective MOS (phase 2) trying to minimize the average estimation error below a certain threshold and d) from the selected models, (phase 3) the performance evaluation to compare our proposed metrics against well-known objectives metrics following the recommendation given by Video Quality Expert Group (VQEG).

The rest of the paper is structured as follows. Section 2 discusses the related work. Section 3 characterizes both the delay and the jitter in cloud infrastructures. Section 4 explains the network infrastructure and test bench, defining the observable variables. Section 5 describes the surveys. Section 6 describes the statistical methods and artificial neural networks used to model the objective video metrics. Section 7 details the results and shows the expressions to define $\widehat{MOS}$ for different approaches. Section 8 analyzes and compares the performance of the proposed metric against well known video quality metrics. Finally, Section 9 concludes the paper.

2. Related work

In the literature we can find several works related to live video streaming over cloud infrastructures. Q. Wang et al. [9] 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. B. Cheng [10] proposes 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 [11] 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 [9–11] 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 [12], 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 the QoS but also the QoE in terms of MOS, estimated using neural networks.

About objective video quality metrics, in recent years have been proposed different FR and NR metrics, such as VQM [13], 3SSIM [14], MSSSIM [15] and O.23 [16]. All these metrics except O.23 are FR. VQM (Video Quality Metric) is a DCT-based metric which exploits the property of visual perception and it is contained in ITU-T recommendation J.144 [17]. Besides, based on SSIM [18] (Structural SIMilarity) we have: a) 3SSIM that analyzes region division (edges, textures and smooth regions) of source frames for luminance, contrast and structural similarity and b) MSSSIM (MultiScale SSIM) that takes into account several downscaled levels of original images. It is worth mentioning that O.23 metric (ITU-T P.1201 [16]) is NR, similar to our NR_{cu} approach, and requires for its calculation: bandwidth, frame rate and size of I frames. Notice that this metric is similar to ITU-T G.1070 based on coding and packet-loss degradation. A performance comparison of some of these previous FR video quality metrics in a subjective manner using H.264/Advanced Video Coding (AVC) are done in [19] and [20], following the recommendations given by [21], concluding that the Spatial MOTion-based Video Integrity Evaluation (MOVIE [22]) index shows the highest performance and Temporal MOVIE the lowest among the studied metrics. In the context of audio and video, the authors in [23] evaluate the different Full and Reduced Reference (which only requires partial information of the original video) quality metrics. They conclude that statistically speaking there are currently no objective metrics available that can replace subjective quality assessments and in particular, Peak Signal to Noise Ratio (PSNR) shows the worst results from the subjective point of view. Similarly, the study presented in [8] concludes that MSSSIM, VQM and the perceptual spatio-temporal frequency-domain based on MOVIE indexes are the most reliable in terms of subjective MOS values.

In addition, different techniques have been used to model QoE. In [24] the authors propose a QoE index for tablet devices based on linear regression, taking into account only the bit rate, packet loss rate, play out delay and transmission interruption of H.264/AVC video sequences transmitted over lossy wireless channels. This index is only correlated with subjective MOS and is compared to SSIM and PSNR. In [25], the authors define a lightweight NR bit stream using linear regression techniques to estimate VQM, based on packet loss rate and the interval between instantaneous decoder refresh frames. Finally in [26], the authors characterize the impact of packet loss on QoE, in a IP-based distribution network and describe a thorough analysis of random and burst packet loss by taking into account several objective video quality metrics.

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