A Hybrid Prediction and Assessment Quality of Experience Approach for Videostreaming Applications over Wireless Mesh Networks

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Abstract. *As Wireless Mesh Networks (WMNs) have been increasingly deployed, the need of new quality measurement schemes became essential since operators want to control and optimize their network resources, while keeping users of multimedia applications with a good quality level. However, currently WMN in-service assessment schemes fails in capturing subjective aspects of real-time multimedia content related to the user perception. Therefore, this paper proposes a new on-the-fly quality estimator approach, called Hybrid Quality of Experience (HyQoE) Prediction, for real-time videostreaming applications. Moreover, performance evaluation results present the benefits and accuracy of HyQoE in predicting the user perception compared to well-know subjective and objective methods in a WMN scenario.*

1. Introduction

Recent advances in wireless communications and real-time multimedia applications, as well as, the explosion in the numbers of users are changing the Internet and creating a wireless content-aware multimedia era. Regarding wireless systems, Wireless Mesh Networks (WMNs) [Akyildiz and Wang 2009], based on the IEEE 802.11 standard, is the most interesting solution for low cost and quality level support in last mile networks. Regarding real-time multimedia, new thousands of users and providers are sharing their content ubiquitously, where quality level assurance is the main requirement to the success of such multimedia systems.

Before the beginning of multimedia communication era, simple network/packet level parameters, such as bandwidth, loss, delay or other network-related metrics were enough to evaluate the Quality of Service (QoS) of applications, because the provided services are plain applications, such as e-mail or file transfer. These applications do not have strict quality level requirements, for example, with file transfer, bandwidth or delay would probably be sufficient to imply quality of service.

However, real-time multimedia applications are being deployed on IP networks and technical parameters can no longer assess accurately the quality of service as it is perceived by human. Users expect to have good perceptual quality that can be derived from many factors, including not only technical parameters, but also user's experience.

The problem is that it is not easy to accurately assess the performance of multimedia applications, as the quality perceived by the end-user is a very subjective concept. In the context of real-time videostreaming applications, QoS measurements become not sufficient for evaluating the quality of delivered video, especially that they do not consider user satisfaction. For this reason, many researches have started to study the evaluations of Quality of Experience (QoE), which can be considered as the overall performance of a system from user's perspective.

Different subjective and objective assessment tools have been developed and applied trying to effectively evaluate the user perception. In brief, subjective assessment [ITU-R 2002] consists of human observers rating the overall quality of an image or a sequence. On the other hand, objective assessment [Park et al. 2006] [Manish and Constantine 2007] stands for the use of techniques (generally signal processing algorithms) to produce automotive, quantitative and repeatable measures of visual quality. However, each approach still has its own limitations. Thus, a hybrid assessment has been proposed in [Rubino et al. 2006] [Bonnin et al. 2008] to cope with the limitations of both subjective and objective methods.

This paper proposes a Hybrid Quality of Experience (HyQoE) prediction scheme that can evaluate the quality level of a video sequence automatically, in real-time and correlates well with the results obtained from subjective tests. In order to assesse the QoE of the video perceived by end-user, a tool was built taking as input the values of a set of parameters related to the video and encoder characteristics, and correspondingly quantifies the video quality.

HyQoE is based on statistic learning using random neural network (RNN) and was trained with real videos generated over a simulated wireless mesh scenario. Performance evaluation results show how the HyQoE tool can evaluate the multimedia quality in a manner that is close to real human observations, and in real-time. Consequently, HyQoE outperforms the well-known objectives metrics and also the subjective methods for evaluating the perceived video quality.

The remainder of the paper is organized as follows. Section II describes some related works. In Section III we introduce a comparison overview of the three assessment approaches. Section IV explains HyQoE for videostreaming over wireless mesh networks. The test environment, scenario, implementations, results of experiments and simulations are described in Section V. Finally, Section VI gives conclusion as well as future works about QoE prediction.

2. Related Works

Real-time videostreaming has strong constrained that lead to a series of specific technical problems. The most important one is that videostreaming quality, as perceived by the user, is very sensitive to frame losses [Cancela et al. 2008].

A hybrid assessment tool called Pseudo-Subjective Quality Assessment (PSQA) has been proposed in [Mohamed 2002] [Rubino et al. 2006] [Bonnin et al. 2008]. Using PSQA, some works have been done using hybrid technique [Piamrat et al. 2009], for example, VoIP over WLANs [Rubino et al. 2006], video application over DiffServ networks or IPTV over peer-to-peer networks [Cancela et al. 2008].

[Piamrat et al. 2009] presents performance evaluation of hybrid approach for assessing QoE in videostreaming application over wireless networks in different network conditions (using variation of loss rate and its distribution), but the results are compared only with Peak Signal to Noise Ratio (PSNR).

Ghareeb and Viho (2010) focus in to determine the most appropriate method for assessing the QoE in the context of Multiple Description Coding (MDC) videostreaming, over multiple overlay paths, in video distribution networks (VDN). For this objective, it compares three different types of QoE assessment approaches (subjective, objective and a hybrid) that can overcome the limitations of both subjective and objective ones. Results show how the PSQA can out perform only the well-known PSNR, as well as, the subjective methods for evaluating the perceived video quality in context of MDC streaming.

Koumaras et al. (2010) proposes, describes and evaluates a novel framework for video quality prediction of MPEG-based video services, considering the perceptual degradation that is introduced by the encoding process and the provision of the encoded signal over an error-prone wireless or wired network.

RNN has received, since its inception in 1989, considerable attention and has been successfully used in a number of prediction applications. Details about RNN out scope of this paper, but, for further information please see a study in Mohamed and Rubino (2002). On the other hand, for QoE evaluating, RNN is better than a traditional neural network [Mohamed 2002] [Timotheou 2009] [Georgiopoulos 2010], and its use is mandatory for future comparison with other techniques for assessing the performance of HyQoE. In Georgiopoulos et al. (2010), a critical review paper is presented and focused on the feed-forward RNN model and its ability to solve classification problems.

HyQoE and PSQA use RNN, but differences can be listed as follows. PSQA is not applied in wireless mesh networks, which is becoming very popular nowadays. HyQoE uses a database of videos obtained by simulation taking advantage of a client's infrastructure backbone. The videos are embedded the Network Simulator, transmitted and reconstructed with the aid of Evalvid and MSU tools. In PSQA proposals, losses are only included in the simulated traces of the videos and not real scenarios.

Using a greater videos variety, HyQoE takes into account six parameters (percents losses in I frame, P frame and B frame, general loss, complexity and motion) that directly impact the quality of the video to Mean Opinion Score (MOS) predict. In general, the other hybrid approaches mostly use only QoS parameters, such as average length of burst, packet loss and without considering the diversity of movement and/or complexity. HyQoE is compared with the PSNR, Structural Similarity Index Metric (SSIM) and Video Quality Metric (VQM) metrics, while others schemes only were compared with PSNR, which not suitable for video QoE assessment.

3. Quality of Experience Assessment Approaches

3.1 Subjective Assessment

The most accurate approach to assess perceived quality is the subjective assessment because there is no better indicator of video quality than the one given by humans.

However, the quality score given by a human also depends on his/her own experience. The subjective assessment consists in building a panel of human observers which will evaluate sequences of video depending on their point of view and their perception. The output of the test is in terms of Mean Opinion Score (MOS) [ITU-T 2000], which is given in Table I.

Table 1. MOS and possible conversion to PSNR

MOS	QUALITY	IMPAIRMENT	PSNR (dB)
5	Excellent	Imperceptible	> 37
4	Good	Perceptible but not annoying	31 – 37
3	Fair	Slightly annoying	25 – 31
2	Poor	Annoying	20 – 25
1	Bad	Very annoying	< 20

Even if this subjective approach is the most accurate because it is evaluated by real human, it is very expensive in terms of man power. Moreover it is time consuming and cannot be used in an automatic measurement or real-time monitoring tools. Thus, they cannot be easily repeated several times nor used in real-time (being a part of an automatic process).

There are standard methods for conducting subjective video quality evaluations, like ITU-R BT.500-11 [ITU-R 2002]. These methods differ only in some metrics according to the application in use, such as the evaluation scale, the referencing video, the length of the video sequence, the number of observers, or the kind of display, etc.

3.2. Objective Assessment

Since the subjective approach is not appropriate for implementation, many researchers have been looking for another approach that can be processed automatically using information such as network parameters. Consequently, they are interested in an objective approach that uses algorithms or formulas and quality of service measurements of a stream given by technical parameters that can be collected from the network.

One of the most commonly and simply used objective measures for video is Peak Signal to Noise Ratio (PSNR) [Park et al. 2006] because it is the most simple objective video quality assessment used by many researchers. PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Table I shows the mapping of PSNR to MOS. PSNR is the logarithmic ratio between the maximum value of a signal and the background noise namely Mean Squared Error (MSE) as equation 1. MSE can be calculated by equation 2, where $M \times N$ indicates the pixels of each frame and $o(m, n)$ and $d(m, n)$ are the luminance pixels in position (m, n) in the frame.

$$(1) \quad PSNR = 10\log\frac{255^2}{MSE} \qquad (2) \quad MSE = \frac{1}{M.N}\sum_{m=1}^{M}\sum_{n=1}^{N}\left|o(m,n)-d(m,n)\right|^2$$

The Structural Similarity Index Metric (SSIM) improves the traditional PSNR and MSE, which are inconsistent with Human Visual System (HVS) characteristics, such as human eye perception [Wang et al. 2004]. The SSIM metric is based on frame-to-frame measuring of three components (luminance similarity, contrast similarity and structural similarity) and combining them into a single value, called index. The SSIM index is a decimal value between 0 and 1, where 0 means no correlation with the original image, and 1 means the exact same image.

Another objective metric is the Video Quality Metric (VQM) method defines a set of computational models that also have been shown to be superior to traditional PSNR and MSE metrics [Revés et al. 2006]. The VQM method takes as input the original video, the processed video, verifies the multimedia quality level based on human eye perception and subjectivity aspects, including blurring, global noise, block distortion and color distortion. The VQM evaluation results vary from 0 to 5 values, where 0 is the best possible score.

3.3. Hybrid Assessment

Apart from the two approaches described previously, one hybrid assessment called Pseudo-Subjective Quality Assessment (PSQA) [Mohamed 2002] [Rubino 2010] has been created to provide accurate QoE assessment as perceived by human. PSQA [Bonnin et al. 2008] allows quantifying the quality of a videostreaming at the receiving end, in a manner that is very close to the human observations, and in real-time.

The hybrid assessment is a subjective evaluation in the methodology, but this stage can be done only once and used as many times as necessary with the help of quality factors (objective parameters previous selected). An important point of HyQoE is that they are based on statistic learning using RNN. The idea of both is to train the RNN to learn the mapping between QoE score and technical parameters so the trained-RNN can used as a function to give QoE score in real-time.

Thus, it is necessary to understand that HyQoE is an application and system-dependent tool, if other network technologies were used, e.g., Wimax, other parameters would be considered and videostreaming quality prediction would be different. Therefore, a new training stage must be done for every new application. However, as mentioned before, the training procedure is done once and then the trained network can be used in real-time and as many times as necessary.

4. QoE-Assessment for videostreaming

4.1. MPEG Video Structure

The MPEG standard [Mitchell and Pennebaker 1996] defines three frame types for the compressed videostreams, namely I (Intra-coded), P (Predictive-coded) and B (Bi-directionally predictive-coded) frames. The frame classification is mainly based on the procedure, according to which each frame type has been generated and encoded. The successive frames between two succeeding I frames define a Group of Pictures (GoP).

In the MPEG literature the GoP pattern is described by two parameters GoP (N, M), where N defines the GoP length (i.e. the total number of frames within each GoP) and M is the number of B frames between I-P or P-P frames, as shown in Figure 1.

In the Figure 1, the arrows indicate the encoding/decoding correlation between the frames and more specifically that the B and P frames depend on the respective preceding and succeeding I or P frames. In the MPEG codec, the I-frame coding technique is limited to process the video signal on a spacial basis, relative only to data within the current I-frame. However, this codec has more efficiency compression in the

P-frames and B-frames since the technique used in theses frames explore temporal or/and time-based redundancies.

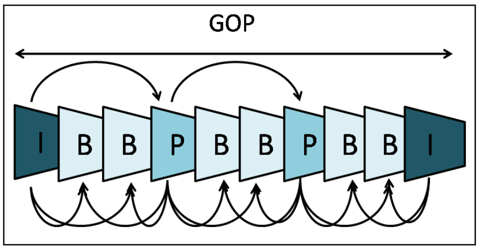


Figure 1: MPEG GoP struture.

As shown in Figure 1, in a GoP an I-frame is the main reference of a P and B frames, and the I-frame are coded with no reference to any other frame. Besides that, P-frames are predicted from I-frames and from other P-frame, although only in the forward time manner. Each P-frame within the GoP is predicted from the frame immediately preceding it (an I-frame or a P-frame). The B-frame uses forward/backward interpolated prediction from the previous I and P frames, as well as from the succeeding I and P frames, as shown on the Figure 1. However B-frames are not used to predict other frames.

4.2. HyQoE for videostreaming MPEG

4.2.1. HyQoE Implementation

In order to implement the HyQoE approach, it is summarized below the four steps that are necessary for its implementation and validation.

4.2.1.1. Quality-affecting factors

The hierarchical structure of MPEG encoding allows to identify different impact levels that an IP packet loss has on viewer's quality of experience. If the network drops, at least, one IP packet within an I-frame, the errors will be propagated through the rest of the GoP, because the MPEG decoder uses the I-frame as the reference frame for all others frames within a GoP. When this occurs, the video quality will be recovered only when the decoder receives an unimpairment I-frame. If the dropped packet is a P-frame, the impairments will be extended through the remainder of the GoP. At last, if the dropped packet is a B-frame, the damage will affect only that particular frame.

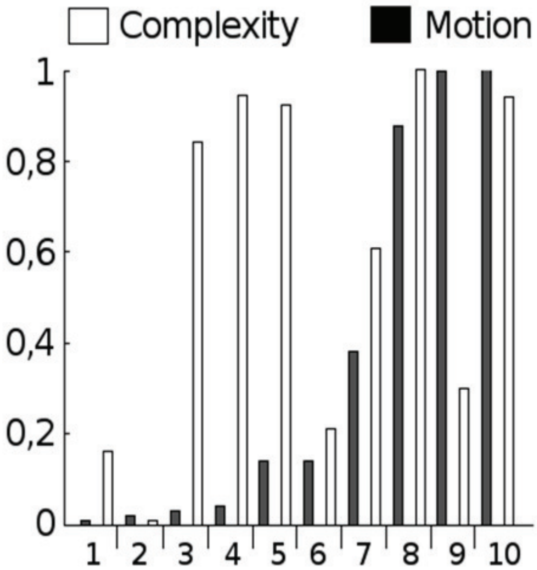
Besides that, the impact of a dropped packet varies with the video motion. This occurs because high-motion content should have low temporal redundancy and this makes the B and P-frames larger. With larger P-frames, a greater probability exists that the loss will affect a P-frame. In comparison, low-motion videos allow the P and B frames to be more compressed, in this case the probability of a loss affect an I-frame is greater.

Another parameter that has impact in the video quality prediction is the complexity. This occurs because when a frame is damaged, the interpolation algorithm in the decoder tries to predict the loss data using neighboring information. If the frame complexity is high, the interpolation algorithm does not achieve high performance because the different kinds of texture that a complex video has.

Finally, in this first stage, it is selected a set of quality affecting factors that have an impact on overall video quality. The selected parameters were: percentage of I-frame, P-frame and of B-frame losses, overall loss percentage, video motion and complexity estimations. As mentioned before, each type of frame can distort differently the quality perceived by the user because each one propagates errors into the GoP differently. The motion parameter was selected because it changes the loss probability of each frame types distributed over the network, while complexity modifies the behavior of the interpolation algorithm of the MPEG.

4.2.1.2. Distorted video database generation

For generate a distorted video database, ten videos were selected from the Video Trace Library (2011). The selected videos have high, medium and low level of motion and complexity. The Figure 2.a) shows that four videos have low motion, two videos have medium motion and four videos have high motion.



a)

Number	Video name	Frames
1	Akiyo	252
2	Mother and daughter	252
3	Hall monitor	252
4	Container	211
5	News	211
6	Silent	252
7	Coastguard	252
8	Mobile	252
9	Football	218
10	Flower	210

b)

Figure 2: a) Motion and complexity video estimation. b) Selected videos

In the Figure 2.a) is possible to see that the relation between motion and complexity is not proportional. In four videos (3, 4, 5 and 9), the difference between motion-complexity was more than 70%. The name and the frame quantity of each video selected is shown in the Figure 2.b), respectively.

To obtain the motion and complexity values shown in the Figure 2.a) an algorithm was used to calculate the motion estimative based on absolute differences between frames. The algorithm used to calculate the complexity estimative was adapted from [ITU-T 2000] proposed for single images which is a measure for image activity that is derived from the amount of edges in an image.

After selecting the set of quality affecting factors, was necessary, in this stage, to choose a mode to vary the selected set of parameters. In order to do this into a simulated scenario and with as different as possible wireless network conditions, a client was positioned randomly into the scenario receiving from the gateway the original video previously selected. During the simulation experiments, users received videos with different quality level (according to current network conditions and video impairment). This stage is visible in the first part of the Figure 3.

4.2.1.3. Subjective Quality Assessment

In the third stage, the video database was evaluated subjectively. For that, its was asked for a panel of human observers to evaluate the distorted videos. The MOS was computed using an average score obtained from all observers and the corresponding MOS was put into two separated databases called *training* and *validation* databases, as shown in Figure 3. For subjective evaluation was used a MOS system based on the [ITU-T 2000] recommendations with a total of 25 non-expert observers.

4.2.1.4. Learning of the quality behavior with RNN

As presented in Figure 3, after humans evaluating each distorted video with specific parameters conditions, the training process was done with the training video database in order to obtain the mapping between the selected parameters and human scores. Upon the tool has been trained, it was proposed a function *f* that can map the selected parameters into MOS. After the training process, the validation task is accomplished with the validation video database to ensure that the training were acceptable.

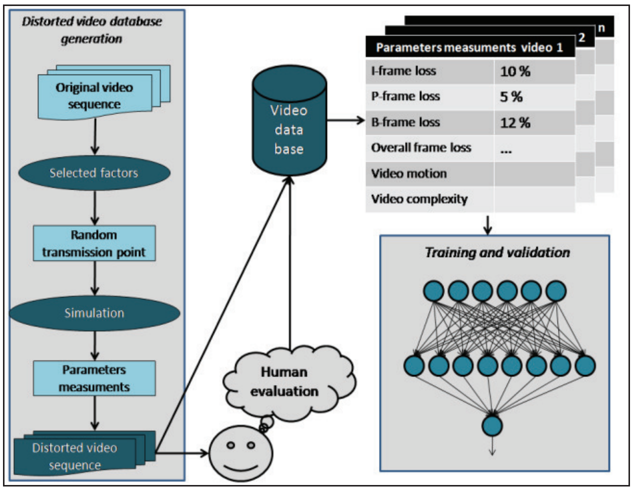


Figure 3. Methodology of HyQoE

Once RNN has been trained and validated, HyQoE can be used for real-time QoE prediction without any interaction from real viewers. It is necessary to measure the quality-affecting parameters at time *t* and to evaluate these values with the RNN to obtain the instantaneous perceived quality. HyQoE gives scores in terms of MOS as close as possible as a human MOS. This is the most beneficial advantage in using HyQoE.

5. Performance Evaluation and Results

5.1. Test Environment and Scenario

Advances in WMNs are essential for the future of next generation wireless systems. Therefore, IEEE 802.11s networks were selected to implement, evaluate and validate HyQoE. As before mentioned in the Figure 2.b), ten videos were encoded with H.264 and have different patterns (duration, complexity and motion).

The selected scenario is based on Federal University of Pará mesh backbone, which is formed of six mesh routers being two gateways as depicted in Figure 4. Additionally to the mesh backbone, a mesh client was simulated receiving videostreaming from the gateway 1 or 2. The client suffers from different loss rate because, for each simulation, the client localization (different wireless conditions) was chosen randomly.

Figure 4: Mesh backbone.

5.2. Implementation

The simulation experimens were carried out by using Network Simulator 2.34 and Evalvid tool [Evalvid, 2011]. For the HyQoE, a RNN was built using the Random Neural Network Simulator 2 [RnnSinn, 1999]. In order to make a comparison between HyQoE approach and existing metrics, it was evaluated together with well-known objective metrics, PSNR, SSIM and VQM, by using the MSU tool [MSU, 2011].

Through Evalvid simulations were able to generate the real simulated video. In order to provide an enough video database, each selected video was simulated 50 times, obtaining a total of 500 videos with different loss patters. From this database, 400 videos was selected for the training base and 100 videos selected for the validation database. This selection was made randomly.

5.3. Results

In this section are shown the obtained scores of MOS, PSNR, SSIM, VQM and HyQoE, respectively. Each of them are discussed and analyzed. The results of objective metrics were normalized by mathematical functions into MOS standard scale.

5.3.1. MOS and Loss

The validation video database consists of 100 videos. The possible MOS scores is 1 to 5 but as shown in Figure 5 the obtained average MOS interval is 1 to 4.5 and the general

MOS average is 2,51. The losses interval is from 1 to 80 percent and the general loss average is 20,04 percent.

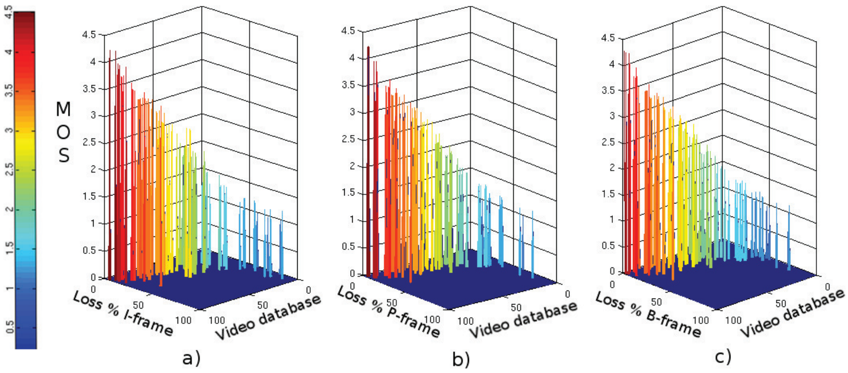


Figure 5: a) Subjective scores of each video and the loss % of I-frame. b) Subjective scores of each video and the loss % of B-frame. c) Subjective scores of each video and the loss % of P-frame.

The Figure 5 shows the percent losses of each frame type related with each video and the obtained MOS. The Figures 5.a), 5.b) and 5.c) illustrate that the MOS values tend to be inversely proportional to the loss frame and the loss pattern for each type of frame are similar. However the Figure 5.a), 5,b) and 5.c) are different mainly due to the mentioned MPEG hierarchal structure. For example, the Figure 5.c) shows that the B-frames are more damaged. This occurs because when a video loss an I-frame or a P-frame, consequently, a B-frame is affected. However, the impact of quality that a damaged B-frame produced is not as relevant as a damaged I-frame.

In general, the Figure 5 depicts that when the loss frame is higher than 50 %, the MOS is close to 1, which means very poor quality. This occurs because the users react strongly to high levels of loss frame (I, P or B). On the other hand, the most difficult videos to evaluate are that ones with loss rage of 0-50%, because in this interval the relation between MOS and loss frame is closer.

5.3.2. PSNR scores

According to [Gross et al. 2004] there is a heuristic mapping of PSNR to MOS as shown in Table I.

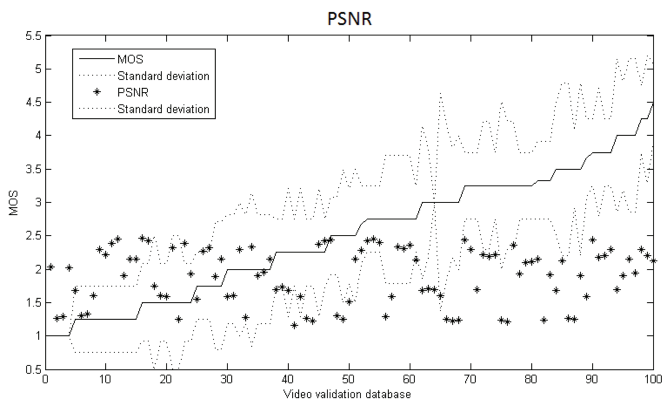


Figure 6: PSNR scores

The obtained PSNR general average score is 1,89 and the Figure 6 shows that PSNR does not have a great variance when the subjective scores are high. For example, in the videos 70-100, the PSNR results were out of the standard deviation interval. These results were poor because the PSNR algorithm does not consider the Human Visual System (HVS) and the MPEG structure during the assessment process.

5.3.3. SSIM Scores

The SSIM metric takes into accounting important user-level parameters, such as color, brightness and structure of a video during its measurement. On average, the SSIM score is 3,45 and, as shown in the Figure 7, the SSIM results are very different for videos with similar loss pattern. For example, in the video database, the SSIM results are concentrated in 2.5 or 4.5. In general, Figure 7 presents that SSIM is not enough to reflect the user opinion when different patterns of loss, motion and complexity are analyzed. Originally, SSIM output range is given in 0 – 1 interval, where 0 is the worst score. To maintain the compatibility between SSIM and MOS a mathematic function was used to transform (normalize) the SSIM original interval to the MOS interval.

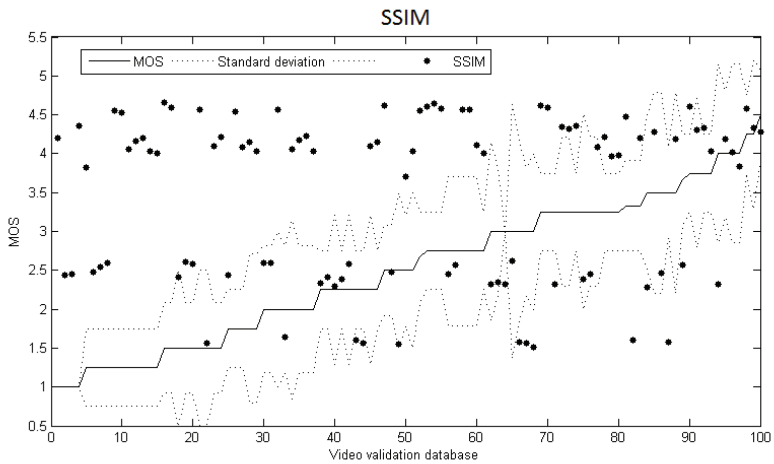


Figure 7: SSIM scores

5.3.4. VQM Scores

The VQM score is based on an algorithm that extracts information from the complexity and motion levels of the video frames. This metric was designed with information also obtained from users. VQM is considered an objective QoE metric, but it has subjective and HVS characteristics.

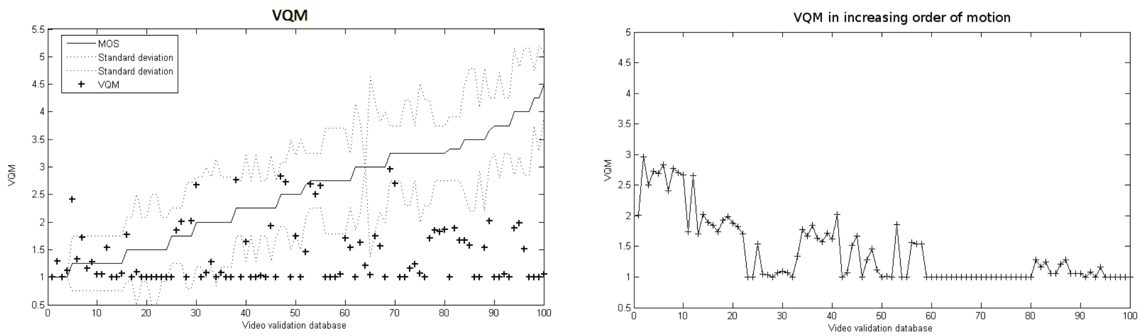


Figure 8: a) VQM scores; b) VQM scores in increasing order of motion.

Figure 8.a) shows the VQM scores obtained in the tested videos. The original VQM output interval is between 0 – 5, where 0 is the best score. Therefore, for the

compatibility of VQM output score and the subjective interval, VQM values were normalized into a subjective interval.

As shown in the Figure 8.a), this metric does not have a satisfactory result for the video database tested. A reason for this lack of performance is that the range of loss, motion and complexity in the test database were very large. As presented before (Figure 2), the video database has 4 videos with low motion, two videos with medium motion and 4 videos with high motion.

In order to introduce the VQM behavior Figure 8.b) illustrates the VQM scores in increasing order of motion and how it tends to be inversely proportional to the motion. The first interval (1 - 40 videos) is composed of four low motion videos and the VQM average is 1,8. The second interval (41-60) is formed of two medium motion videos and VQM average score is 1,31. The third interval (60 - 100) includes four high motion videos and the VQM average score is 1,04. Therefore, all these features in the tested videos contributed to VQM generate low scores.

5.3.5. HyQoE Approach

Figure 9 depicts the HyQoE and MOS scores. Each point in the Figure 9 is the HyQoE score when it was submitted to the validation database. It is possible to observe that for videos with MOS under 2, HyQoE approach sometimes super estimate the MOS, but the difference between them do not exceed 1,5 MOS point and rarely the prediction is far from the standard deviation interval. This super estimation is because humans pay more attention to the period of video where they have seen the worst quality and then they give pessimistic scores.

The general average score of HyQoE approach is 2,47. The results present that the scores given by the HyQoE have better accuracy than the others QoE metrics analyzed. These results demonstrate that the training database has an enough quantity of information for RNN learning and the chosen parameters selected have a great relation with the subjective score.

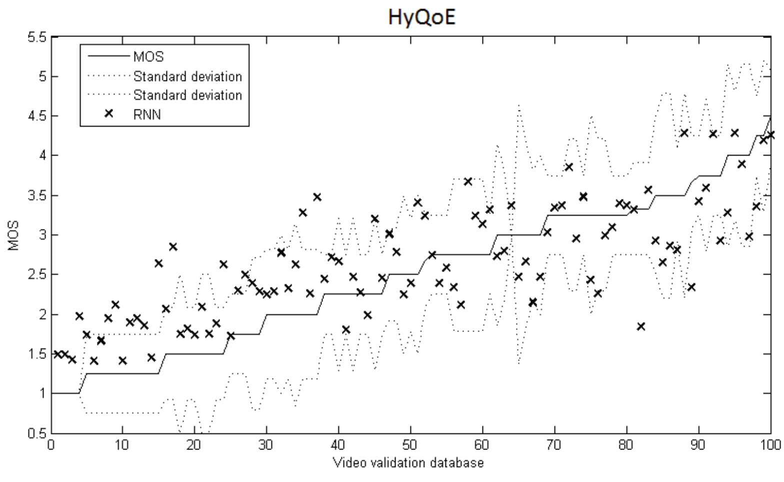


Figure 9: HyQoE scores

6. Conclusions and Future Work

This paper has presented different QoE measurement approaches. It can be seen that HyQoE approach has advantages from both subjective and objective approaches, because it is accurate and it can be implemented for real-time video quality prediction. The scope of HyQoE is QoE analysis and prediction, including information from both QoS and QoE levels

The results show that HyQoE is a powerful tool to provide real-time video quality prediction in future multimedia systems. The HyQoE output can be used also for QoE optimization operations, where based on the predicted video quality score, network management mechanisms (e.g., routing, load-balance, seamless mobility and resource reservation) can be triggered to improve the usage of networks resources and the user perception. Although HyQoE was analyzed in the context of a WMN, it is independent of underline wireless technology and can be easily adapted for other wireless, wired and optical technologies. Future works include the integration of HyQoE with seamless mobility and resource reservation mechanisms.

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