Mobile Video Quality Prediction (MVQP) for Long Term Evolution (LTE)

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***Abstract*—A novel method for Mobile Video Quality Prediction (MVQP) for Long Term Evolution (LTE) is introduced. The MVQP aims to predict the quality of streaming video service over user datagram protocol (UDP) in LTE cellular networks. The MVQP measures cellular network parameters using only smart phone and eliminates the need for expensive LTE receivers. The MVQP prediction achieved high correlations with the human subjective Mean Opinion Score (MOS) testing.**

The study presents the results 100 subjective video quality evaluations using smart phones and based on the ITU-T P.910 recommendation. The MOS was compared with packet loss results showing how these quantities are related to each other and how they impact the final video quality rating. This paper explains Phase 1 and 2 of the MVQP project.

***Index Terms*—LTE, MVQP, Packet loos, Subjective video quality assessment, Video quality**

I. Introduction

Cellular network traffic has increased significantly with the advent of cellular technologies and widespread use of mobile phones. Mobile applications that are using more data have become popular and have congested cellular networks. Many applications, such as video streaming, consume both data and voice and play a major role in increase of the overall traffic.

Video streaming increases as new technology continues to advance. Recent surveys and measurements show a drastic increase in the amount of video streaming by users of smart phones and other hand-held devices. All of this is made possible by fast Internet service provided by cellular network providers [1][2]. Research is now being done to suggest enhancements in video quality assessment.

There is a recognized need to improve video quality to meet user expectations in terms of video resolution and speed of access. Users are spending more for latest smart phones. These phones have the best technology for running high quality video as well as for subscriptions to data plans that enable watching videos without interruption. There is strong competition among service providers in their efforts to satisfy customers by improving their cellular networks. As a result, the providers need to carry out video quality measurements and continuously evaluate the performance of their network. Based on these measurements they make changes of network parameters to provide better service. There is a need to evaluate the quality of video streaming at both the provider's end and the consumer's end so that the improvements can be made.

A. Importance of Video quality from users' point of view

Many thought that mobile phone screens were too small for a high quality video watching experience and that cellular networks would not be able to provide good quality video streaming to their users. The current trend, however, contradicts that perception as people are increasingly using their phones to access video. People watch regular TV programs, sports highlights, movies, and news. Whatever the purpose or the network, users are expecting to have a good video quality experience. Meeting these expectations depends on a variety of factors, including cellular network parameters, user's perception regarding quality, pricing and cost of service, and the type of device used. Users see the service providers as having the responsibility for providing the best possible quality and user experience.

B. Importance of video quality measurements from cellular network provider point of view

Video quality depends on network factors such as frame rates, bit rates, and packet loss. These factors make mobile video services difficult to handle due to bandwidth limitations and device capabilities [3]. Improvement of video streaming services requires a profound understanding of these parameters.

Mobile television and video services have been launched in many countries with success being measured largely by the subjective quality perception of the end user. An understanding of these quality perceptions is necessary in making improvements to reach an acceptable quality level [3].

Clearly, if service providers fulfill user needs and expectations, they will keep existing customers and get new customers. It is known that some cellular companies have more users because their quality is perceived to be better and compares favorably against other providers.

C. Video Quality Measurements Methods

The field of video communication has grown rapidly in the past few years with new technologies leading to mobile videos. It is now important to measure video quality in assessing performance of a digital video system. In general,

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there are two approaches for measuring the quality of video subjective assessment and objective assessment.

Subjective quality assessment is the most accurate method for measuring video quality. In this process, subjects are asked to watch test videos and to rate their quality from 1 to 5 depending upon their perception of the video. After the test viewings, the mean opinion score (MOS) of the values for each test sequence are calculated. Subjective assessment is time consuming and can be expensive since it depends on the availability of the subject viewers and space to hold the test and involves more data processing time. It generally provides a relatively smaller number of tests in a given time period [4].

Objective assessment is a computational model that predicts video quality automatically (i.e. without test subjects) and can be used to optimize algorithms and parameter settings. It has three basic categories: with full reference, with reduced reference, and with no reference - depending on the availability of the original video [5].

II. MVQP Project for LTE

An important issue related to mobile devices that is not yet fully addressed is the ability to predict video streaming quality over a Long Term Evolution (LTE) network. There are some objective methods available for evaluation of video streaming quality over Wi-Fi networks [6]. The MVQP project introduces a novel method for predicting the quality of video streaming over User Diagram Protocol (UDP) through an LTE cellular network. The MVQP measures cellular network parameters using only smart phone which eliminates the future needs for expensive receivers. The MVQP method is divided into two phases as shown in Figure 1.

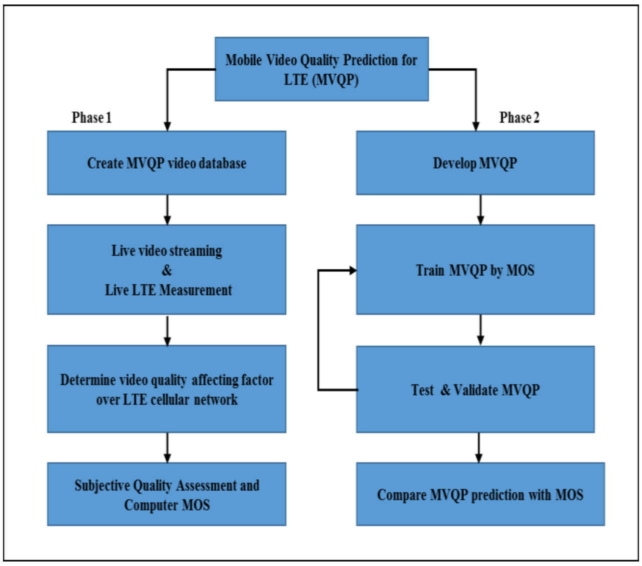

Fig. 1. MVQP Application Rating Screen

III. MVQP Phase 1

The MVQP Phase 1 is explained in [7] and [8]. This paper builds upon the work presented in [7, 8]. Figure 2 shows the MVQP phase 1.

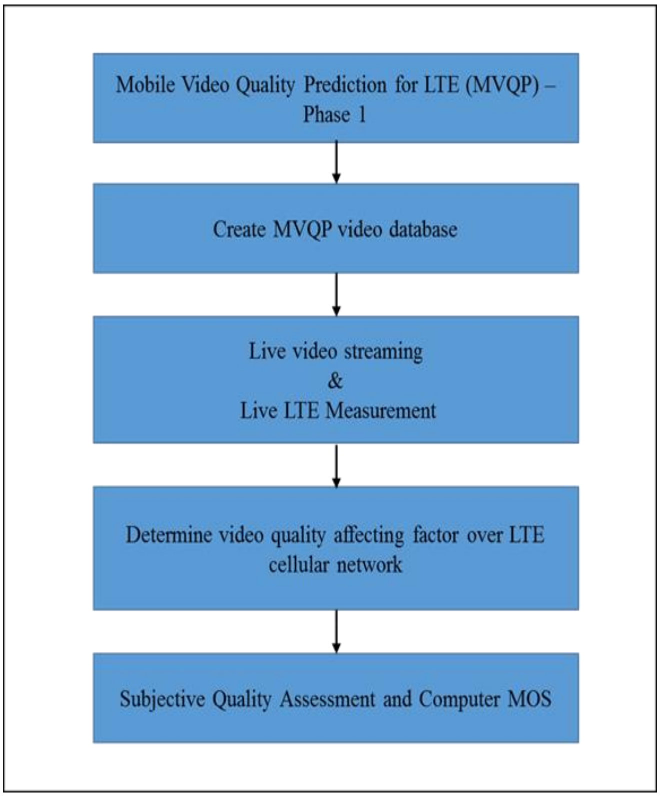

Fig. 2. MVQP Phases 1

A. *MVQP Database*

In [7] a comprehensive 4k resolution raw videos for MVQP project and researchers on video quality assessment is introduced. The MVQP database has a total of 40 videos that have different attributes like motion, contents and type of shots. A group of those videos have been used in MVQP phase 1 as described in [8]

B. *Determine Video Quality Affecting Factors over LTE cellular network*

A video must be coded before it is sent from a transmitter to a receiver. This involves many factors causing distortion. The MVQP project works to determine those distortion factors as part of its aim to predict video streaming quality.

In [8] a set of LTE parameters is evaluated. The study shows consistency and correlation among the Reference Signal Strength Indicator (RSSI), Reference Signal Received Power (RSRP), Reference Signal Receiver Quality (RSRQ), and lost packets. A decrease in RSSI, RSRP, and RSRQ cause increased of lost packets. These parameters impact video quality over an LTE cellular network.

C. *Live Measurements and Distorted Videos Experiment*

Live measurements experiment is explained in [8]. Results of this experiment show high consistency and correlation between the RSSI, RSRP, RSRQ, and lost packets. For RSRQ, lower values than -10 dB correspond to high packet losses in the video. The study also shows that some location are not suitable for video streaming, possibly due to congestion or higher distance from the serving cell. This implies that the quality of service varies at different locations with the cellular network.

D. Subjective Mobile Video Quality Assessment

1. Source and Distorted Videos

This study evaluates 100 videos streamed live from different locations that were selected based on the LTE signal strength over the cellular network. These videos were then saved in MVQP client laptops as described in [8]. The videos were all recorded on or near the campus of Florida Institute of Technology (FIT) campus in Melbourne, Florida. These 100 videos were taken from the following 10-source videos, (each streamed lived at 10 different location).

a) Garden (ga). Shot at FIT's campus. The camera tilts the trees from bottom to top.

b) Building (bu). Shot at FIT's campus on a sunny afternoon. The camera pans from left to right.

c) Playground (pl). Shot in a park on a sunny afternoon. Children are playing on slides.

d) Basketball Training (bt). Shot inside Clemente Center at FIT. Players show fast and complex motions. The camera was stationary.

e) Tree (tr2). Shot near the side of a road on a sunny afternoon. The camera pans across the scene from top to bottom.

f) Basketball Training (bt2). Shot inside Clemente Center at FIT. Different ratios of light are shown with the movement of players. The cameral was showing steady movement.

g) Lawn Service (ls). Shot at FIT campus where a man is mowing lawn. The camera tracks him from left to right.

h) Students at Library (sl). Shot in main library at FIT on early morning. The stationary camera zooms out.

i) Swimming Pool 2 (sw2). Shot at FIT swimming pool on a sunny afternoon. Shows a man jumping into the swimming pool with the bright twinkle of waves clearly visible in water. The camera pans from right to left.

j) Melbourne Downtown (md). Shot from the top of a roof on a cloudy afternoon. The entire area is comprised on tall buildings and trees. Various cars are moving on the road. The camera pans from right to left.

2. Subjective Evaluation Procedure

The method used for the subjective assessment is based on the Absolute Category Rating (ACR) method. ACR is known as the single stimulus method and is set forth in the ITU-IT recommendations [9]. This method is considered the most acceptable method for evaluating quality of telecommunications services. It presents test sequences one at a time to viewers who rate each one independently. The viewer watches a video for 15 seconds and then immediately within the next 10 seconds rates the quality of that video on a scale of 1 to 5. Figure 3 describes the "Stimulus Presentation in the ACR Method".

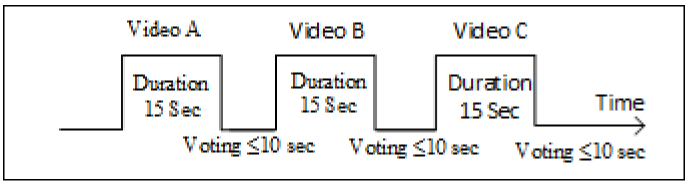

Fig. 3. Stimulus presentation in the ACR method

In this study a non-expert group of individuals (subjects) at FIT and at English Language services (ELS) was asked to watch a set of videos that vary in quality and rate them. A special android application ("MVQP Rating") was developed for this purpose to make the subjective evaluation process easy and efficient. The MVQP Rating application displays a list of videos as shown in Figure 4.

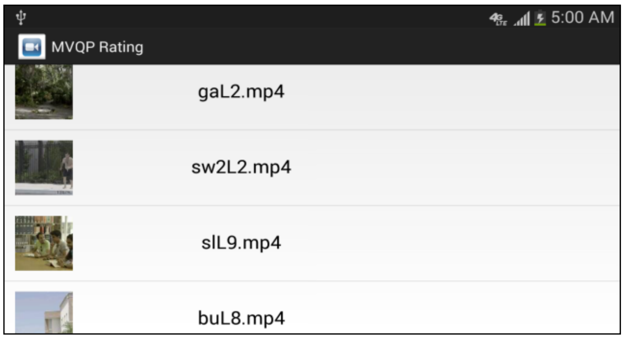

Fig. 4. MVQP Application Main Screen

A subject viewer evaluates a video by first selecting it from a list. After selection, the MVQP application plays the video. When the video is finished playing, a rating screen appears showing the rating scale on a bar of one to five stars. A subject viewer is able to rate the selected video by touching the screen where one star represents the lowest quality and five stars represent the highest quality. See Figure 5, "MVQP Application Rating Screen"

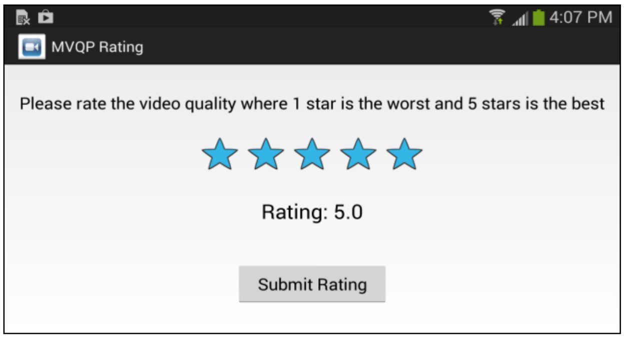

Fig. 5. MVQP Application Rating Screen

The post-rating activity involves steps in which the application deletes the video temporarily and goes back to the video list screen so that each subject viewer evaluates each video only once. A total of 1000 evaluations are conducted from among 100 different individual subject viewers. Both females and males ranging from ages 18 to 40 years old are included. The study is designed so that each video receives 10 evaluations from 10 different individual subject viewers. After evaluations are received for a particular video, the MVQP rating application deletes that video permanently from the video list and save the rating results in MVQP server.

The handset device used in this study is the Samsung Galaxy s3 that has a 4.8-inch screen with a resolution of 1280 x 720. Four such identical handset devices were used for subjective assessment in this study. The videos vary in quality based on the total packet loss during live streaming. Figure 6, "Source Frame" and Figure 7, "Distorted Frame" illustrate how distortion occurs from packet loss.

Fig. 6. Source Frame

Fig. 7. Distorted Frame

3. SUBJECTIVE STUDY ANALYSIS AND RESULTS

Subject viewers evaluated a total of 100 videos that were saved during live radio frequency (RF) signal measurements in [8]. These 100 videos vary in quality based on total packet loss during live streaming. The MOS for each video is shown in Figures 8 – 17 below. In addition to the MOS, 95% confidence intervals of the subject ratings are also calculated to ensure accuracy of the results.

Results of this study show the amount of consistency and correlation between packet loss and MOS. As expected, packet loss and MOS are found to be inversely proportional to each other. Study results also show a small percentage packet loss can have a major impact on video quality.

The graphs in figure 8 to figure 17 represent the relationship between the MOS values and packet loss. The evident trend is that when packet loss increases, MOS decreases. It is also noteworthy that packet loss is high at locations 5 and 9 in the study, which correlates to our previous study of RSSI, RSRP, and RSRQ, values in [8]. The "students at library" (sl) graph in Figure 15 is a good demonstration of this relationship.

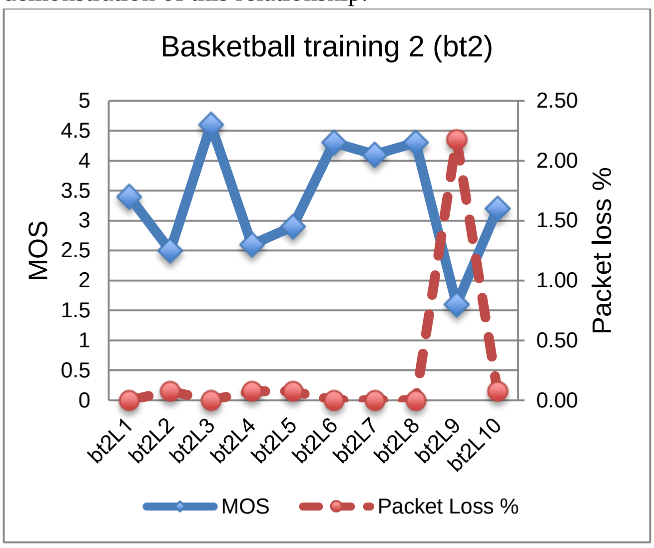

Fig. 8. Basketball training 2 (bt2) video

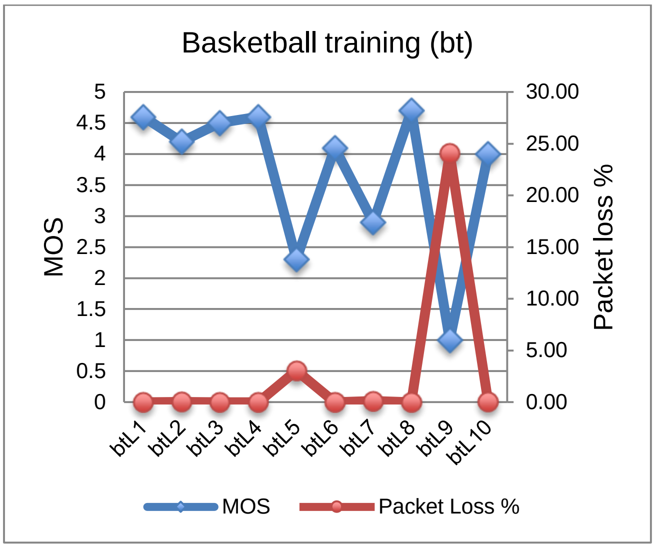

Fig. 9. Basketball training (bt) video

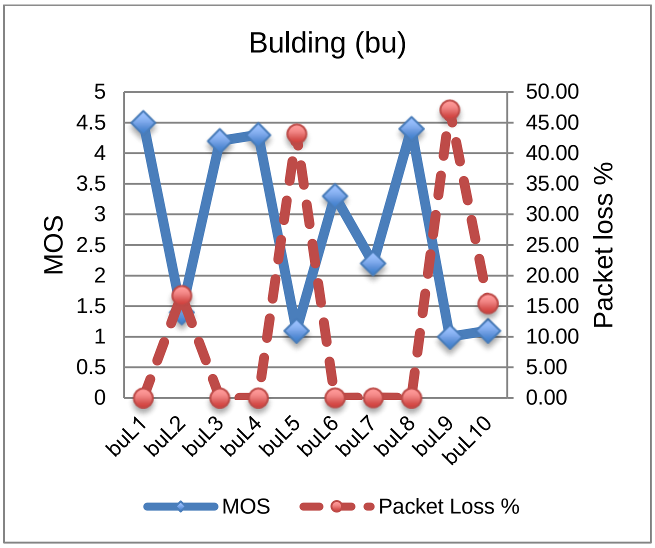

Fig. 10. Building (bu) video

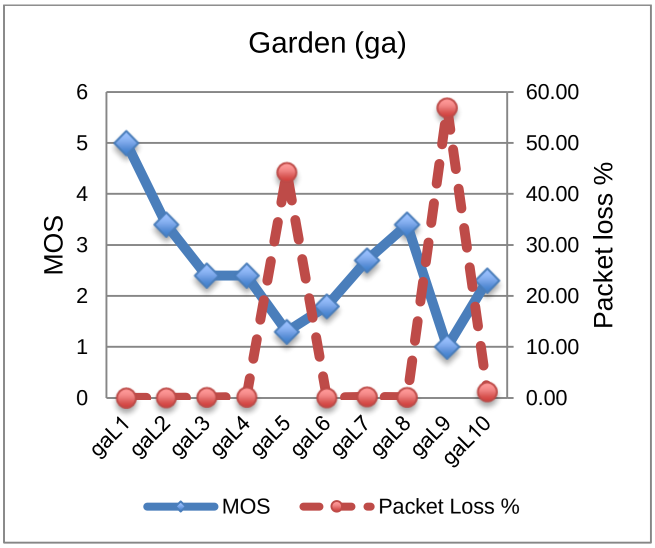

Fig. 11. Garden (ga) video

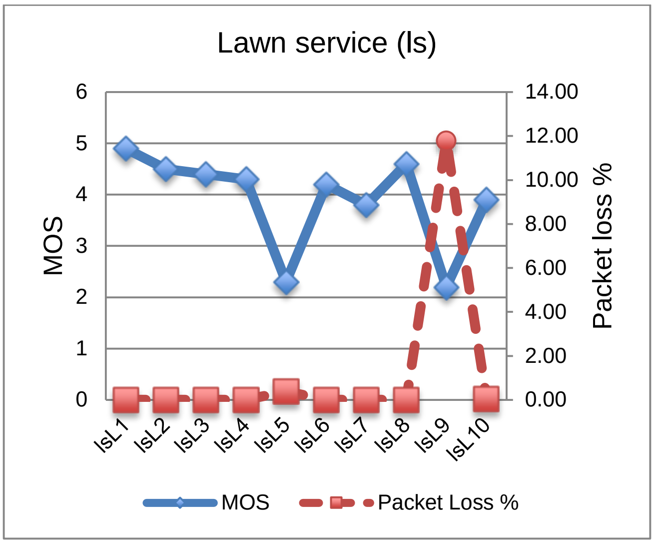

Fig. 12. Lawn services (ls) video

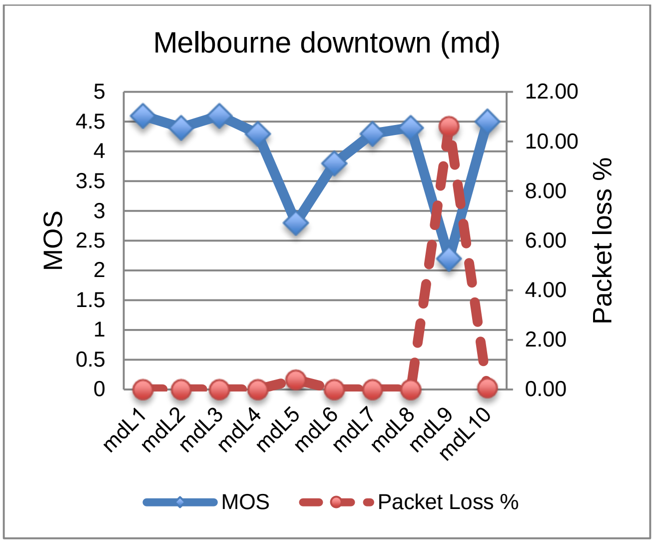

Fig. 13. Melbourne downtown (md) video

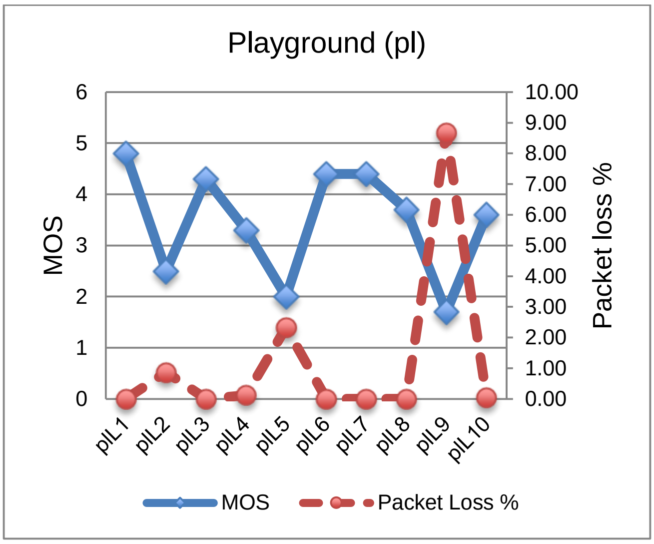

Fig. 14. Playground (pl) video

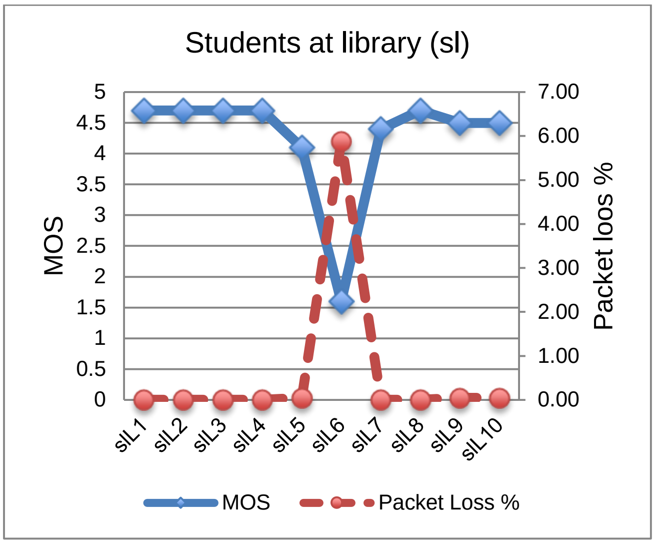

Fig. 15. Students at library (sl) video

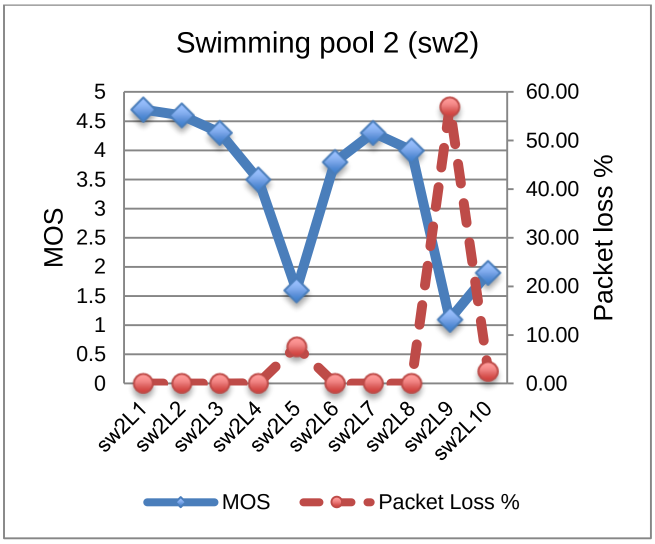

Fig. 16. Swimming pool 2 (sw2) video

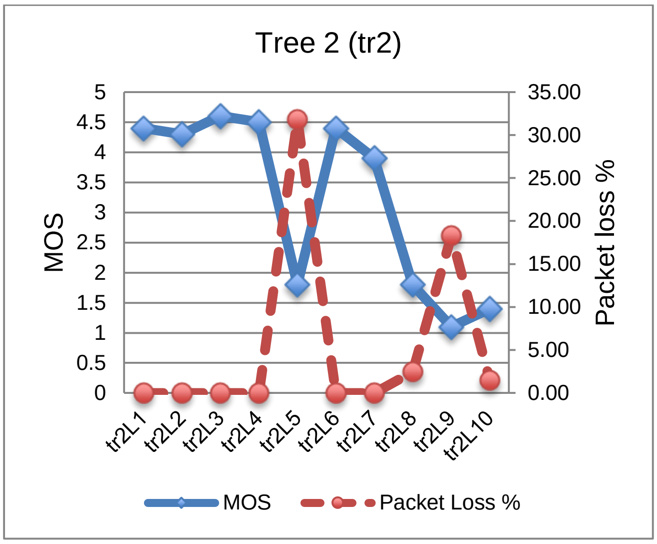

Fig. 17. Tree 2 (tr2) video

IV. MVQP PHASE 2

A. MVQP Design

After studying the LTE network structure and videos quality affecting factors live measurements experiments were conducted. In MVQP phase 1 data were collected and analyzed in both experiments live measurement in [8] and subjective assessment in [12]. Analyzes of these data show high consistency and correlation between the RSSI, RSRP, RSRQ, lost packets, and MOS. The MVQP project considered to be a black box where it is fed by input factors and predict the output MOS. The input factors measurements started when the video streaming starts and recorded any changes in RSSI, RSRP, and RSRQ. This measurements are run in the MVQP background while the streaming run in the foreground which is the main screen of the MVQP application. At the completion of video streaming the lost packets and the average of LTE parameters are calculated then sent to the MVQP black box where the MOS will be predicted using the radial basis function neural network. Figure 18 shows high level design of MVQP

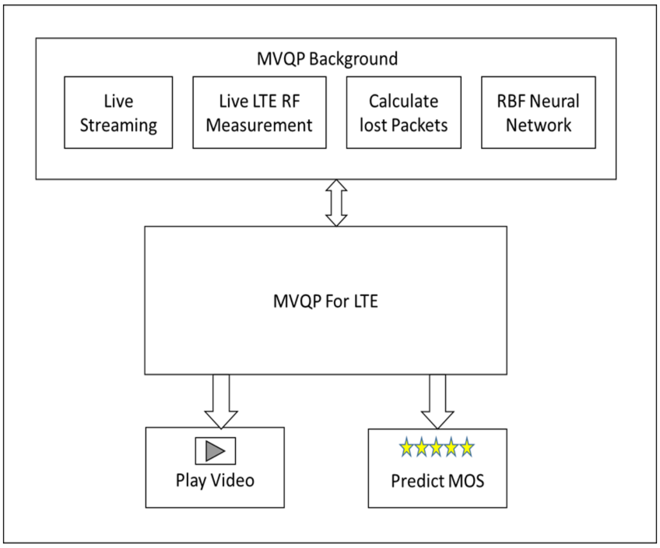

Fig. 18. MVQP high level design

The MVQP is designed to do the following functions

1) Receive streaming video from the server by using the FFMPEG library.
2) Play the received video in the smart phone
3) Record the radio frequency measurements during the streaming process and graph the cellular network parameters
4) Calculate the lost packets during the streaming process.
5) Predict the electronic mean opinion score of video quality

B. MVQP Implementation

MVQP for LTE was implemented in android platform using Java. The MVQP is used radial basis function neural network for prediction. It consists of three layers input, hidden and output, with each layer fully connected to the next one as shown in figure 19. Hidden layer include the nonlinearly-activating nodes, and Output layer include the linearly-activating nodes. Gaussian activation function was used to calculate the nodes on hidden layer. On output layer, gradient reduction algorithm was used to calculate the weights.

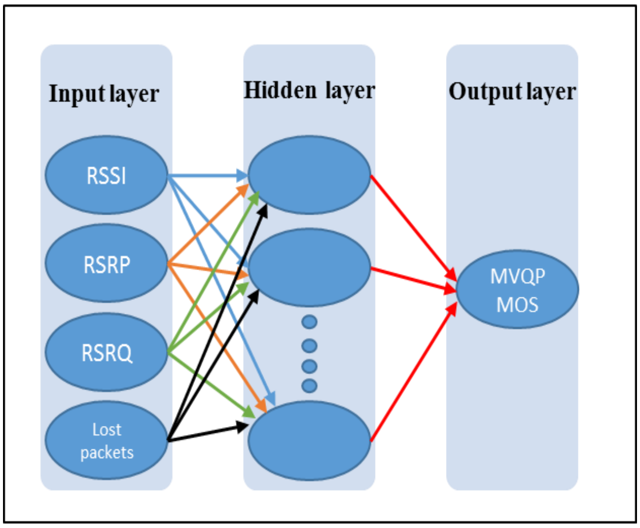

Fig. 19. MBQP – RBF Neural Network

C. Algorithm

1) Read inputs and target output from external source
2) Initialize network parameters i.e. the no. of neurons in the layers, learning rate (η), stop condition error threshold and number of training cycles (epochs).
3) Initialize the centers and the radius
4) Initialize the weights such that they fall in the range [-1, 1]
5) For each iteration in training cycle perform following steps
   a) Choose a random data from training set

   Calculate output of hidden layer as

$$hiddenOutput = \exp\left(-\frac{||input - center||^2}{2 * radius^2}\right)$$

   b) Calculate output of network as

$$predictedOutput = bias + \sum hiddenOutput * weight$$

   c) Calculate error as

$$error = targetOutput - predictedOutput$$

   d) Adjust hidden-output weight as

$$newWeight = previousWeight - (\eta * error * hiddenOutput)$$

   e) Calculate average error
6) Repeat step 4 till maximum number of epoch is reached or average error is reduced to desired number.

D. Train MVQP

During the RBF training process a set of input factors corresponding with their output value are provided in the learning process. The input factors were fed to the input layer and the MVQP -MOS is predicted at the output layer. For each neuron the error, which is the difference between the predicted MOS and the desired MOS, is calculated. The average error then reduced by adjusting the weights and biases. When the average error reach the acceptable rate then the MVQP will stop the training process. Figure 20, 21 and 22 shows the MVQP prediction MOS versus the human subjective MOS in the training phase.

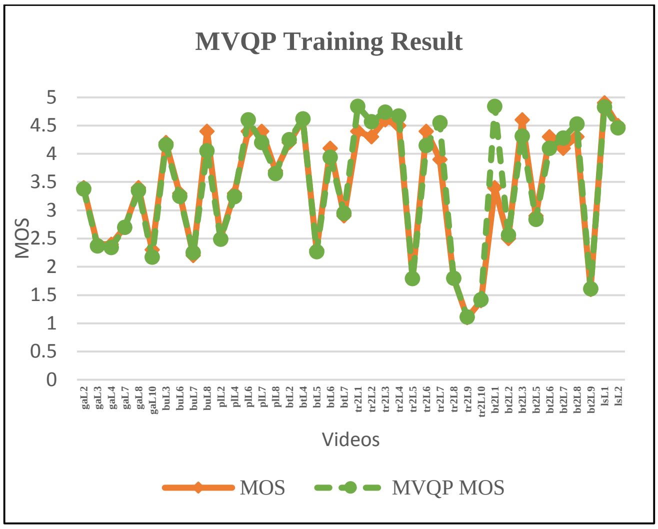

Fig. 20. MVQP MOS VS Subjective MOS – Group 1

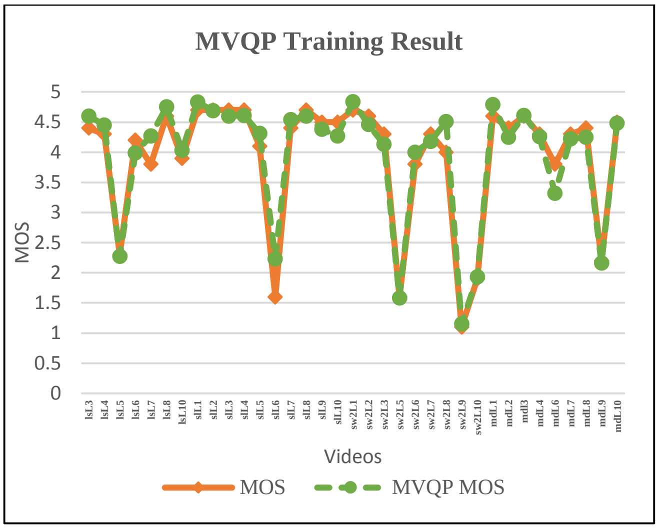

Fig. 21. MVQP MOS VS Subjective MOS – Group 2

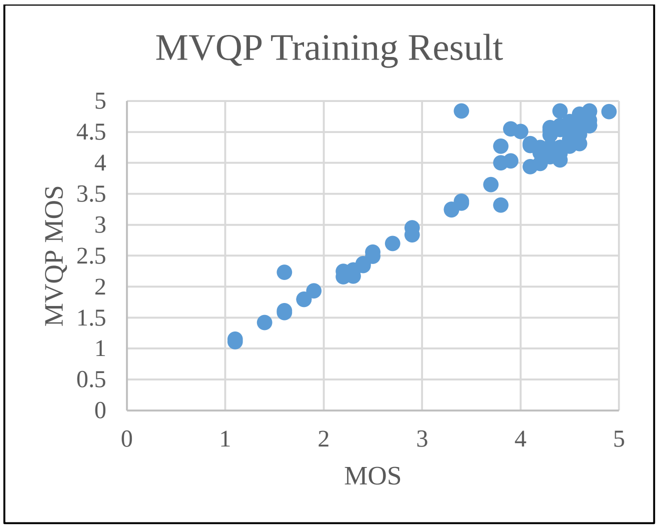

Fig. 22. MVQP MOS VS Subjective MOS

E. *Testing & Validation*

Twenty five unknown data set to the MVQP that haven't been used in the training possess were used to test the MVQP and validate the accuracy of the MVQP prediction. The MVQP prediction achieved high correlations with the human subjective MOS. Figures 23 and 24 shows the comparison between the human subjective evaluation MOS and the prediction MOS from the MVQP. Figure 25 shows the MVQP prediction screen and the figure 26 show the MVQP graph screen.

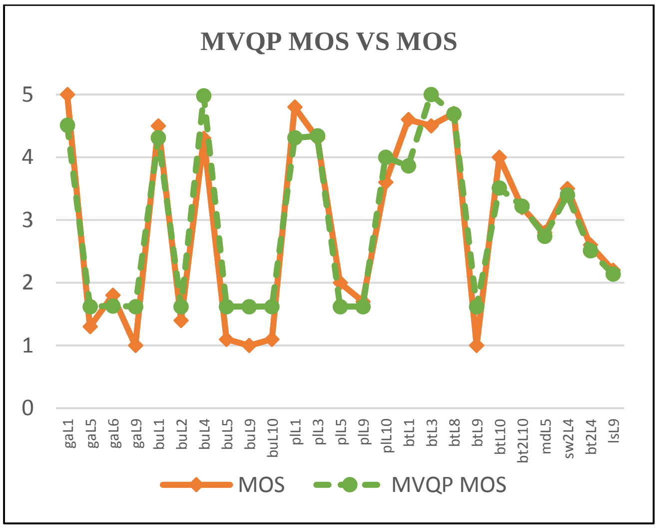

Fig. 23. MVQP Prediction VS MOS

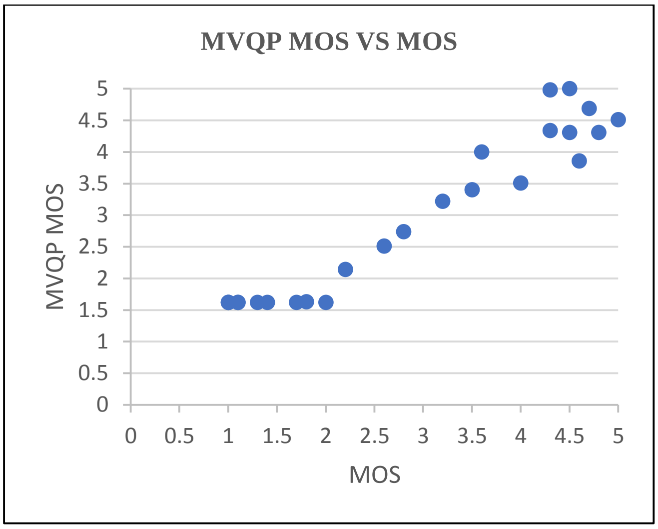

Fig. 24. MVQP Prediction VS MOS

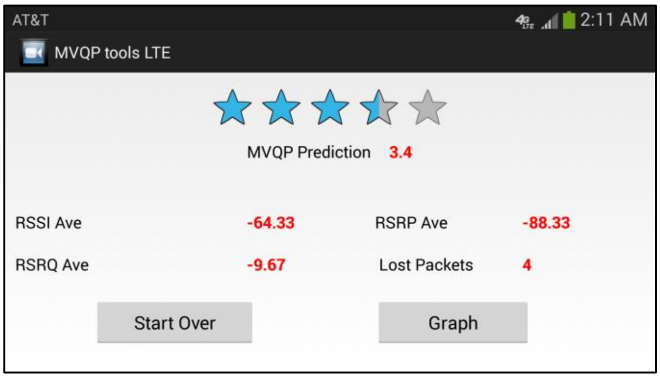

Fig. 25. MVQP Prediction

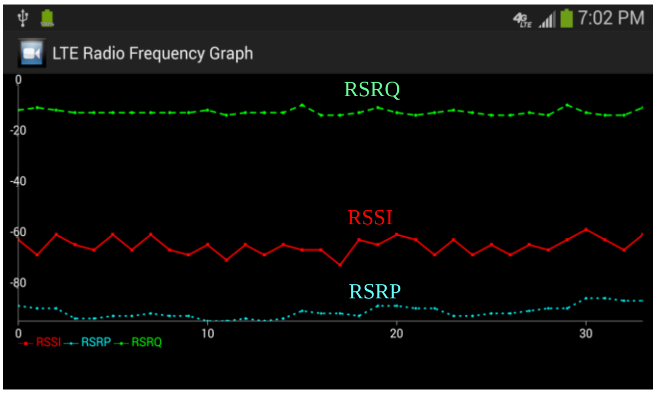

Fig. 26. LTE signal strength and signal quality

V. Conclusion

The MVQP project introduced a novel method for predicting the quality of video streaming over User Diagram Protocol (UDP) through an LTE cellular network. The MVQP prediction achieved high correlations with the human subjective MOS as shown in figure 23 and 24.

The goal of MVQP is to analyze the effects of radio frequency parameters on the live video streaming over live LTE cellular network. This analysis aims to help RF engineers in evaluation of cellular networks. The results of the evaluation should lead to optimization of network parameters and improvement of the service quality. To the best of authors' knowledge the MVQP for LTE is the only method that can currently predict the MOS over live LTE cellular network.

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