Mapping Smart-device, Network and Video Quality of Service Parameters to Quality of Experience

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***Abstract*—Studies have shown that video streaming is one of prominent cellular applications. Apart from improved network capacity, its growth is also catalysed by usage of smart-devices. It is therefore important for service providers to understand how key characteristics of smart devices, network and video simultaneously influence users' Quality of Experience (QoE). This paper presents a mapping function which was derived after a series of subjective experiments to study users' responses on video streaming QoE conducted over a wireless test-bed. It achieved a good prediction accuracy of different video types streamed in a wireless environment.**

***Keywords*—QoE, QoS, video streaming; mapping function**

I. Introduction

Mobile video has experienced an exponential growth in cellular networks due to the advancement of end-device and network technologies. According to Ericsson Mobility Report of 2016, there were 3.9 billion smart devices connected to cellular networks worldwide by then, and by 2022 the number is expected to reach 6.9 billion. Similarly, it is projected that mobile subscription in Enhanced Data rates for GSM Evolution (EDGE) shall have decreased at a Compound Annual Growth Rate (CAGR) of 20%, while in Wideband Code Division Multiple Access (WCDMA) and Long Term Evolution (LTE) shall increase at a CAGR of 5% and 20% respectively; between 2016 and 2022 [1]. Moreover, Cisco Visual Networking Index (VNI) report of 2017 forecasts that mobile video will grow at a CAGR of 54% between 2016 and 2021 generating 38 exabytes [2]. From these observations, it is evident that mobile video is accelerated by the presence of smart devices and high capacity networks. Nevertheless, video streaming has found significant applications in various aspects such as tele-health, e-learning and entertainment [3]–[5]. Furthermore, as such services increase in telecommunication market, their success, however depends on users' satisfaction. Therefore, it is important to understand end-users' QoE based on key factors in multimedia services delivery process so that necessary optimization steps can be done.

The International Telecommunication Union (ITU) defines QoE as the overall acceptability of an application or a particular service as perceived subjectively by the end-users. It includes the complete end-to-end system effects (client, terminal, network, service infrastructure, etc.) and influenced by user expectations and context [6]. Moreover, Möller maintains that QoE is the degree of delight or annoyance of the user by an application or service, in the context of communication services, and it is influenced by content, network, device, application, user expectations and goal, and context of use [7], [8]. Since QoE is a measure of users' satisfaction, several researchers have devoted time to find models which can quantitatively map it to Quality of Service (QoS) parameters. As an attempt to model QoE, researchers have given an immense attention to the mapping of QoE to either network or content QoS parameters alone [9]–[12]. Nonetheless, QoE is also affected by other factors such as devices characteristics, on top of network and video characteristics. Hence, it is important to formulate a mapping function which takes in the effects of other impairments, apart from network and/or video impairments.

This paper therefore investigates the effects of some key characteristics of smart devices, network and video, and then formulates a mapping function to predict video streaming QoE.

The contributions of this paper are twofold:

i. To investigate the effects of key variables of smart-device, network and video characteristics on video streaming QoE.

ii. To derive a function which maps smart-device, network and video characteristics to QoE.

This paper is organized as follows: Section II provides a review of related works and shows the research gap. Section III describes our experimental study describing the materials and methods used. Section IV describes the data analysis techniques used. Section V presents the model derivation process, parameters estimation and validation; and lastly, section VI presents the conclusion.

II. Related Work

The need to map end-users' QoE to measurable QoS parameters has been an active study in the field of multimedia services and networked systems. There are many efforts mostly looking into objective techniques to map network and video QoS parameters to users' QoE. A work reported in [10] proposes a logarithmic relationship to map users' QoE to network QoS parameters for web browsing, e-mail and downloads applications. In [11], authors presented a correlation neural model trying to map 3G network QoS parameters to QoE for web browsing, video streaming and download applications. Furthermore, in [13] a generic formula which uses an exponential function to map users' QoE to QoS parameters, known as IQX hypothesis was proposed. The formula relates the changes of QoE with respect to QoS and to the current level of QoE. Nonetheless, the work reported in [14] proposes a logistic function to predict video QoE based on network delay, packet loss, jitter and throughput. Some researchers have tried to introduce hybrid models by considering parameters from other factors apart from network. A fuzzy logic model reported in [15] considered network and application layers QoS parameters to predict QoE of video contents. Similarly, studies reported in [16] and [17] propose a fuzzy logic prediction model based on content and network QoS parameters. It is observed that existing mapping models tend to consider either network and/or content characteristics but not including smart-devices characteristics. Moreover, a number of researchers agree that device features can significantly affect viewing experience [18]–[20].

Therefore, this study proposes a function which simultaneously maps the effects of smart device, network and video QoS parameters to users QoE in order to reflect real scenario users' experiences of video streaming application.

III. Experimental Study

A. *Video Content Selection*

The video contents from soccer, movie and news clips were extracted from YouTube channel to represent fast moving (FM), medium moving (MM) and slow moving (SM) contents respectively, which differ in spatial and temporal characteristics [21], [22]. All clips were extracted from high definition contents of H.264 format, with 1280 x720 pixels, frame rate 30fps and bit rate 2048kbps. Using adobe media encoder the durations of each video were limited to 10 seconds in order to reduce boredom during experimentation. Fig.1 indicates the images of video clips used during subjective experiments.

Fig. 1. Images of video used in experiments

B. *QoS Parameters*

The chosen QoS parameters were selected from device, network and video contents. The parameters screen size and resolution were selected from smart devices and presented in terms of Pixel Density Index (PDI) which is the ratio of resolution to screen size. From the network, delay (DL) and Jitter (JT) were selected while from video contents, the content type (CT) and bit rate (BR) were selected while frame rate was fixed at 30fps as shown in Table I.

TABLE I. QOS PARAMETERS

Parameter	Values
Content type (CT)	SM, MM and FM video contents
Bit rate (BR)	0.192Mbps, 0.512Mbps, 2.048Mbps
Jitter (JT)	5ms, 20ms, 50ms
Delay (DL)	10ms, 150ms, 300ms
Pixel density index (PDI)	149ppi, 264ppi, 320ppi

C. *Subjective Experiments*

Subjective experiments were designed using Taguchi method. It is a multi-factor experimental method whereby the effects of more than one variable with more than two levels can be studied at the same time [23]. This method has been widely used to evaluate the quality of engineering processes and products [24]. Its strength is due to the use orthogonal array which determines minimum number of experiments necessary to test experimental conditions [25]. This paper investigated the effects of five variables on video streaming QoE, each varied at 3-levels as shown in Table I. By using factorial design, this study would require 243 experiments to tests all 3^5 variables combinations. Nevertheless, by using Taguchi method, only 27 experiments are sufficient to investigate necessary variables combinations as depicted in Table II.

TABLE II. VARIABLES COMBINATIONS

Experiment	CT	PDI	BR	DL	JT
1	FM	149	2.048	10	5
2	FM	149	2.048	10	20
3	FM	149	2.048	10	50
4	FM	264	0.512	150	5
5	FM	264	0.512	150	20
6	FM	264	0.512	150	50
7	FM	320	0.192	300	5
8	FM	320	0.192	300	20
9	FM	320	0.192	300	50
10	MM	149	0.512	300	5
11	MM	149	0.512	300	20
12	MM	149	0.512	300	50
13	MM	264	0.192	10	5

14	MM	264	0.192	10	20
15	MM	264	0.192	10	50
16	MM	320	2.048	150	5
17	MM	320	2.048	150	20
18	MM	320	2.048	150	50
19	SM	149	0.192	150	5
20	SM	149	0.192	150	20
21	SM	149	0.192	150	50
22	SM	264	2.048	300	5
23	SM	264	2.048	300	20
24	SM	264	2.048	300	50
25	SM	320	0.512	10	5
26	SM	320	0.512	10	20
27	SM	320	0.512	10	50

D. Emulation Procedure

In this study, the combined effects of various QoS parameters from device, network and video factors on video streaming QoE were investigated. Hence it required an end-to-end video streaming QoE evaluation process. Thus, a wireless network test-bed was designed and used for emulating a wireless network behaviour using network emulator (netem) in the linux kernel of Ubuntu 10.4 installed in a two port computer.

The variables DL and JT were varied by using netem according to experimental sequence described in Table II. Also, participants watched video contents stored in the local server by using smart-devices with features described in Table III. The experiments followed the absolute category rating (ACR) method as recommended by ITU whereby viewers were allowed to view video clips and rate QoE at the end of each one [26]. The rating criteria were the initial time to play, the rate of video interruptions while playing, and general video clarity. The process was repeated for all 44 participants.

TABLE III. DEVICES FEATURES

	Device 1	**Device 2**	**Device 3**
Screen size	10.1’	5’	5.5’
Resolution	800x1280	1182x720	1280x720
PDI	149ppi	264ppi	320ppi
Processor	1.2 GHz	1.3GHz	1.3GHz
Device model	Galaxy Tab 4	Techno C5	Techno J8

IV. DATA ANALYSIS

In order to establish statistical relationship between dependent variables and QoE, the 5-way analysis of variance (ANOVA) was conducted on the QoE dataset obtained from subjective experiments [27]. All 1,188 test conditions (44 participant x 27 conditions) were tested in order to determine the effects of all five parameters on QoE together with their combined interaction effects. The interpretation of results from ANOVA is such that; a parameter with a p-value small than 0.05 indicates that its effect on QoE is significant [27]. From this study, the individual effects of BR, DL and CT were found to be significant on QoE while those due to PDI and JT were not. Nevertheless, the interaction effects of PDI and BR, PDI and DL were significant on QoE. Furthermore, the interaction of JT and BR with JT and CT were found to affect QoE significantly. Therefore the effects of all five variables were considered as significant on video streaming QoE.

The most important parameter affecting QoE was CT because its effect was the highest of all. The BR was the second most effective parameter which influenced the effects of PDI. This means, the effects of low PDI devices can be reduced by videos of high bit rate. The third most effective parameter was DL, followed by JT and the PDI. Moreover, the effects of JT depended on CT and DL. Therefore reducing link DL can reduce the impact of JT on video streaming QoE. Generally, ANOVA has revealed the significance of each variable in predicting QoE; which guided the derivation process of a mapping function.

V. DERIVING A MAPPING FUNCTION

A. Input and Output Responses

The inputs considered in QoE modelling were BR, DL, PDI and JT, while CT was used as an intermediate variable, whose effects were accounted for using different video types during the modelling process. Fig. 2 and Fig. 3 show the variations of QoE due to different inputs.

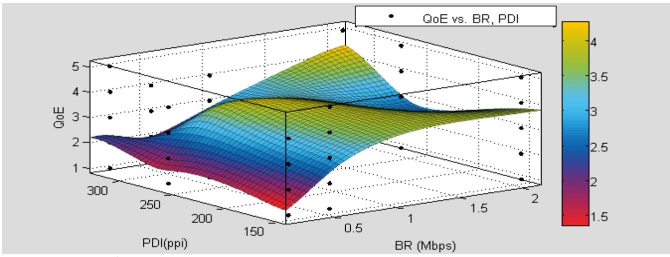

Fig. 2. Plot of QoE vs. BR and PDI

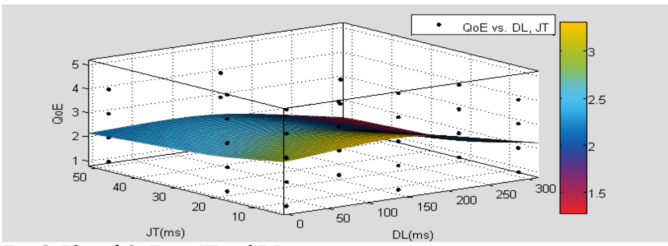

Fig. 3. Plot of QoE vs. JT and DL

The following assumptions were then made to represent the relationship between each variable and its corresponding QoE variation.

$$f_1(BR) = \beta_1 \ln(BR) \quad (1)$$

$$f_2(PDI) = \beta_2 \times PDI \quad (2)$$

$$f_3(DL) = \beta_3 \times DL \qquad (3)$$

$$f_4(JT) = \beta_4 \times JT \qquad (4)$$

Where β_1, β_2, β_3 and β_4 are constants while $f_1(BR)$, $f_2(PDI)$, $f_3(DL)$ and $f_4(JT)$ are QoE variations due to BR, PDI, DL and JT respectively.

The generalized linear equation was adopted to integrate individual functions into one function as shown in (5).

$$y = f_1(x_1) + f_2(x_2) + f_3(x_3) + ... + \varepsilon \qquad (5)$$

Substituting (1), (2), (3) and (4) into (5), then

$$y = \beta_1 \ln(BR) + \beta_2 \times PDI + \beta_3 \times DL + \beta_4 \times JT + \varepsilon \qquad (6)$$

$$g(y) = \frac{1}{1+e^{-y}} \qquad (7)$$

Substituting (6) into (7) in order to normalize its output between 0 and 1, it follows that

$$g(y) = \frac{1}{1+e^{-(\beta_1 \ln(BR)+\beta_2 \times PDI+\beta_3 \times DL+\beta_4 \times JT+\varepsilon)}} \qquad (8)$$

$$g(y) = \frac{1}{1+e^{-\beta_1 \ln(BR)} \times e^{-\beta_2 \times PDI} \times e^{-\beta_3 \times DL} \times e^{-\beta_4 \times JT} \times e^{-\varepsilon}} \qquad (9)$$

Let $e^{-\beta_2} = \gamma$, $\beta_3 = \beta_4 = \beta$ and $e^{-\varepsilon} = \delta$ be the constants then;

$$e^{-\beta_2 \times PDI} = \gamma^{PDI} \qquad (10)$$

$$e^{-\beta_3 \times DL} \times e^{-\beta_4 \times JT} = e^{-\beta(DL+JT)} \qquad (11)$$

$$e^{-\varepsilon} = \delta \qquad (12)$$

By using exponential function properties,

$$e^{-\beta_1 \ln(BR)} = e^{\ln(BR)^{-\beta_1}} = BR^{-\beta_1} \qquad (13)$$

Substituting (9), (10), (11) and (12) into (8),

$$g(y) = \frac{1}{1+\delta \times BR^{-\beta_1} \times \gamma^{PDI} \times e^{-\beta(DL+JT)}} \qquad (14)$$

However, the normalized value of a function is also defined as,

$$g(y) = \frac{y^* - y_{\min}}{y_{\max} - y_{\min}} \qquad (15)$$

where, y is an average function output, $y_{\max}$ is a maximum output of a function, $y_{\min}$ is a minimum output of a function, and is a normalized function output.

Since y^* and $g(y)$ are both normalized values of y, (14) and (15) are equated. In this study, $y_{\max}$ =5 and $y_{\min}$ =1 presenting the maximum and minimum values of QoE respectively.

$$\frac{y - y_{\min}}{y_{\max} - y_{\min}} = \frac{1}{1+\delta \times BR^{-\beta_1} \times \gamma^{PDI} \times e^{-\beta(DL+JT)}} \qquad (16)$$

Finally, the mapping function is presented by

$$y = \frac{4}{1+\delta \times BR^{-\beta_1} \times \gamma^{PDI} \times e^{-\beta(DL+JT)}} + 1 \qquad (17)$$

B. *Parameter Estimation*

The function parameters in (17) were estimated using Gauss-Newton algorithm through Minitab 17.1.0 software. The dataset used for parameter estimation were collected from a subjective experiment by using the combination of FM, MM and SM video contents. The algorithm estimated parameters of the function which attained the minimum root mean square error (RMSE) between users and model predicted QoE in each content type. Table IV describes the function parameters estimated in fours settings of video contents. The function parameters differ due to variation of users' responses influenced by content characteristics.

TABLE IV. FUNCTION PARAMETERS AND EVALUATION

	Parameters Estimates					
CT	δ	β_1	γ	β	*RMSE*	*R*
FM	0.0344	0.5340	1.0114	6.7601	0.134	93.2%
MM	0.0500	-1.199	1.0064	7.6606	0.135	91.7%
SM	0.0414	-1.034	1.0064	7.5464	0.216	75.2%
All contents	0.4737	-0.673	1.0003	4.0347	0.228	90.1%

C. *Function Testing and Validation*

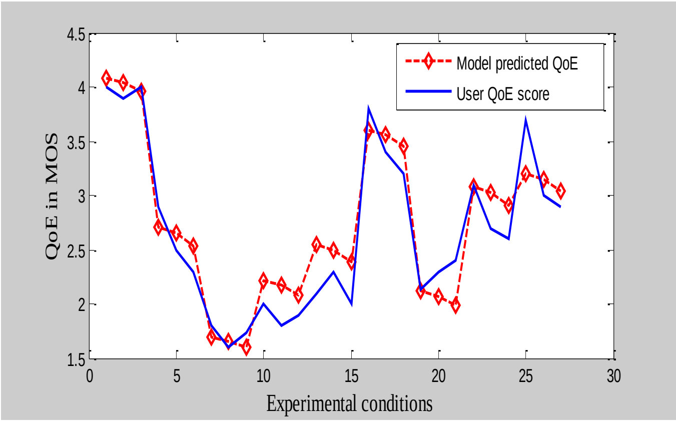

Fig. 4. Line graph showing predicted and user QoE scores

The mapping function (17) was used to predict QoE of untested conditions in three content types using parameters described in Table IV. Subjective experiments were then conducted to collect users' QoE due to untested conditions. The derived function was then validated using R^2 correlation and root mean square error (RMSE) in each content type. The function attained R^2 correlation of 93.2% and RMSE of 0.134 in FM contents, R^2 correlation of 91.7% and RMSE of 0.135 in MM contents and R^2 correlation of 75.2% and RMSE of 0.216 in SM contents. Moreover, the function attained R^2 correlation of 90.1% and RMSE of 0.228 in mixed contents of FM, MM and SM as described in Table IV. The accuracy of the function was observed to decrease from FM, MM to SM contents. Moreover, the function maintained a high accuracy with QoE predictions of combined contents as described in Fig.4 and Fig.5.

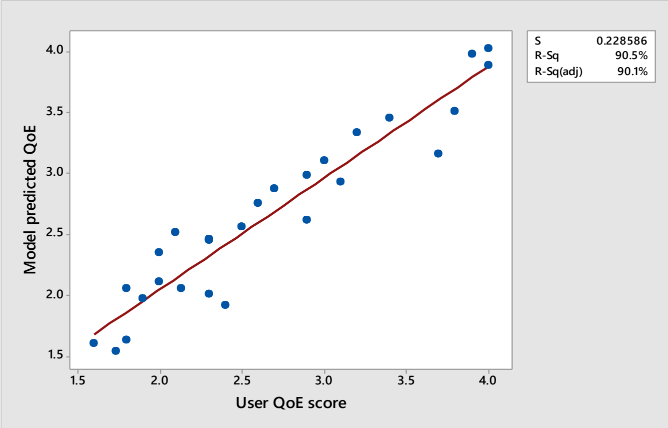

Fig. 5. Predicted QoE vs User QoE

VI. Conclusion

In this paper, a function to map QoS parameters to users QoE of video streaming in wireless networks was derived. The formulae consolidates the effects of key QoS parameters from smart-device, network and video contents. The effects of QoS parameters were studied through a wireless network test-bed in a laboratory. Subjective experiments were conducted to collect users QoE due to the changes of CT, BR, DL, JT and PDI. The data collected was analysed by using a 5-way ANOVA to statistically establish the impact of each parameter and to identify the most influential parameters. This study found that CT had the highest impact on QoE, followed by BR, DL, JT and PDI. Moreover, by basing on these findings a mapping function was derived and achieved a high prediction accuracy of 0.901 and RMSE of 0.228.

Hence, the paper contributes to the on-going research in the field of study by proposing a mapping function which consolidates the effects of variables from smart-device, network and video contents; by considering simultaneous effects of key variables on video streaming QoE. Nevertheless, future work should focus on the effects of parameters which were not considered in this study.

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