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Full Length Research Paper

Analyzing the Influence of Smart-device Visual Features, Viewing Distance and Content Factors on Video Streaming QoE

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ABSTRACT

Quality of experience (QoE) over wireless networks has attracted attention from industry and academia due to an increase in video streaming applications. Several researchers have attempted to understand the factors affecting QoE and design appropriate quality control strategies. Normally, video streaming is initiated by a user who accesses video content over a network using a smart device that may be held at various viewing distances. Each aforementioned factor has the potential to affect QoE. However, several studies explore the behavior of wireless networks on video streaming QoE. To understand the effects of other factors on QoE, this paper investigates the influence of the device's visual features and viewing distance when accessing video content of different types. The study adopted an emulation technique to conduct multi-factor experiments designed using the Taguchi method. The 5-ways ANOVA analysis revealed that the effects of smart-device visual features, viewing distance, and content types are significant on video streaming QoE at $p<0.05$. Moreover, smart devices with a pixel density index of more than 200 pixels per inch (ppi) produce high QoE, when the viewing distance is limited to 45 cm. Lastly, the video bitrate greater than 1024 kbps produces a good QoE regardless of the frame rates and content types.

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INTRODUCTION

Over a decade now, the use of smart devices for mobile video streaming has experienced exponential growth due to advanced electronic technologies. A lot of people prefer smart devices for the consumption of video streaming content. Mobile smart devices are portable computing devices such as smartphones and tablet computers. The devices can be connected to other devices or networks using different wireless protocols such as Bluetooth, Wireless Fidelity (Wi-Fi), and Universal Mobile Telecommunications Standards (UMTS). According to the Erickson Mobility Report of 2021, there are about 6.3 billion smartphones and 300 million mobile personal computers and tablets subscriptions that generate traffic in the mobile networks at an average of 11.4GB per month (Ericcson, 2021). In Tanzania, the number of people connected to mobile networks accounts for 91% meanwhile the Internet penetration rate stands at 50% of about 60 million population (TCRA, 2022).

This increase is due to the market competition where various vendors and dealers present smart devices at prices affordable to the majority of people. For instance, one can purchase a basic smartphone at a price as low as Tshs.70,000 famously known as “Smart-Kitochi”, having the ability to connect to the 4th generation network[1]. The prices of smartphones vary due to features such as processor, memory, storage, screen size, screen resolution, and the number of processor cores. In the communication ecosystem, QoE may be influenced by variables that are grouped into device, network, and content factors (Callet, Möller, & Perkis, 2012; Mongi, Mvuma, & Justinian, 2017).

The QoE is defined by the International Telecommunication Union (ITU) as the overall acceptability of an application or particular service as perceived subjectively by the end-users, it includes the complete end-to-end system effects (client, terminal, network, service infrastructure, etc.), also influenced by user expectations and context (ITU-T SG12, 2007). Furthermore, Callet et al., 2012; and Möller, (2010) define QoE as the degree of delight or annoyance of the user of an application or service, in the context of communication services it is influenced by content, network, device, application, user expectations and goal, and context of use.

Studies reported by Alreshoodi et al. (2015); Rivera et al. (2013) focused on the effects of network impairments on video streaming QoE. The authors indicated the significant impact of network impairment on video streaming QoE. Moreover, studies by Buberwa and Mbise (2021) and Mongi and Mvuma (2015) put focus on the impact of network impairment caused by parameters such as packet loss, jitter, packet corruption, delay, and data rate on video streaming QoE. In both cases discussed, the authors focus on the network parameters to explain the level of video streaming QoE felt by viewers on smartphones. However, as mobile networks advance, some of the network impairments such as packet delay, loss, and data rate become absolute. For instance, the fifth network generation (5G) will support a download speed of more than 1Gbps and a delay of less than 5ms in the user plane which are sufficient enough to provide the best video streaming QoE (Osseiran et al, 2016). As the network technology advances, the negative influence of the network on QoE decreases because most of the parameters are optimized. Nevertheless, QoE is affected by other variables associated with devices and contents, therefore, it is very important to understand the extent of the impact on video streaming QoE in a communication network environment.

Schatz and Egger (2012) conducted a study on the effect of device performance and screen size on video streaming QoE. The authors reported some significant relationships. Nevertheless, Yin and Chu, (2015) found different results by observing no linear effect of device screen size, and the reading distance of the screen on QoE. As per the QoE definition, given by ITU-T SG12, (2007), Möller (2010), and Callet et al. (2012), it is necessary to investigate the issue of QoE in wireless broadband beyond network factors. This paper, therefore, attempts to analyze the influence of smart devices' visual features, viewing distance, and content type on video streaming QoE.

The paper consists of six key sections organized as Introduction, Literature review, Methodology, Observations, Data Analysis, and Conclusion.

METHODS AND MATERIALS

The generic architecture of a wireless broadband network

The generic architecture of wireless broadband networks consists of four key entities which are mobile terminals (MT), wireless access point (WAP), the core network (CN), and service provider (SP).

MT is an entity that utilizes the connectivity provided by the AP to access the services. While AP offers a wireless

[1] https://www.tigo.co.tz/phones

interface to the MT other broadband technologies such as optic fiber may be used to interface AP with CN to enhance the carrying capacity of aggregated traffic. SP nodes are interfaced with the CN for easy provision of various services. Examples of services hosted by the SP are such as gaming, messaging, wireless internet, music, and video streaming applications. The capacity of WAP depends on the technology deployed. For instance, the 3G radio downlink, transmits data at the rate of around 2Mbps, while the 4G radio downlink may go up to 100Mbps (Kondi et al, 2009). With the new 5G technology, the radio downlink can offer a speed of up to 1Gbps. Figure 1, presents some key components of a generic wireless broadband architecture.

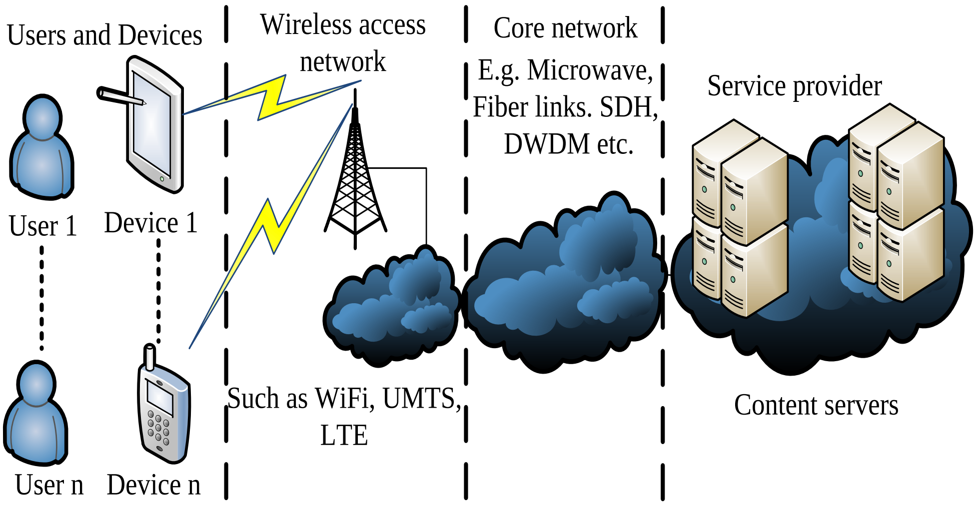

Figure 1: Generic wireless broadband architecture

Related Work

Schatz and Hossfeld (2012) studied the impact of screen size and resolution on QoE in a wireless network environment. In their findings, these authors claimed that users who viewed video through 4 inches screen and 800 x 480 resolution gave a higher QoE score of 4.7 than those who used a 3.2- and 3.5-inches screen with 480 x 320 resolution. Moreover, these authors recommended that the impact of pixels distribution per screen size should be further investigated. Also, Dimitrios et al. (2013) investigated the perceptual quality of three smartphones having screen sizes of 3.5, 4.3, and 5.3 inches and 320x480, 800x1280, and 480x800 screen resolutions respectively. The authors claim that the screen size had some effects on user-perceived quality. Another study done by Yiting et al. (2013) investigated the impact of display size and screen resolution. The investigation was based on a TV set of 42 inches, a tablet of 10.1 inches, and a smartphone of 4.8 inches. Authors claim that people always have a higher expectations when viewing a video using a larger screen. Moreover, Schatz et al, 2012 reveal that higher QoE is obtained for users of large-screen devices of 9.7 inches, compared to small screen sizes such as 3.5 inches and 4.3 inches. Apart from screen size, the ITU-T, recommends that viewing distance from the device screen should be considered when investigating perceptual quality/QoE because viewing distance controls the intensity of light entering the eye retina for image formation (ITU-T Rec. J.247, 2008). A study done by Kuipers et al. (2008) claims that viewing distance affects the perceived video QoE, on a monitor. Similarly, Catellier et al. (2012) argue that resolution, viewing distance, and screen size of a television set monitor have an impact on video QoE. In the same direction, Dostal et al. (2014) argue that viewing distance should be used as one of the variables which influence users' QoE to devices screen size. Nevertheless, Yin and Chu (2015) studied the impact of viewing distance on devices with screen sizes 3.5 inches, 7.9 inches, and 9.7 inches at viewing distances between 15cm and 55cm and did not find any linear relationship between reading distance and screen size in improving QoE. Nonetheless, a study by Hadi et al., (2021) established the influence of viewing distance on video quality.

The focus of the reviewed works was either on the influence of screen size, screen resolution, or viewing distance. There is a limitation in understanding the effects of viewing distance and screen visual features on video streaming QoE.

Experiment Design

Several studies such as Mok et al. (2011) and Song and Yang (2014) adopted experiment techniques to investigate the quality of services in communication systems. The experiment technique enables a researcher to understand the influence of independent variables on a dependent one, mostly by manipulating the independent variables under a controlled environment. The three basic features of experiment design are Replication, Randomization, and Blocking. Replication involves the collection of the same experiment responses from different respondents or samples. It is not the same as repetition which involves the re-doing of the same experiments to the same sample (Yogesh, 2006). Further, replication aims to obtain a precise estimate of the factors studied in the experiment. Randomization is a random allocation of samples for conducting experiments and the order of experimentation. It reduces extraneous effects of variables during experimentation. The blocking technique is applied to improve the precision of an experiment by eliminating the effects of noise factors (Krishnaianh and Shahabudeen, 2013).

An experiment that involves more than one factor at a time is called a multi-factor experiment. Communication networking applications are normally transferred through a wireless network and are subject to impairment of more than one factor at a time. Thus, the multi-factor experiment design is suitable for studying the relationship between QoE and its influencing factors (Field, 2013). The studies by Louis Anegekuh et al. (2015) and Tavakoli et al. (2014) investigated the effect of several factors on QoE. The nature of the design adopted was multiple factor experiments. In these studies, the factors investigated were varying at less than two levels, which results in manageable factor combinations. As factors and variation levels increase, the combinations become more complex and the need for a robust design such as the Taguchi approach becomes necessary.

Taguchi approach was proposed by Japanese scientist Dr. Genich Taguchi in 1966 while working with Bell Labs. It is the design of experiments method using Orthogonal Arrays (OA) developed by a French mathematician in early 1897. It reduces the size of the experiment since full factorial designs are too numerous to manage. Orthogonal arrays indicate the possible combinations of rows and columns which offer a minimum number of experiments and possible variable combinations as reported in Taguchi et al. (2005).

To determine the orthogonal arrays to be selected in an experiment, one needs to identify four important things.

i. The number of variables investigated, (m)

ii. The levels through which the variables are fixed, (s)
iii. The number of experiments, (N) and
iv. The strength of orthogonal arrays, (t)

The array size is N rows by k columns with entries from 1 to s. The experimental design OA ensures combinations of all possible parameters up to t occur equally which ensures the balanced level of any parameter or interaction of parameters (Taguchi et al., 2005). As t increases, there are more parameter interactions, and the larger the orthogonal arrays become. When one or more columns of OA are deleted from the previous design, the remaining columns are still making OA with a smaller number of columns. This property is very useful since it offers flexibility during parameter selection. In addition to that, OA is a highly fractional factorial design where N experiments are performed instead of s^m experiments that are required to perform the full factorial design. The Taguchi design offers great flexibility in designing experiments compared to other approaches such as factorial or fractional factorial design. For instance, an experiment, where 4 parameters are varied at 3 levels, will require 3^4 or 81 experiments. However, with Taguchi's approach, the orthogonal array L_9 defines nine (9) experiments that are sufficient to give variable combinations that give the same results as 81 combinations. The generic orthogonal arrays may also be presented as $L_N(s^m)$ described in Table 1.

Table 1: Taguchi orthogonal arrays

Two-levels series	Three-levels series	Four-levels series	Mixed-levels series
$L_4(2^3)$	$L_9(2^4)$	$L_{15}(4^5)$	$L_{18}(2^1, 2^7)$
$L_8(2^7)$	$L_{27}(3^{13})$	$L_{64}(4^{21})$	$L_{36}(2^{11}, 3^{12})$
$L_{16}(2^{15})$	$L_{81}(3^{40})$		
$L_{32}(2^{31})$			
$L_{12}(2^{11})$			

Emulation Approach

Emulation is a hybrid experimentation technique intended to bridge the gap between simulation experiments and real-world testing. The advantage of emulation is its ability to reproduce in real-time and in a controlled environment the key functionality of a network so that it can interact with other real systems (Jurgelionis et al., 2011). The network emulation approach applies the technique of emulation to the field of networks both for network equipment, whose behaviour is reproduced, and for the communication conditions between devices, which are modelled and reproduced in a controlled way in the emulated network, thus providing flexibility and repeatability (Razvan, 2013).

Some researchers in the field of communications have applied the emulation approach in evaluating network performance on users' experiences. For instance, Becke et al., (2011) performed a link-level emulation to investigate the performances and limitations of netem and dumnet software on the data link layer. Because of its strength, emulations produce experimental results which are close to reality, and observations are directly applicable to real situations. Hence, network emulation is a powerful tool for evaluating network equipment, protocols, and applications, for research and education purposes, as well as for pre-deployment assessments.

METHODOLOGY

(a) Research Approach

This study adopted a quantitative research approach whereby quantitative data were collected during experiments that were conducted in an emulation environment.

The quantitative data used in the study are pixel density index (PDI), video bit rate (BR), frame rate (FR), viewing distance (VD), and QoE. The QoE was measured using the ITU tool, known as the Mean Opinion Score (MOS) which is an average of the users' scores on quality brought by different content types (CT).

(b) *Sample size*

According to ITU-T Recommendations, the number of people for a subjective quality of experience (QoE) may be between 5 and 30. In this study total of 24 subjects participated in 27 experiments generating a total of 648 data points.

(c) *Video content selection*

The video contents from movies, soccer, and news clips were extracted from YouTube channels to represent fast, medium, and slow-moving contents respectively, which differ in spatial and temporal characteristics. The clips were extracted from high-definition contents of H.264 format, with 1280 x720 pixels, frame rate 30fps, and bitrate 2048kbps. Using an adobe media encoder, the duration of each video was limited to ten (10) seconds to avoid the boredom of subjects during experiments. Figure 2 indicates some of the images of video used in subjective experiments.

Figure 2: Images of video used in experiments (Source: http://www.youtube.com)

(d) Subjective experiments procedure

The investigated video clips were extracted from high-definition quality content covering sports, news, and movie genres. Frame and bit rates of video clips in each session were pre-encoded to different values using an adobe media encoder and stored in a multimedia server. The network variables were set at minimum levels i.e. packet loss 0%, delay 0ms, and jitter 0ms, because, in this experiment, the network impairments were ignored. A total of 27 sessions each with a duration of 30 seconds were conducted. The total time for the experiment was about 15 minutes as per ITU's recommendation. (ITU-T, 1999).
Pilot sessions were done to familiarize the participants with the test bed, devices, and procedures. Participants used smart devices to stream video clips through a wireless testbed. Participants viewed all video content and at the end of each session, each one was required to give a rating on QoE. The ratings were done by basing on audio-visual clarity and visibility, after being exposed to experimental conditions as depicted in Table 2.

Table 2: Experiment variables and level combinations

Exp	CT	PDI (ppi)	FR (fps)	BR (Mbps)	VD (cm)
1	FM	149	30	2.048	30
2	FM	149	30	2.048	45
3	FM	149	30	2.048	60
4	FM	264	15	0.512	30
5	FM	264	15	0.512	45
6	FM	264	15	0.512	60
7	FM	320	10	0.192	30
8	FM	320	10	0.192	45
9	FM	320	10	0.192	60
10	MM	149	15	0.192	30
11	MM	149	15	0.192	45
12	MM	149	15	0.192	60
13	MM	264	10	2.048	30
14	MM	264	10	2.048	45
15	MM	264	10	2.048	60
16	MM	320	30	0.512	30
17	MM	320	30	0.512	45
18	MM	320	30	0.512	60

Exp	CT	PDI (ppi)	FR (fps)	BR (Mbps)	VD (cm)
19	SM	149	10	0.512	30
20	SM	149	10	0.512	45
21	SM	149	10	0.512	60
22	SM	264	30	0.192	30
23	SM	264	30	0.192	45
24	SM	264	30	0.192	60
25	SM	320	15	2.048	30
26	SM	320	15	2.048	45
27	SM	320	15	2.048	60

OBSERVATIONS

a) *Effects of BR and FR on QoE of different contents*

Generally, it was observed that bit rate possesses the highest impact on video streaming QoE in all content types. In slow-moving contents, the QoE was above 4, for BR above 0.5Mbps, while fast and moderate moving contents, achieved the same QoE when the BR was above 1Mbps. Moreover, as frame rate changes, the corresponding QoE was also recorded. For slow-moving content, the frame rate below 15fps caused QoE below 1.5 which almost doubled at 30fps.

These observations suggest that slow-moving contents seem to be less affected by impairments than the fast and moderate-moving contents when exposed to the same conditions as seen in Figures 3-5.

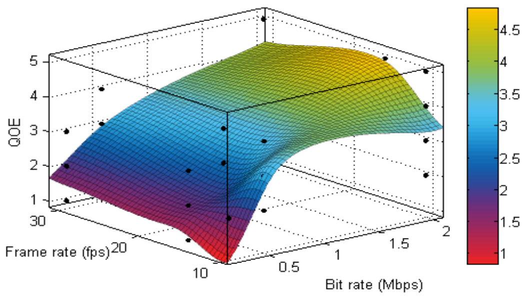

Figure 3: QoE vs FR vs BR in FM Contents

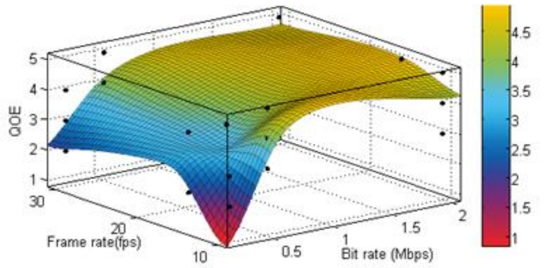

Figure 4: QoE vs FR vs BR in SM Contents

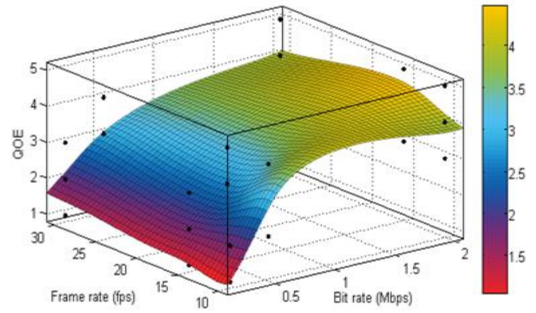

Figure 5: QoE vs FR vs BR in MM Contents

b) *Effects of PDI and VD on video streaming QoE*

It was observed that for a device with PDI below 150ppi, the QoE score goes below 2. QoE varied between 3 and 3.5 when viewing distances decreased from 50cm to 40cm. For the devices with PDI beyond 200ppi, the QoE score ranged between 3.5 and 4.5 when viewing distances changed between 30 cm and 40cm. In this experiment, it was noted that both variables had effects on QoE regardless of video content types as indicated in Figures 6-8.

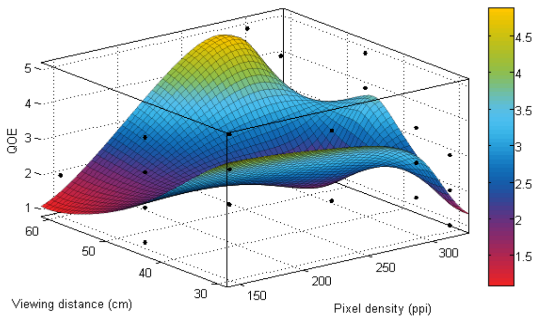

Figure 6: QoE vs VD vs PDI in FM Contents

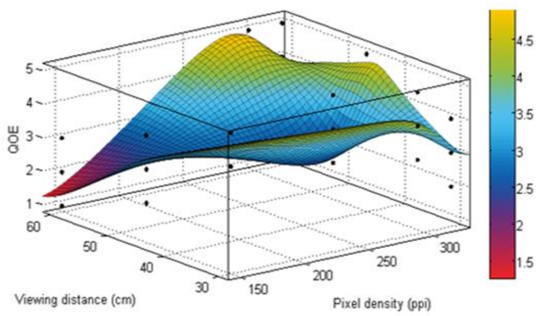

Figure 7: QoE vs VD vs PDI in SM Contents

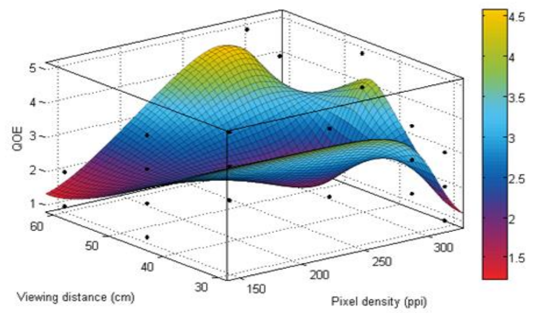

Figure 8: QoE vs VD vs PDI in MM Contents

ANOVA DATA ANALYSIS

To establish a statistical relationship between dependent variables and QoE, the 5-way analysis of variance (ANOVA) was conducted on the QoE dataset obtained from subjective experiments. All 648 test conditions (24 participants x 27 conditions) were tested with 5-way repeated ANOVA to determine the impact of all five parameters on QoE together with their combined interaction effects.

The results obtained from ANOVA with a small p-value indicate that QoE is significantly affected by the parameters investigated. This study found that the effects of CT, PDI, FR, BR, and VD were statistically significant on video streaming QoE at $p<0.05$. There was also a significant interaction effect between CT with PDI, and CT with BR at $p<0.05$. This means the type of content viewed can interfere with BR and/or PDI to influence video streaming QoE. Moreover, the most influencing variable that affected QoE was BR followed by CT, PDI, VD, and FR by basing on the F-value obtained as shown in Table 3

Table 3: Analysis of variance for investigated variables

Source	DF	Adj SS	Adj MS	F-Value	P-Value
CT	2	62.276	31.138	64.59	0.000
PDI	2	33.486	16.743	34.73	0.000
FR	2	4.325	2.163	4.49	0.012
BR	2	474.337	237.169	491.96	0.000
VD	2	13.547	6.774	14.05	0.000
CT x PDI	4	6.601	1.650	3.42	0.009
CT x FR	4	4.280	1.070	2.22	0.066
CT x BR	4	5.193	1.298	2.69	0.031
CT x VD	4	4.391	1.098	2.28	0.060

CONCLUSION

This paper investigates the effects of smart-device visual features and viewing distance on video streaming QoE. The emulation technique was used to conduct multi factors experiments on a wireless network testbed. The analysis indicates that smart-device visual features and viewing distance affected video streaming QoE at $p<0.05$. The study found that devices with pixel density index below 150 ppi produce poor QoE. It was also observed that viewing distance affects QoE, and beyond 45 cm, the QoE becomes poor. Furthermore, the content acted as an extraneous factor that influences QoE. The video content with a frame rate below 15fps and bitrates below 192 kbps potentially results in a poor QoE that annoys viewers. These results recommend that the viewers should consider the visual features of smart devices, viewing distance, and content characteristics for an optimal QoE.

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