Modeling and Understanding the Quality of Experience of Online Mobile Gaming Services

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***Abstract*—Mobile gaming has the largest market shares of all gaming domains, accounting for an estimated $77.2 billion in 2020. In recent times, one can witness an increase in highly interactive mobile online games. However, the gaming Quality of Experience (QoE) can be strongly influenced by network degradations, concretely by delay and packet loss. Thus, network providers need to ensure fast and reliable connections between the gaming servers and the users' clients. To maintain a satisfying user experience, QoE prediction models are fundamental. Aiming at the development of such a model, a detailed parameter space consisting of various delay and packet loss conditions will be investigated in this paper. Here, especially the importance of jitter is of interest. Next, it will be examined whether a recently published opinion model for cloud gaming, the ITU-T Rec. G.1072, can also be used for online mobile gaming. Finally, a new proposal for a model targeting online mobile gaming services will be presented and evaluated concerning its performance.**

***Index Terms*—Gaming, QoE, Mobile, Modeling, Test Design**

I. Introduction

Mobile gaming is the most popular form of gaming services globally, which reached 51 % share of total gaming revenue worldwide in 2018 [1]. Such a rise in popularity is coupled with the increase in the number of high-end mobile devices and the portability of this type of device. With the advancement of mobile network technologies, Online Mobile Gaming (OMG) has become a popular online service, especially in the East Asia market. Online gaming refers to "a service that enables a video game to be either partially or primarily played over a broadband network. The service renders the game at the client device while the game's updated states are transferred over a broadband network" [1].

Contrary to Cloud Gaming (CG), no video is streamed over the network in online gaming services. Thus, the service is mostly prone to network depredations, including delay, packet loss, and jitter. OMG is one form of online gaming provided for mobile devices and typically played with touch input. Like other multimedia services running on the top of the IP network, quality assessment is an essential step to ensuring user satisfaction. While several studies are conducted to develop gaming Quality of Experience (QoE) prediction models for CG service, notably ITU-T Rec. G.1072 [2], to the best of the authors' knowledge, there is no research work available to predict the OMG quality. The recently published ITU-T Rec. G.1072 is an opinion model predicting gaming QoE for CG services. This recommendation has a modular structure that splits the video coding-related impairments (that are not relevant for OMG service) and impairments affecting the interaction quality. Since CG and OMG have common influencing factors affecting the gaming QoE, ITU-T Rec. G.1072 can potentially be used for predicting gaming QoE of OMG services. Besides the difference between the services in terms of technology, G.1072 targets PC gamers using keyboard and mouse inputs. This raises the question of whether such a model would be a suitable model for gaming QoE predictions of OMG service. Thus, the present paper focuses on developing a gaming QoE model for OMG services based on two popular video games, Fortnite and Playerunknown's Battlegrounds (PUBG). In addition, a comparison between OMG and CG will be presented.

In particular, the paper aims to answer the following research questions (RQs):

1) Can a model developed for CG be used for OMG?
2) How important is jitter when investigating the impact of packet loss on gaming QoE?
3) Which quality features contribute the most to the overall gaming QoE during online mobile gaming?
4) How can gaming QoE be modeled using only information about network parameters?

The remainder of this paper is organized as follows. In Section II, an overview of related research is given. Next, in Section III, the methodology and test setup for a subjective experiment will be described. A statistical analysis to answer the RQs is provided in Section IV. Finally, Section V provides a discussion of the findings and possible future work.

II. Related Work

In this section, a short overview of research in gaming QoE and online (mobile) gaming is presented. This information is by no means comprehensive but should allow the reader to understand the decisions made in the design of a subjective experiment and a general understanding of the motivation behind the work. QoE assessment in interactive services such as gaming is very challenging as players are emotionally attached to their activities, and a player's actions can significantly

[1] https://www.statista.com/topics/1906/mobile-gaming/

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impact the QoE. Möller et al. [3] proposed a gaming QoE taxonomy to understand the QoS and QoE aspects related to gaming services. The taxonomy differentiates and categorizes influencing factors, interaction performance metrics, and quality features in three layers. The influencing factors are any characteristics of the user, system, and context whose actual state or setting may influence QoE [4]. Quality features refer to perceivable, recognized, and nameable characteristics of the individual's experience of a service that contributes to its quality [4]. The gaming quality features considered in the taxonomy include player experience features (e.g., flow, immersion), input quality, and video quality which are also considered in the recent standardized QoE model for CG, the ITU-T Rec. G.1072 [2].

For online gaming services, three important influencing factors, namely packet loss, delay, and jitter, are the dominant system-related factors influencing the gaming QoE. Various techniques could be employed to compensate for packet losses, such as forward error correction (FEC) and retransmission to conceal packet losses. The retransmission itself can be a source of additional delay. The negative influence of delay in gaming QoE has been investigated in several studies. Quax et al. [5], investigated the influence of delay and delay variation in a First-Person Shooter (FPS) game on traditional online gaming. It was concluded that players perceive the impairments caused by delay, but jitter does not play a prominent role in the acceptance of the service as much as delay does. Beznosyk et al. [6] further investigated jitter on online gaming and showed that high levels of jitter such as 100ms on top of a 200ms fixed delay could negatively influence the gaming QoE.

Delay compensation techniques can strongly compensate the influence of delay in online gaming. These techniques can be categorized according to [7] into predictive techniques, delayed input techniques, and time-offsetting techniques. Predictive techniques, such as Dead Reckoning, predict the next state of the game based on the latest information from the server. For example, with the last information about the movement direction and speed of an enemy, the next position can be predicted. However, mispredictions often occur when this information is not frequently updated due to delay, and the position should be corrected. Delay input techniques such as bucket local lag [8] add delay to the user local input until they are propagated to other players. Finally, time-offsetting techniques store a snapshot of previous states of the game and enables rolling back.

Delay compensation techniques in CG are not as advanced as online gaming yet. Thus, the delay compensation techniques are one of the main differences in the perception of delay in CG and online gaming service. In addition, for online gaming, where only the game states are transmitted but, on contrary to CG, not the video scene itself, the perception of delays might be different. Therefore, it is expected that online gaming would be less prone to delay degradation compared to CG.

While most researchers focus on the impact of influencing factors on gaming QoE, some others investigate the importance of game content in the perception of network degradation. Notably, within ITU-T Study Group 12, an effort has been made to develop game classifications for different degradation types. Among these, the ITU-T Rec. G.1072 proposes different model coefficients depending on a game's sensitivity towards network delay, also presented in [9].

Finally, researchers tried to fundamentally model the user experience in the context of gaming in presence of delay. Among them, Claypool [10], [11] modeled the influence of delay on user performance by considering velocity and angle in addition to the distance and size from Fitts' law. It describes the time to select a target as a function of the distance and the size of the target item [12]. Claypool et al. [10] attempted a fundamental approach to develop a model that can predict the user experience of a task that requires selecting a moving target with a mouse under different levels of delay. Selecting a moving object is a fundamental action for many computer-based multimedia applications such as computer games. The authors suggested a model of target selection time with exponential relationships based on two parameters of delay and target speed. Claypool [11] complements the research by extending the study and using a game controller with a thumbstick instead of a mouse as an input device. The results revealed a very similar trend of exponential relation of target selecting time with the increase of delay and target speed. Sužnjević et al. [13] conducted an extensive study evaluating an online game, World of Warcraft, under four types of degradations, delay, packet loss, frame rate, and jerkiness. Frame rate and jerkiness relate to client device computation capabilities when rendering the scene. The paper modeled the QoE based on linear and non-linear models for the tested game.

III. Methods

Even though many studies are available that investigate the influence of various network parameters and game characteristics on gaming QoE, so far, no standardized and generalizable QoE model for OMG is available. Thus, in a first step, it was decided to evaluate many combinations of different delay and packet loss conditions for the well-known battle royal game, Fortnite. This approach targeted three initial goals: a) investigate whether a model for CG can also be used for OMG, b) reducing the required test conditions to derive an accurate model, c) find out which quality features are suitable for predicting gaming QoE. Building up on the first findings, which are presented in Sections IV.A to IV.C, an additional study using another famous battle royal game called PUBG was conducted using the same test method but with reduced dependent variables.

A. Test Conditions

While based on previous research network delay (the round-trip time is considered here) and packet loss were identified to cause impairments on gaming QoE, it must be noted that a simulation of constant delay and uniform packet loss does not represent real network conditions very well. Thus, the planned experiment had to consider also variations in delay, i.e. jitter, as well as burst rates for packet loss conditions. However, combining all these four parameters to a full factorial test design would result in an unfeasible effort. To reduce the parameter space, it was decided to focus on three delay levels (0ms, 100ms, and 200ms), and four packet loss rates (0%, 30%, 40%, and 50%). The parameter range was derived from a pilot test using experts. Next, for each delay and packet loss rate, the jitter and burst rate values that are present with the highest probability in real networks were assigned, respectively. We derived these values by using a crowdsourcing approach measuring the network performances due to network probes of cellular networks, i.e., Long Term Evolution (LTE). These assessments resulted in the following two equations that describe the relationships between delay and jitter, as well as the successive loss probability (SLP) to the corresponding packet loss rate (PLR):

$$Jitter = 4/17 \cdot Delay \tag{1}$$

$$SLP = \begin{cases} 4 \cdot PLR & \text{if PLR} \leq 10 \\ 40 + 0.33 \cdot PLR & \text{otherwise} \end{cases} \tag{2}$$

For the distribution of delay, a Pareto distribution was used due to its resemblance with real networks. For the 100ms, 200ms, and 400ms delay conditions, also a combination with no jitter, and a three-times the jitter derived from the network evaluations was used. Lastly, conditions using a delay of 50ms, a delay of 1000ms, and a delay of 100ms combined with 20% PLR were added to the condition plan.

B. Experimental Design

The conditions described above result in a total number of 36 conditions. To allow conducting a within-subject design experiment, these conditions were split into two separate subjective tests to avoid participants' fatigue. The participants were reinvited to participate in the second part of study. The order of the presented stimuli was randomized using a Latin square design. In general, the test design adhered closely to the ITU-T Rec. P.809 and to the experiments carried out for the development of the ITU-T Rec. G.1072.

The experiment started with general questions about demographics and video gaming preferences. Afterward, participants played a training condition to learn the controls of the game. Here, also some examples of the impaired test conditions were shown. Next, the participants played the real test stimuli each for 90 seconds. Participants were enabled to start a stimulus with a touch command that executed an app to fade the screen to gray and pausing the game after 90 seconds to avoid an abrupt break potentially influencing immersion-related aspects. After each condition, the participants answered digital questionnaires on a separate computer.

The dependent variables included the overall gaming QoE, video quality and video discontinuity (following ITU-T Rec. P.918 [14]), input quality, self-judgement of playing performance, as well as seven features of player experience (PX): positive affect, negative affect, tension, competency, challenge, flow, and immersion. The input quality, sometimes called playability or interaction quality, is measured as the mean of the quality features responsiveness (e.g., "My inputs were applied smoothly."), controllability (e.g., "I felt that I had control over my interaction with the system."), and immediate feedback (e.g., "I received immediate feedback on my actions."). An overview of the concrete items for the input quality features can be found in [15].

For assessing the PX features, the in-game Game Experience Questionnaire (iGEQ) [16] was used. The questionnaire uses two items per feature. The overall gaming QoE and video quality were assessed using the extended 7-point continuous rating scale (with the labels "extremely bad", "bad", "poor", "fair", "good", "excellent", "ideal"), as proposed in [1]. To avoid confusion by using differently designed scales, we adjusted the discrete 5-point iGEQ scale (with labels "not at all", "slightly", "moderately", "fairly", "extremely") by also applying the extended continuous scale. An example of the scale is shown in Fig. 1.

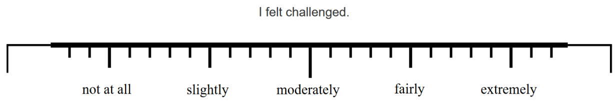

Fig. 1: Seven-point extended continuous rating scale for iGEQ. This example shows an item to assess challenge. Note that due to the overflow area of the scale, the first label "not at all" was coded as a 2 whereas the label "extremely" was coded as a 6.

C. Experimental Setup

For the experimental setup, a local network and the network emulator NetEm were used. Before each condition, a shell script set up the network conditions and to monitor the traffic to the game server. As a client device, the 5.7" Pixel 4, which offers a low touch latency of 69ms, was used and connected using a USB-C to Ethernet adapter to the emulator laptop. This allowed an accurate simulation of the network conditions. The test room fulfilled typical test room requirements proposed in the ITU-T Rec. P.910. The game's audio was played using the mobile phone, which also runs the games under test. As a game scenario for both Fortnite and PUBG, a deathmatch mode was used instead of the typical battle royal mode, as the latter would cause many dull moments leading to bad comparability between the conditions and participants. In each test session, four participants played against each other in Fortnite, and in a team of four players against another team in PUBG.

D. Participants

For the Fortnite study, subjective ratings of 22 participants (4 female, 18 male) were collected. The participants were, on average, 26.9 years old (ranging between 19 to 34 years). While 27% stated to know the game and its concept, 36% played similar games before, and the other participants already played Fortnite. Asked about their gaming expertise, 41 % of participants described themselves as "intermediate", 9 % as "novice" and 50 % as "highly experienced" or "expert" gamers. The majority of participants (60%) were PC gamers.

IV. Results

A. Online Mobile Gaming vs. Cloud Gaming

In a recent publication of the ITU-T, an opinion model predicting the gaming QoE of CG services was released [2]. It would be highly beneficial to be able to use parts of this model also for OMG. Thus, to target the RQ1, a comparison between the overlapping delay conditions (uniform without jitter) is presented in the following. The authors of the ITU-T Rec. G.1072 shared the subjective ratings of gaming QoE for two very similar games compared to Fornite, namely Overwatch and CSGO. The mean values and 95% confidence interval (CI) are illustrated in Fig. 2 for all three games and five different delay conditions.

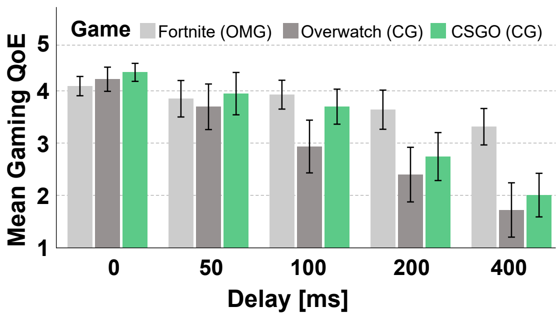

Fig. 2: Bar plots of means and 95 % CI of gaming QoE for Fortnite (OMG) as well as Overwatch and CSGO (CG) using five delay conditions.

It can be observed that the impact of delay, despite all games being shooting games with (mechanical) high delay sensitivity according to [9], is far greater for the CG service than the OMG service. This observation can also be supported by a two-way mixed Analysis of Variance (ANOVA) using the game as a between-subject factor and the delay as a within-subject factor.

For the gaming QoE, the ANOVA yielded a significant interaction effect of game and delay, $F(10,266) = 4.91$, $p < .001$, $\eta_p^2 = .15$. A simple main effect of game resulted, $F(2,54) = 11.88$, $p < .000$, $\eta_p^2 = .31$, and pairwise comparisons confirmed significant differences of the QoE ratings for Fortnite to both other games, and, thus, to CG. Consequently, there is a need for a new OMG QoE model.

B. Interaction of Jitter and Packet Loss

To investigate whether all 36 conditions are required with a focus on the selected jitter values (RQ2), all jitter and packet loss conditions for a delay of 100 ms are analyzed using a two-way repeated measure ANOVA. The subjective ratings are depicted as a bar plot of the mean values of gaming QoE and the corresponding 95% CI in Fig. 3.

The ANOVA resulted neither in a main effect of jitter, $F(2,34) = 1.175$, $p = .32$, $\eta_p^2 = .07$, nor in an interaction effect of jitter and packet loss rate, $F(8,136) = 0.109$, $p = .99$, $\eta_p^2 = .01$. Also for a delay of 200 ms, no interaction effect of jitter and packet loss rate was revealed, $F(6,102) = 0.124$,

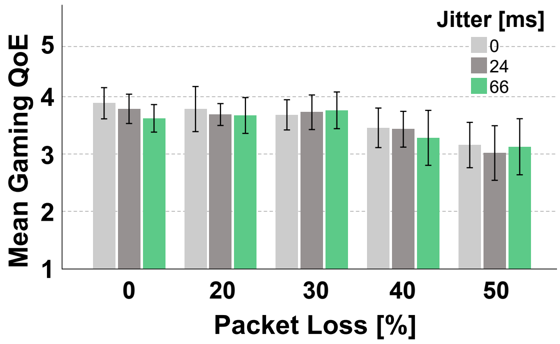

Fig. 3: Bar plots of means and 95 % CI of gaming QoE for various jitter and packet loss rate combinations at an average delay of 100ms.

$p = .99$, $\eta_p^2 = .01$. Finally, also for the 400ms delay, there was no significant main effect of jitter, even when comparing the constant delay ($M = 3.26$, $SD = 0.81$), i.e. no jitter, to an additional jitter of 234ms ($M = 2.90$, $SD = 0.95$), $F(2,34) = 1.68$, $p = .20$, $\eta_p^2 = .09$.

Consequently, it appears that the very detailed parameter space, including multiple variations of jitter is not required for further studies. Instead, the most probable appearance of jitter depending on the network delay as explained in Section III.A can be used. Thus, the parameter space can be reduced to the 16 conditions presented in Fig. 4

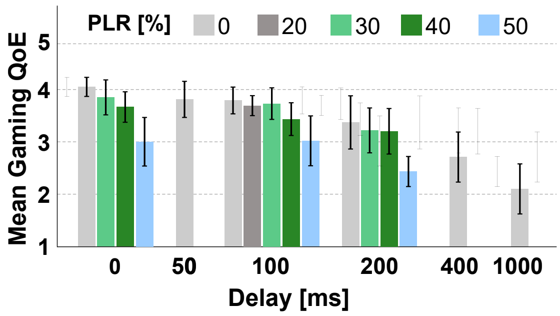

Fig. 4: Bar plots of means and 95 % CI of gaming QoE for various delay and packet loss rate combinations for Fortnite

C. Relationships between Quality Features

Not only the parameter space is important for a QoE model development but also the selection of quality features suitable to predict gaming QoE (RQ3). If suitable features can be found, they might be used as an impairment factor based on its subjective ratings, allowing further reduction of the number of network parameters, e.g., by knowledge about the fact that a bitrate does not influence video discontinuity. For the ITU-T Rec. G.1072, a distinction was made between impairments on the input quality, spatial video quality, and temporal video quality. Thus, in Table I the correlation matrix of the assessed quality features of the conducted experiment using Fortnite (mobile) is presented. Additionally, for a comparison with the quality features assessed for Overwatch using a CG service (cf.

Fig. 2), the correlations among the features are also presented in the table. While a slightly higher correlation of the PX features with the overall gaming QoE can be observed for OMG, a noticeable difference for the input quality as well as video quality and discontinuity can be observed between OMG and CG. While the video quality difference is not surprising as OMG does not include a video stream with spatial artifacts per se, it appears that for OMG using the specific game Fortnite, the input quality covers the variance in the gaming QoE ratings nearly completely. Apparently, the added delay but also the packet losses strongly influenced the input quality similarly. It must be noted that also the correlation of video discontinuity with gaming QoE for OMG is very high. This most likely is because not only a high PLR led to temporal artifacts in the video scene but also a high delay. This is typically caused by delay adaptation techniques predicting upcoming game states. If these predictions are not accurate enough, the game state must be reset to some extend, leading to interruption in the visual representation, i.e., jerkiness (also called rubber banding in the gaming domain). Consequently, for the OMG game Fortnite, a split into multiple impairment factors as done in ITU-T Rec. G.1072 seems not beneficial.

TABLE I: Correlation matrix of quality features for OMG (left of diagonal) and CG (right of diagonal). For the PX, the mean over all iGEQ features (except challenge) was calculated.

Quality Feature	QoE	IPQ	VD	VQ	PX	CH	PR
Gaming QoE	1	0.78	0.50	0.51	0.76	0.19	0.73
Input Quality (IPQ)	0.98	1	0.43	0.20	0.66	0.22	0.75
Discontinuity (VD)	0.93	0.93	1	0.53	0.42	0.04	0.38
Video Quality (VQ)	0.90	0.92	0.52	1	0.43	0.04	0.31
Player Exp. (PX)	0.90	0.79	0.87	0.85	1	0.06	0.69
Challenge (CH)	0.07	0.05	0.01	0.05	0.26	1	0.15
Performance (PR)	0.87	0.85	0.75	0.77	0.88	0.32	1

D. Parametric Model of Online Mobile Gaming Service

In this section, an initial opinion model predicting the gaming QoE of an OMG service for the game Fortnite will be presented (RQ4). The performance of model prediction will be evaluated using Pearson Linear Correlation Coefficient (PLCC), Spearman's Rank Correlation Coefficient (SRCC), and Root Mean Square Error (RMSE). In addition to the latter, a statistical metric called epsilon insensitive RMSE (known as RMSE*) recommended by ITU-T Rec. P.1401 [17] is calculated. It considers the uncertainty of the subjective scores by considering the 95 % CI of the individual MOS scores.

As a first and most complete model, all three network parameters, i.e., delay, jitter, and packet loss (with its corresponding most likely burst rate), will be used. To begin with, the mean values per conditions are calculated and, in line with the ITU-T Rec. G.1072, transformed to the R-scale. The R-scale, which results from an s-shaped conversion of the MOS scale, ranges from 0 (worst) to 100 (best). It can help counter the habit of participants who tend to avoid using the extremes of rating scales. Finally, the difference for each condition to the reference condition ($M_{max} = 4.02$) is calculated and used for modeling. The following model was developed to predict the impairment of gaming QoE on the R-scale using a = -13.09, b = 59.97, c = 1.354, d = 0.003623, e = 0.9047, and f = 0.00692:

$$\Delta R_{QoE} = a + \frac{b}{1 + e^{c - d \cdot (Delay + e \cdot Jitter)}} + f \cdot PLR^2 \quad (3)$$

As shown in Section IV.B, no moderation effect of jitter on the impact of packet loss was shown. Thus, also a model with a lower number of test conditions only using the most probable jitter corresponding to the delay values is proposed. The Eq. 1 still remains but the coefficients are adjusted to a = -16.08, b = 62.92, c = 1.161, d = 0.004283, e = 0, and f = 0.006957.

To evaluate the performance of both models, which represented only training data, the predictions are converted back to the MOS-scale using the method presented in [18]. Furthermore, the means for all 16 conditions assessed for PUBG are used as an independent test dataset. The performance of the models is summarized in Table II and a scatter plot of the Fortnite model on the training data is shown in Fig. 5. The scatter plot for PUGB (test dataset) is visualized in Fig. 6.

It can be observed that for 100ms delay, 24ms jitter, and 50% loss, the prediction on the test dataset has one point with a larger prediction error, whereas the overall performance is very good. However, overall the predictions are slightly higher (M = 3.37) than the assessed gaming QoE (M = 3.20).

TABLE II: Performance evaluation of the proposed online mobile gaming models for the training and test datasets.

Model	RMSE	RMSE*	PLCC	SRCC
Training (all conditions)	0.14	0.05	0.953	0.947
Training (reduced conditions)	0.16	0.00	0.960	0.968
Test (reduced conditions)	0.30	0.23	0.892	0.912

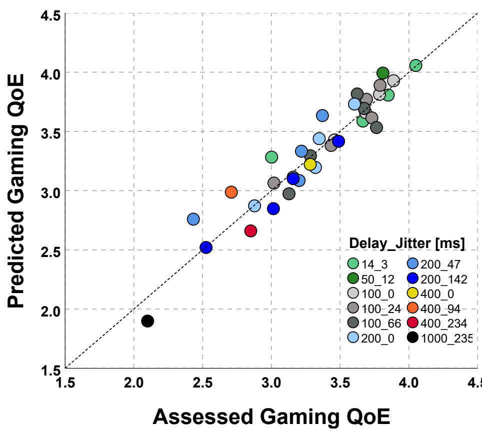

Fig. 5: Scatter plot of predicted and assessed gaming QoE for the training dataset using Fortnite (36 conditions).

V. Discussion and Conclusion

Based on the direct comparison with respect to the impact of network delay and due to the correlation analysis among

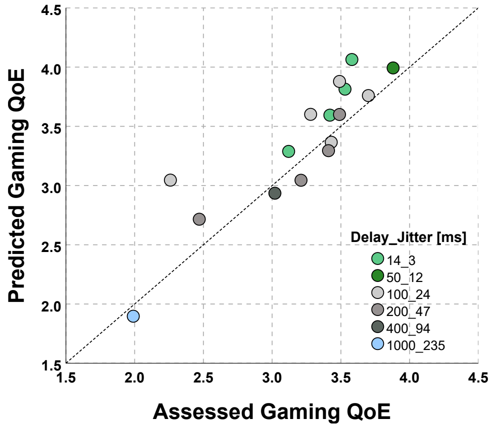

Fig. 6: Scatter plot of predicted and assessed gaming QoE for the test dataset using PUBG (16 conditions).

quality features, it was shown that the existing CG model cannot be used to predict the QoE of OMG services. This is most likely caused by different methods applied to OMG in terms of compensation techniques used, which are not applicable to CG services, as well as the different rendering location. While it was concluded and investigated further that a multidimensional impairment model is not suitable to model the gaming QoE of Fortnite (mobile), one cannot conclude that this applies to all online mobile games. Depending on the implemented methods to handle network impairments, there might be various games for which a split into input quality and video discontinuity impairments is beneficial.

Due to the need for new models to predict the QoE of OMG services, the analysis showed how to reduce and select an appropriate parameter space, i.e., levels and combinations of delay and packet loss rates. Furthermore, a method to simulate realistic network conditions was proposed, which used the highest jitter and SLP probability in real networks to their corresponding delay and packet loss rates. It was shown that it is sufficient to consider these value pairs instead of more jitter levels. In general, one can conclude that network delays represent a more dominant network impairment than packet loss in the typical range of these parameters. Lastly, it was shown that OMG is less prone to network issues than CG.

It must be mentioned that the presented research also faces some limitations with respect to considered influencing factors. In particular, neither core gamers nor social/context effects are considered for the work. Furthermore, the gender distribution of participants was not well balanced. Finally, some technical insights into aspects such as the concrete server tick rate, implemented error concealment and adaptation methods of the used games are unknown to us.

Nevertheless, within this scope, the proposed model presented in this paper for OMG services reached a very good performance on the training and test dataset. It was thus also shown that the model can also be applied to similar games. However, it must be noted that the model is only based on a limited number of games. Consequently, in future work, we aim at increasing the dataset using additional games to derive a more generalizable and game-independent model.

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