Modeling of Cognitive Bias of Video Viewing Users Based on Quantum Decision Making

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***Abstract*—Recently, the need for watching videos as comfortably as possible in streaming services is increasing with the growing amount of video traffic. User satisfaction depends not only on the network quality but also on various factors such as the video content. Estimating the user's Quality of Experience(QoE) and using it for network control is effective to improve user satisfaction. Therefore, we need to estimate the QoE accurately. Various QoE models using network quality have been studied. However, the QoE can vary with cognitive bias, which is a bias that occurs in our cognitive processes. For the QoE control, we need a QoE model with cognitive bias and quantum decision-making has gained attention as a method for modeling cognitive biases. In this paper, we propose a QoE model that includes cognitive bias with quantum decision-making. Then we simulate the QoE to show that our proposed method with quantum decision-making can estimate the QoE and represent video viewers' cognitive bias.**

***Index Terms*—QoE, Video Streaming, Quantum Decision Making, MPEG-DASH**

I. Introduction

Recently, the traffic of video is rapidly increasing with the growing popularity of video streaming services [1]. This trend leads to congestion and poor network quality, which annoys users of these services. Enhancing user satisfaction in such a network environment is a significant problem for service providers. For a better service experience, it is necessary to control the network according to how users feel. Therefore, we need to estimate the satisfaction level of the user. User satisfaction with streaming video services mainly depends on network quality. However, other factors also affect it, for example, the video content, user's mood, or viewing environment. Measuring network quality is not enough to estimate it.

We use Quality of Experience (QoE) to express the satisfaction level of the user. QoE is the subjective evaluation of the service experience by users. Various QoE models have been proposed [2], [3] to represent how users feel accurately.

Meanwhile, humans sometimes make irrational decisions including statistical and memory errors. Both internal factors, such as their experience, and external factors, such as the way information is provided, result in that situation. This kind of irrational decision-making is called cognitive bias in the field of cognitive science. Since QoE is a subjective evaluation, whether the QoE is good or bad is left to their choices. This means that cognitive bias occurs in the process of recognizing the QoE. For example, Sackl A et al. [4] show that even if video content is of the same quality, the QoE differs whether users themselves selected the image quality or not. This results from one of the cognitive biases called cognitive dissonance. It is a bias that avoids contradiction in our brain when there is a conflict in what we recognized. In this case, it makes users believe that the image quality selected by themselves is better than the one selected automatically. Since this example shows cognitive bias among video viewing users, it is needed to consider the effect of cognitive bias in the QoE.

Therefore, we propose a QoE model including cognitive biases in this paper. Video viewers may have a variety of cognitive biases, not just cognitive dissonance. Accordingly, it is necessary to include them comprehensively in the QoE model. For this reason, we use quantum decision-making to model cognitive biases. Quantum decision-making is a method of modeling human cognitive states by mapping them to quantum states in quantum theory. It is expected to be a general-purpose model for cognitive biases since it can represent the irrationality of decision-making. Several studies have used quantum decision-making to model various cognitive biases [5]–[9]. Hence, quantum decision-making is a suitable method to model them.

While watching videos, the cognitive state of viewers changes as new information is given. We need to include changes in the cognitive state in the QoE model. On the other hand, when we use quantum decision-making for modeling the QoE, there is a problem that the time evolution of the state as receiving new information has not been sufficiently discussed in previous studies. To solve this problem, we represent changes in cognitive states through modeling cognitive biases with receiving new information. One example of this type of biases is the anchoring effect. The anchoring effect means that information has a large impact on the subsequent decision [10]. It is showed that the anchoring effect occurs while watching TV, which suggests it can be found while watching video streaming [11]. Therefore, we represent cognitive state change by modeling the anchoring effect with quantum decision-making.

We also specify the cognitive biases of the video viewing users to be modeled in this paper. It is the bias before and after the change in image quality. We show a schematic of this bias in Fig.1. This bias is that the QoE is higher after the video quality recovery than before the quality decrease even if the actual quality is the same level. We found some such biases in the behavior of actual video viewers.

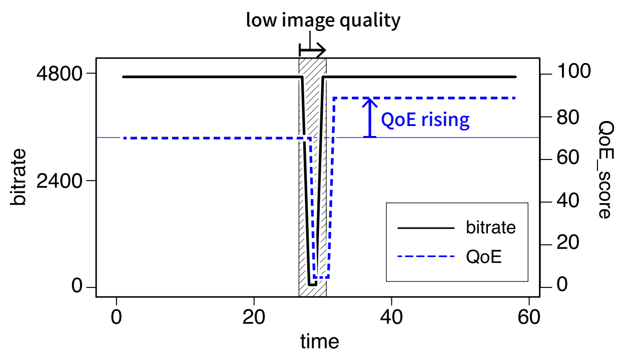

Fig. 1. A schematic diagram of cognitive bias before and after image quality change

The main contributions are summarized as follows:

- Clarify the effect of cognitive bias on QoE
- Estimate QoE closer to how people actually feel by constructing a QoE model that includes the cognitive bias
- To evaluate the accuracy of QoE estimation with our proposed QoE model by comparing actual QoE and estimated QoE

II. Related Work

A. Previous QoE Models

Recently, QoE is used as an evaluation metric for video streaming applications. Existing QoE models mainly use metrics related to network quality such as packet loss rate or jitter [2], [3]. However, cognitive biases that occur while recognizing QoE also affect it since it is subjective. Therefore, we need to consider cognitive bias in constructing QoE models.

In these circumstances, a QoE model with the Memory Effect, as an example of cognitive bias, has been proposed [12]. The memory effect denotes a bias that users' experience influences the QoE in the paper. The authors showed that the memory effect occurs while watching videos and affects the QoE, and their proposed model describes it to some extent. On the other hand, their model can only be applied to the Memory effect and is not comprehensive enough to include other cognitive biases. Quantum decision-making may help solve this problem because it has the advantage of dealing with various cognitive biases comprehensively. Thus, we propose a QoE model that uses quantum decision-making to represent cognitive biases in this paper.

B. Quantum Decision-Making

Quantum decision-making is a model that represents cognitive states by mapping them to quantum states. In this model, decision-making is modeled by the probability theory that quantum follows. Quantum decision-making can be an inclusive model of cognitive biases because the deviation between the probability theory in quantum and classical probability theory represents cognitive bias.

Some studies have modeled cognitive biases with quantum decision-making. For example, a model of order effect based on quantum decision-making has been proposed [5]. Order effect is a cognitive bias that changing the order of giving information influences decision-making. Moreover, other cognitive biases, such as the Ellsberg paradox or gambler's and hot hand fallacies, are modeled by quantum decision-making in previous work [6]–[9]. Thus, quantum decision-making is suitable for modeling the QoE of streaming video viewers since they may have multiple cognitive biases. In the following, we describe the basics of quantum decision-making to prepare for our QoE model. Firstly we explain the mapping between quantum states and cognitive states. Then we describe how the cognitive state shifts and the process of making decisions in quantum decision-making.

1) Mapping quantum states to cognitive states: In quantum decision-making, the cognitive state corresponds to a quantum state. The quantum state is expressed as the source of the Hilbert space $|\psi\rangle \in \mathscr{H}$. The quantum state $|\psi\rangle$ corresponds to a probabilistic choice for an option. For example, we consider a decision-making problem with two options $i (i = 1, 2)$. When we are not sure which option to choose, the cognitive state is denoted as:

$$|\psi\rangle = p_1|\pi_1\rangle + p_2|\pi_2\rangle \tag{1}$$

where $|\pi_i\rangle$ is a basis and p_1, p_2 are probability amplitude. When the Eq.(1) holds, quantum state $|\psi\rangle$ is called the superposition of $|\pi_1\rangle$ and $|\pi_2\rangle$. This state corresponds to the cognitive state that alternative π_1 is chosen with probability $|p_1|^2$ and alternative π_2 is chosen with probability $|p_2|^2$.

2) Decision-making and Cognitive State Change: In quantum theory, when the quantum state is in the superposition state such as the Eq.(1), physical quantities of the system are not fixed. When an observer observes a specific physical quantity, the superposition state is resolved then a physical quantity fixes. As for decision-making, decision-makers don't know which option to choose at first. The cognitive state is updated when they make a decision upon a trigger such as a question for them or asking themselves. This update of the cognitive state is called "decision-making" and "observation" in quantum theory refers to the trigger for decision-making.

In the following, we describe a mathematical model corresponding to the update of cognitive state. Decision making is represented by Hermitian operator $\hat{A}$ on Hilbert space $\mathscr{H}$ and eigenvector $|a_1\rangle, |a_2\rangle, ..., |a_n\rangle$ of $\hat{A}$ corresponds to each cognitive state selecting option $a_1, a_2, ..., a_n$. Probability $P(a_i)$, which mean selecting a_i in cognitive state $|\psi\rangle$, is defined as:

$$P(a_i) = \| |a_i\rangle\langle a_i||\psi\rangle\|^2 \tag{2}$$

where $\langle x|$ is transposed the complex conjugate of $|x\rangle$ and $|x\rangle = \sqrt{\langle x||x\rangle}$ denotes norm on Hilbert space. Here, we define

$\hat{A}$ as making a decision and consider $\hat{A}$ in cognitive state $|\pi_i\rangle$. When a_i is selected by $\hat{A}$, cognitive state $|\psi\rangle$ is updated to $|a_i\rangle$ discontinuously. In other words, decision-making lets cognitive state $|\pi_i\rangle$ update as:

$$|\psi\rangle \rightarrow |a_i\rangle \text{ with probability } P(a_i). \tag{3}$$

For which $|b\rangle$ different from $|a_1\rangle, |a_2\rangle, ..., |a_n\rangle$, $P(b)$ has a deviation from the classical probability $p(b) = \sum p_i p(b|a_i)$. This deviation $P(b) - p(b)$ is called interference term. It represents quantum cognitive biases.

C. The cognitive bias with time evolution

In this paper, we propose a QoE model with cognitive bias using quantum decision-making. The problem with quantum decision-making is that the time evolution of cognitive states has not been sufficiently discussed. To describe the change in the cognitive state while watching videos, we introduce cognitive bias with time evolution into the QoE model.

We include the anchoring effect in the QoE model as a cognitive bias with time evolution. The anchoring effect is that information given just before decision-making strongly influences the decision [10]. The information given in this situation is called an anchor. A mathematical model of the anchoring effect has been proposed by Lieder et al [13]. We build a model of the anchoring effect with quantum decision-making based on the mathematical model. In the following, we describe the mathematical model briefly.

In this model, the update of the cognitive state is represented as the update of the $\hat{x}$ for the estimated target x:

$$x_{t+1} = x_t + \delta \quad (\text{if } P(x_t + \delta|K) > P(x_t|K)) \tag{4}$$

where the δ is a random mutation of the sample point and K is all knowledge about the estimated target x. If the cognitive state is updated over enough time, the estimated result equals the one $P(x|K)$ under all knowledge. Conversely, if the state update terminates before all knowledge of the estimated target x is obtained, the estimation is affected by the initial value of the sample x_0. This initial value $x_0 = a$ is an anchor, which causes the anchoring effect.

III. Modeling of cognitive bias based on quantum decision-making

In this section, we define a QoE model of video streaming service users including cognitive biases with quantum decision-making. To construct a QoE model with quantum decision-making, we need to represent the change in cognitive state when new information is given. We firstly discuss modeling the anchoring effect with it, which is a cognitive bias involving time evolution, with quantum decision-making. After that, we will move on to apply the model to the QoE of video viewers.

A. Quantum Decision-Making Model with Time Evolution

First, we discuss modeling the anchoring effect with quantum decision-making based on the mathematical model in SectionII-C. In the following, x is a quantum state. x is an undecided state between alternatives (g, b), which is a superposition of $|g\rangle$ and $|b\rangle$. The time evolution in the quantum state is mapped to the anchoring effect and is denoted by the Schrodinger equation:

$$i\hbar \frac{d}{dt}|x(t)\rangle = \hat{H}|x(t)\rangle \tag{5}$$

where $\hat{H}$ is the Hamiltonian operator determined by the energy of the system, i is the imaginary unit, and $\hbar$ is Dirac constant. Regarding the update of the cognitive state denoted as Eq.(4) in the mathematical model, it is denoted as the Hamiltonian operator:

$$\hat{H} = \begin{pmatrix} b & -(a + c(t)) \\ -(a + c(t)) & b \end{pmatrix}. \tag{6}$$

Now for modeling the cognitive bias of video viewers shown in Fig.1, it is expressed by the order effect. The Hamiltonian depends on the bitrate at the time t because the order effect is expressed as the non-commutativity of the operator in quantum decision-making. For this reason, $C(t)$ is determinant as:

$$\begin{aligned} c(t) &= \frac{d(t) - N_1}{N_2} \\ (d(t) &: \text{bitrate on time } t, \\ N_1 &: \text{threshold of } |g\rangle \text{ and } |b\rangle, \\ N_2 &: \text{normalized constant}). \end{aligned} \tag{7}$$

We also define $|x^*_{t+1}\rangle = x(t + \tau)\rangle$ as the solution of the Schrodinger equation: Eq.(5) with minute time interval τ. Cognitive states are updated through updating samples as:

$$|x_{t+1}\rangle = \begin{cases} |x^*_{t+1}\rangle & \text{(when update)} \\ |x_t\rangle & \text{(when stay)} \end{cases} \tag{8}$$

The cognitive state gets closer to the state with all knowledge K as updating samples repeatedly. Here, the anchoring effect is the deviation between the state with all knowledge K and the one without sufficient updating. Therefore, the anchoring effect becomes weaker as time passes. In addition, the update of samples is probabilistic, depending on whether it gets closer to the cognitive state under all knowledge K. The probability of updating samples is:

$$\begin{aligned} &P(|x^*_{t+1}\rangle|K) > P(|x_t\rangle|K)) \text{: always update} \\ &P(|x^*_{t+1}\rangle|K) \leq P(|x_t\rangle|K)) \text{: update with probability} \\ &\qquad\qquad\qquad\qquad \text{of } \frac{P(|x^*_{t+1}\rangle|K)}{P(|x_t\rangle|K))}. \end{aligned} \tag{9}$$

B. QoE Model with Quantum Decision-Making

Secondly, we adapt the model in the previous section to the QoE during video viewing. In this case, we assume that the anchoring effect occurs with image quality changes as an anchor because video viewers' QoE usually gets higher or lower with the video quality.

1) Definition of QoE: First of all, we specify QoE for our model. We define two states of QoE: the good state $|g\rangle$ and the bad state $|b\rangle$. QoE is expressed by the probability of selecting $|g\rangle$: $P(g)$. $P(g)$ is denoted by Eq.(2) which is the same as the existing quantum decision-making model. Since $P(g)$ does not contain the interference term, we can estimate the size of the interference term with the deviation from $P(g)$. In the evaluation, we use a normalized version of $P(g)$: $P(g)'$. $P(g)'$ is expressed as:

$$P(g)' = \frac{P(g) - \min P(g)}{\max P(g) - \min P(g)}(\max Q - \min Q) + \min Q \tag{10}$$

where Q is the actual QoE score in a video.

Then we consider the distribution of QoE for a given bitrate based on the dataset used in the simulation [14]. To illustrate the distribution of QoE, we show the normal Q-Q plot of QoE scores in the dataset [14] in Fig.2. The figure shows how well the distribution of QoE for a given bitrate matches the normal distribution for the dataset. The more the QoE distribution (blue line) overlaps with the normal distribution (black line), the closer the QoE is to the normal distribution. Fig.2 shows that they overlap almost equally at all bitrate. Although the tail of the distribution deviates from the normal distribution for higher bitrates, they can be roughly approximated by the normal distribution so that we can assume the QoE follows a normal distribution. Therefore, we assume that $P(x_t|K)$ in

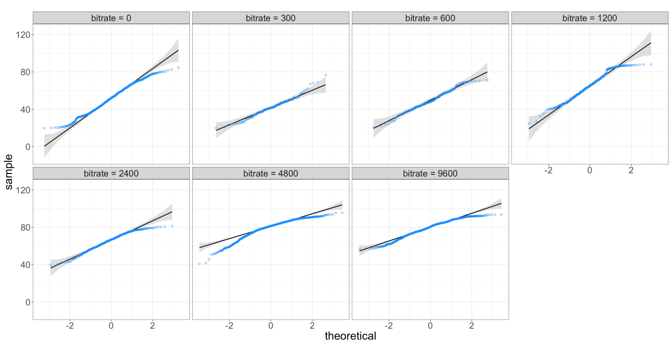

Fig. 2. The distribution of the QoE in the dataset

the state update (Eq.(9)) is given in a normal distribution as shown in Fig.3, depending on the bitrate of time t. Note that the horizontal axis of Fig.3 is the value of QoE, and the vertical axis is the probability density.

In other words, assuming that r is the bitrate of time t, $P(x|r)$ is given by the following Eq.(11). Here, all knowledge K refers to the bitrate from the start to the end of a video. The mean of the normal distribution is given by the monotonically increasing function $\mu(r)$ for bitrate r. $\mu(r)$ is represented by Eq.(12), where R is the maximum bitrate of the video to normalize the bitrate. In addition, the variance was set to $\sigma^2 = 0.17$ in the evaluation.

$$P(x|r) \sim N(\mu(r), \sigma^2) \tag{11}$$

$$\mu(r) = \frac{r}{R}. \tag{12}$$

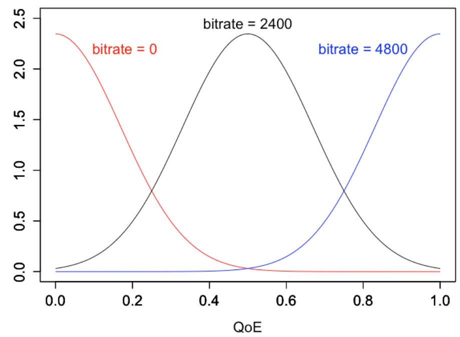

Fig. 3. Example of bitrate and QoE distribution

2) Input to the QoE model: We use bitrate as the input to the QoE model. To describe a correlation between bitrate and QoE accurately, we take the logarithm of the bitrate. Moreover, QoE may vary depending on each viewer's recognition speed and how fast they input QoE scores. To express these differences in QoE, we take the moving average of bitrate between the last few seconds as the input. The time range of the bitrate for the moving average is randomly set from 0.5 to 5 seconds in increments of 0.1 seconds for each simulation. For example, in one simulation, we use the bitrate of the previous 2.0 seconds as input, then we use the bitrate of the previous 4.1 seconds in another simulation, and so on. The difference in the time range of the moving average can be regarded as differences in QoE according to each individual.

IV. Evaluation

A. Simulation Setup

We simulated the video viewer's QoE with our proposed model and a dataset that includes videos, bitrate values of them and QoE scores. In the simulation, the QoE was estimated from bitrate of the dataset. We also evaluated the QoE estimation accuracy by comparing the estimated QoE scores of the QoE model with the users' actual QoE scores.

1) Dataset: We used LFOVIA Video QoE Database [14] in the simulation. The dataset is made up of 36 videos. Videos are processed to include decreasing and increasing bitrates to affect user satisfaction. To apply these videos to simulations, it also includes time-series bitrate and QoE scores per second.

QoE scores in the dataset were obtained from subject experiments. 21 Subjects reported their QoE with a slider on their smartphones, and the value was read every second. The QoE per second is its average. The bitrate transitions for each video are different. In the following, we use f as the decreasing interval of bitrate and t as the duration of low bitrate. f means the number of times that bitrate decreases per minute and t means the duration for which the bitrate is zero. The title of videos consists of its quality, framerate, the decreasing interval of bitrate, and duration of low bitrate. For example, "TV01(FHD, 30fps), $f = 1, d = 7$" means a Full HD video with a framerate of 30 and decreasing bitrate 7 seconds per minute.

2) Calculation of QoE: We calculate the QoE score per second with our proposed model. The input to the model is the time-series bitrate of the dataset.

In addition, the estimated QoE differs for each simulation because whether updating cognitive states or not is determined probabilistically as shown in Eq.(9). Therefore, we run the simulation 10 times and use the average of estimated QoE scores as a result.

3) Parameters:

- a: was formulated with the average of the bitrate change speed in each video. The videos in the dataset are divided into two groups: fast and slow groups of image quality change. The group with the slower image quality change contains 19 out of 36 videos in the dataset. In this group, a is determined by the following Eq.(13).

$$\begin{aligned} &a = -0.0003301x + 76.17 \\ &(x : \text{amount of image quality change per second}) \end{aligned} \tag{13}$$

  The group with faster image quality change contains the rest 17 videos of the dataset. In this group, a is determined by the following Eq.(14).

$$a = -0.0003781x + 76.44 \tag{14}$$

- N_1: was set to 600 because the poor image quality was perceived when the bitrate was below 600 in most videos.
- N_2: was set to 1300.

B. Results

1) Accuracy of QoE estimation: We evaluated our proposed QoE model by comparing the estimated QoE score and the actual QoE score. The evaluation metrics are COR(correlation coefficient) and RMSE(root-mean-square error). The average results of the simulations for all 36 videos in the dataset are shown in Table I. To compare with the our model, we also show the results of simulations with the Memory Effect model [12] in the table.

	COR	RMSE
Quantum Decision Model	0.5969	6.2106
Memory Effect model [12]	0.7664	4.6538

TABLE I
AVERAGE OF SIMULATION RESULTS FOR LFOVIA VIDEO QOE DATABASE

We also give the average of the results using only videos with slow image quality change. We can see that our proposed method can predict the QoE transition accurately for videos with slow image quality change. Meanwhile, the RMSE is large because the estimated QoE does not exactly match at intermediate bitrate with min-max normalization Eq.(10). Since we focus on the good or bad status of QoE, COR is more important than RMSE.

	COR	RMSE
Quantum Decision Model	0.7857	7.2207

TABLE II
AVERAGE OF SIMULATION RESULTS FOR LFOVIA VIDEO QOE DATABASE - ONLY VIDEOS WITH SLOW QUALITY CHANGE

2) Simulation results for the individual video: In the following, we give examples of simulation results for individual videos and discuss them. To show that incorporating the anchoring effect into the model can represent the time-series change in QoE, we present two results.

One of the features of video viewing users is that when the bit rate increases gradually, the QoE also increases slowly along with it. Firstly, we show the simulation result for movie1 in Fig.4 to prove that the feature can be expressed in the behavior of our QoE model. Comparing the average of the QoE estimates with the actual QoE in the dataset, their behavior is similar when the bitrate changes. Especially, using the moving average of the bitrate over a random range of time as the input lets the QoE model represent the gradual decline of the QoE estimate after the bitrate decreases. We can also express the gradual increase in the QoE when the bitrate slowly increases to the maximum.

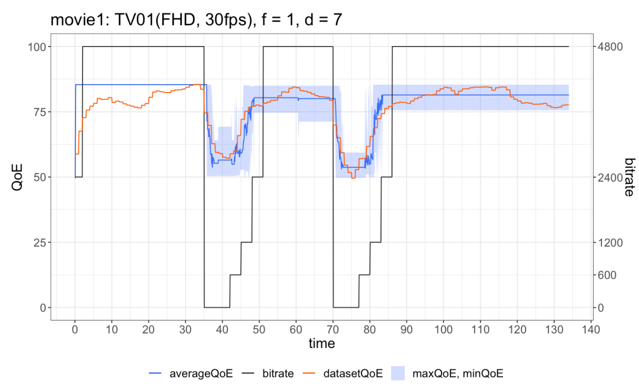

Fig. 4. The simulation result for movie1 ($r = 0.8485$)

Secondly, we give the simulation results for movie36 in Fig.5 to evaluate the behavior of the model when the bitrate reaches relatively high instead of the highest value. Our proposed method can also estimate how the QoE recovers when the bitrate reaches 1200, which is relatively high, and then declines again, as shown in this Fig.5. These results reveal that incorporating the anchoring effect can accurately represent the time-series change in QoE at any bitrate and model the behavior of video viewers.

Then we present another result in Fig.6, which contains the order effect as an example of how our model expresses cognitive bias in Fig.1. This movie contains the order effect after 60 seconds. The bitrate has gone up and down a few times, and each time the QoE has gone up by a little bit. The simulation result shows that each time the QoE goes down and then up, the estimated QoE increases little by little. This indicates our model can express the order effect.

On the other hand, proposed method has several limitations. Since the proposed method uses only the bitrate as an input, the QoE is constant when the bitrate is not switching although

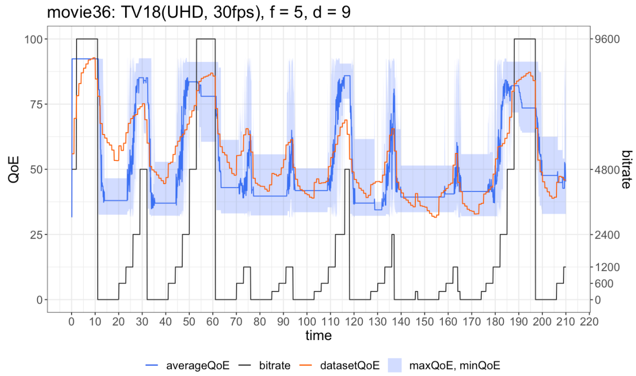

Fig. 5. The simulation result for movie36 ($r = 0.8242$)

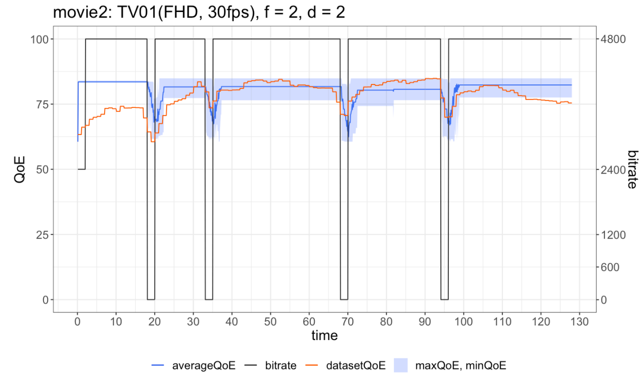

Fig. 7. The simulation result for movie2 ($r = 0.1748$)

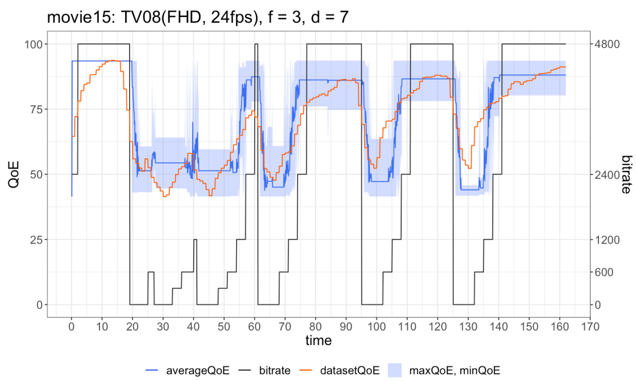

Fig. 6. The simulation result for movie15 ($r = 0.8557$)

the content of the video may change the QoE. Thus, when the bitrate stays fixed, the QoE estimate is sometimes far from the actual QoE. For example, the QoE fluctuates depending on the video content despite the bitrate is stable while 0 to 30 seconds and 90 seconds or later in Fig.4.

Our model also has issues with the behavior in videos with faster bitrate change. If the duration between the bitrate decreases and returns to the maximum such as Fig.7, the proposed method results in a slow decrease in the QoE estimate relative to the rate of change of the bitrate. Therefore, the correlation with the QoE of the dataset is low. We need to improve the model for such videos so that it can represent the change in QoE in response to the instantaneous change in bitrate.

V. Conclusion

In this paper, we proposed a QoE model that includes cognitive bias based on quantum decision-making to estimate QoE including cognitive bias. Then we simulated the QoE with our proposed QoE model and estimated the QoE over time. As a result, our proposed model with quantum decision-making can express some of the cognitive biases of video viewing users. We also showed that the model could estimate the QoE from actual video viewers. On the other hand, the proposed model does not deal with instantaneous bitrate changes well. The future work is to improve the response of the model to these bitrate changes.

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