Implementation of Quantum Decision-Making Based Recommendation Method for Adaptive Bitrate Streaming

Tatsuya Otoshi†, Masayuki Murata†
†Graduate School of Information Science and Technology, Osaka University
1-5 Yamadaoka, Suita, Osaka 565-0871, Japan

***Abstract*—Various services including video streaming are provided via the Internet. In the future, as network virtualization technology advances, building and controlling a network for each service is expected to make the network suitable for the service. In this case, it is necessary to design the network construction and operation from the viewpoint of the quality of experience (QoE) of users. Although research on modeling QoE of users has been advanced, the QoE changes according to the user's psychological effect, so it can be hard to model the complete QoE in the conventional model. On the other hand, quantum decision-making has begun to be drawing attention in recent years as a model for expressing human cognitive state and decision-making. In quantum decision-making, it is possible to represent human behavior, which is hard to express in the conventional cognitive model, and it is expected as a more general model. In this paper, we implement the recommendation algorithm in MPEG-DASH, which recommends the user to select the appropriate bitrate by avoiding the cognitive bias captured by the quantum decision-making model.**

***Index Terms*—Bitrate Recommendation, Quantum decision-making, QoE, Video Streaming, MPEG-DASH**

I. Introduction

Recently, Internet users enjoy various types of service such as video streaming. Since the quality of these services is affected by the quality of the communication, user's satisfaction depends on the network condition. Thus, the service provider should consider not only the service itself but also the dynamic network condition changes for application design.

One effective way to keep the service quality during the network condition change is changing the encoding of the contents. For instance, in the video streaming protocol called MPEG-DASH (Dynamic Adaptive Streaming over HTTP) [1–3], a server prepares multiple profiles of the same video contents whose bitrates are different. The video data is split into segments by each profile. The video player can choose the video profile dynamically by requesting the next segment for the selected video profile. The profile selection is not only automatic (by video player) but also manual (by the user itself). Thus, the user could keep watching the video with feasible quality even when the network condition changes.

However, it is difficult to determine which encoding is desired by the user. It depends not only on the network condition but also on the user's psychological behavior including cognitive biases [4–6]. In [6], the satisfaction of the user watching a streaming video is affected by a type of cognitive bias called *cognitive dissonance*. The study shows that the user's satisfaction is improved when the user selects the video quality by oneself while the same video quality selected automatically gives lower satisfaction. Although the user's satisfaction has been modeled from the viewpoint of the quality of experience (QoE) in previous literature [1, 7, 8], modeling the comprehensive user's psychological behavior has not been achieved.

Thus, the recommendation is better for improving the user's QoE than pushing a certain video profile to the user. If the user is rational, the user's manual choice is close to what he/she desires. On the other hand, the user would select a wrong decision by the cognitive effect. Moreover, it is tiresome for the user to select the video profile at each time. Therefore, the automatical supports to select the bitrate is also required. The recommendation is a promising compromise plan to take the advantages of the manual and automatic bitrate control. That is, the recommendation only gives the user the push to change the bitrate, then the actual decision is made by the user his/herself.

In order to lead the user to the right decision, the recommendation should be conducted by considering how the recommendation affects the user's decision. Although there is no quantitative model to predict how the user obeys such recommendation while watching a video, the research on the psychological experiments, fortunately, has modeled how a person makes the decision when the decision is requested [9–13]. The model is called *quantum decision-making model* which applies the mathematical framework of the quantum theory to describe the human's decision-making. According to quantum decision-making, the cognitive effect such as cognitive dissonance and order effect is explained as the quantum effect in the model. Thus, the quantum decision-making model is expected to represent the user's behavior during video streaming.

In this paper, we propose a bitrate recommendation method which avoids the cognitive bias captured by the quantum decision-making model. In the model, the frequent recommendation discourages the user against changing their mind. This cognitive bias called *quantum Zeno effect*. To avoid this effect, our recommendation algorithm carefully selects the timing to show the recommendation based on the user's behavior predicted by the model.

To demonstrate our algorithm works well, we implement the recommendation algorithm in the MPEG-DASH video streaming system. Implementing the recommendation engine as an independent agent, we achieve the following:

- (1) the recommendation engine gets the user's terminal information quickly by deploying the agent close to the user's terminal
- (2) the user's terminal does not suffer from an additional consuming resource for the recommendation.

The rest of this paper is organized as follows. Section II shows an overview of Quantum decision-making to understand our user model. Section III shows the proposed method to recommend the appropriate video quality to the user by using the user's decision-making model. Section IV shows the implementation for the proposed recommendation algorithm in the MPEG-DASH. Section V shows the simulation results of our recommendation method. Section VI concludes this paper.

II. Quantum decision-making

Quantum decision-making is one of the models of human decision-making. This model is expected to explain the psychological effect of the human which cannot be explained by previous models such as the expected utility model and prospect theory. In this section, we briefly explain the general quantum decision-making.

In quantum decision-making, there are roughly two stages, i.e, thinking about the possible selections before the decision and determining a selection when it is forced to make a decision. For the first stage, people consider which selection to choose in their mind. In this stage, each selection has a probability to be chosen according to their cognitive state. The cognitive state is described as a quantum state which reflects the probability of each selection. In the second stage, people choose one selection as a decision according to the probability. This stage is modeled as a quantum measurement in which one measurement value is observed with the probability according to the quantum state.

In this section, we briefly introduce the mathematical formula of the quantum decision-making. We describe the following (1) how to represent cognitive states as quantum states, (2) how to model the decision-making as the quantum measurement, (3) how to describe the update of the cognitive state, and (4) how the quantum effects explain the psychological effect.

A. Cognitive State

In quantum decision-making, the cognitive state of the human is modeled as a quantum state. The state is denoted as an element of Hilbert space $\mathcal{H}$. The quantum state is represented by a bra vector such as

$$|\psi\rangle \in \mathcal{H}. \tag{1}$$

The linear combination of certain states is also a quantum state. When a quantum state is denoted by the linear combination of $|\pi_1\rangle, |\pi_2\rangle$ such as

$$|\psi\rangle = \psi_{\pi_1} |\pi_1\rangle + \psi_{\pi_2} |\pi_2\rangle, \tag{2}$$

the state $|\psi\rangle$ is called *superposition state*. The coefficients $\psi_{\pi_1}, \psi_{\pi_2}$ called *probability amplitude* indicates that the measurement result of $|\psi\rangle$ is $|\pi_i\rangle$ with probability $\|\psi_{\pi_i}\|^2$.

In quantum decision-making, a superposition state corresponds to hesitating over which selection to choose. That is, the human selects the selection π_i with probability $\|\psi_{\pi_i}\|$.

For the video streaming user, the selection π_i represents the video profile.

B. Decision-making

In quantum theory, the physical quantity is not determined until the measurement is conducted. After the measurement, the quantum state jumps into a certain state in which the measurement value is confirmed.

Similarly, decision-making is conducted by the "measurement" of the quantum state in quantum decision-making. In this context, the measurement means to ask a question to the human including asking himself/herself. Getting the question, the human determines his/her decision by answering the question.

The measurement is represented as an operation over the Hilbert space. We denote the operator $\hat{A}$ which is the Hermite operator over $\mathcal{H}$. The eigenvectors $|a_1\rangle, \cdots, |a_n\rangle$ of $\hat{A}$ decides the possible selections that the decision $a_1, \cdots, a_n$ is selected with probability 1, respectively.

When the user in the state $|\psi\rangle$ selects his/her decision with $\hat{A}$, the probability to select the decision a_i is determined as

$$P(a_i) = \| \langle a_i|\psi\rangle |a_i\rangle \|^2 \tag{3}$$

where $\langle x|y\rangle$ denotes the inner product of $|x\rangle$ and $|y\rangle$ and $\| |x\rangle \|$ means the norm of $|x\rangle$.

Once the user selects the decision a, the state $|\psi\rangle$ jumps into a state $|a\rangle$ in which the human selects the decision $|a\rangle$ with probability 1. This transition of the state is described by following

$$|\psi\rangle \to |a_i\rangle \text{ with probability } P(a_i). \tag{4}$$

This non-continuous transition of the state is one characteristic feature of the quantum decision-making. The probability to select a certain choice depends on the decision the human selects before. That is, the decision directly affects the cognitive state of the human in the quantum decision-making.

C. Quantum Reinforcement Learning

Since people change their mind with new information from the environment, the cognitive state should be updated with the observed information. In quantum decision-making, *quantum reinforcement learning* is one model for the state update with observation [10, 14].

The quantum reinforcement learning is the process that the probability of a specific decision is enhanced when the observation. Once the new information x is given at time t, the state $|\phi(t)\rangle$ is updated as

$$|\psi(t+1)\rangle = Q(x)\,|t\rangle \tag{5}$$

where $Q(x)$ is the operator which amplifies the probability of a certain decision suitable to the observed information.

The operator $Q(x)$ is defined as follows [10]:

$$Q(x) = (Q_2 Q_1(x))^L \tag{6}$$
$$Q_1(x) = I - (1 - e^{i\phi_1}\,|\pi_x\rangle\,\langle\pi_x|) \tag{7}$$
$$Q_2(x) = (1 - e^{i\phi_2})\,|\phi(t)\rangle\,\langle\psi(t)| \tag{8}$$

where π_x represents the choice whose probability increases by obtaining the observation x, and L, ϕ_1, ϕ_2 are parameters.

Typically, ϕ_1 and ϕ_2 are set to $\phi_1 = \phi_2 = \pi$, and L equals to the revenue for selecting the choice x [10].

By repeating the amplification of the probability every when the new observation is obtained, the probability to choose an optimal choice becomes high. Thus, the decision-making with this quantum reinforcement learning leads to reasonable choice after when sufficient information is collected from the observation.

For the user of the video streaming, the amplified selection π_x is such as the optimal video profile which maximizes the user's satisfaction F^k. Assuming the partial rationality for the user, cumulating information amplifies the probability to select objectively optimal selection. Thus, F^k would be an objective QoE which is determined by some QoS metrics. For instance, in [1], QoE is defined as the weighted summation of average bitrate, average bitrate changes, rebuffering and startup delay:

$$F^K = \sum_{t=1} Kr(t) - \lambda|r(t+1) - r(t)| - \lambda_d d(t) - \lambda_s T_s \tag{9}$$

where $d(t)$ is the time when the video stopped by rebuffering, T_s is the startup delay, and $\lambda, \lambda_d, \lambda_s$ is weight for each factor.

1) Quantum Zeno Effect: The quantum decision-making can explain the cognitive effect with the quantum effect in the quantum cognition model. In this subsection, we briefly introduce some of these special features in the quantum decision-making, unlike classical decision model.

An important characteristic of quantum decision-making is *wave function convergence*. Once the decision is made, the cognitive state is changed into a certain state in which the probability of the selected decision is 1 and the probability of otherwise is 0. This quantum effect causes that the continuous decision tends to conclude the same decision. Such persistence to their own decision called *cognitive dissonance* in the psychology [6].

Since the cognitive state changes with time, this tendency depends on the time interval between continuous decisions. If the second decision is conducted long after the first decision, the persistence to the first decision is weak. On the contrary, the persistence is strong with a short time interval between two decisions.

When the time interval becomes close to zero, the decision tends to be fixed to one choice. This effect is called the *Quantum Zeno effect* and it is confirmed with experimental results [12].

Thus, the frequent recommendation to induce the user to change bitrate may cause the user's persistence to the current bitrate. In section III, we propose a recommendation method to avoid such a quantum effect and lead the user to a better choice.

III. Bitrate Change Recommendation

To achieve both providing the high quality to the user and selecting the video bitrate by the user him/herself, the recommendation is a promising solution. That is, the user is recommended to change the current video bitrate when the bitrate is no longer suitable to the current network condition.

Repeating recommendation would encourage the user to change the video bitrate. However, too frequent recommendation prevents the user from switching the video bitrate due to the quantum Zeno effect.

Considering this cognitive effect predicted from the quantum decision-making model, we propose a recommendation method to induce the user to select a better bitrate. proposed method avoids such cognitive dissonance effect by carefully choosing the timing to recommend by estimating whether the user sticks to the previous decision.

A. Overview

The recommendation module can be placed at the video player, video server, or middlebox such as proxy. The module gets the current state of the playing video from the video player such as network throughput and buffered video length. With this information, the module understands the current situation and updates the cognitive state which is the estimated state for the user. If the current bitrate is not suitable to the current network condition, the module recommends the user to change the video profile. However, to avoid the cognitive dissonance, the module waits to present the recommendation until the probability that the user selects the desirable choice is high.

Thus, the key functions of the recommendation module are (1) how to update the estimated cognitive state with observed value, (2) how to detect whether the current bitrate is inadequate to the current situation, and (3) how long the module postpone the recommendation.

The rest of this section describes how to detect the situation change when switching the bitrate is required and how to determine the recommendation timing.

B. Detecting Situation Change

The module detects whether the current bitrate equals to the best bitrate in the aspect of the QoE under the current observation. If the current video profile q is not optimal video profile π_x with the current situation x, the module determines that the recommendation is required to change the profile.

C. Determining Recommendation Timing

To avoid the wrong selection by the cognitive effect, the recommendation should wait for the timing when the probability to select the best profile is close to 1. Although the cognitive state of the user approaches to selecting the best video profile by the update with observed information, the cognitive effect distorts the user's decision from the best profile. For instance, frequent recommendation fixes the user's decision regardless of the current network condition.

On the other hand, postponing the recommendation delays the response to the changing network condition. If the module recommends the user to switch profile too long after the network condition change, the buffer may be empty and rebuffering occurs.

Moreover, the repeating recommendation is acceptable if the user selects the wrong video profile with the previous recommendation. Even when the user changes to the best video profile with 2 or 3 times recommendation, the QoE degradation is avoided unless the profile is changed before the rebuffering occurs.

Thus, the recommendation module should select the recommendation timing so that the user can decide to change to the best profile quickly with repeating recommendations. That is, the recommendation module calculates the recommendation timing to minimize the time to change the user's decision to the best profile.

We describe the probability of user to select the optimal video profile π_x at time t as $p_{\pi_x}(t)$. If the recommendation is conducted each time when the probability becomes $p_{\pi_x}(t)$, the number of recommendation n_t required to lead the user to select optimal decision follows the *geometric distribution* with parameter $p_{\pi_x}(t)$. Thus, the expected value of n_t required to select the optimal profile is $\frac{1}{p_{\pi_x}(t)}$.

The total time required to change to the optimal profile by the user's decision is $t \times n_t$. In order to minimize the total time, the recommendation module should recommend to the user with the time interval t^{opt} :

$$t^{opt} = \arg\min_t E[t \times n_t] = \arg\min_t \frac{t}{p_{\pi_x}(t)}. \qquad (10)$$

With the interval t^{opt}, the recommendation module periodically recommend the user to change the video profile.

IV. Implementation

To evaluate the above recommendation method in a realistic situation, we implement the recommendation system which comprises the recommendation engine in the MPEG-DASH streaming environment.

In the literature, most of the bitrate control algorithms are implemented in the video player which is running on the user's terminal [1, 2]. This is because the bitrate optimization requires the newest information of the video player to decide the best bitrate for the current player appropriately. However, it is desirable that the calculation on the user's terminal is avoided since the user's terminal usually does not have rich computation power. There is also the server-side bitrate control method [3]. Although the calculation is conducted on the server with the rich computation resource, the information for the calculation is delayed because of the communication between the server and the user's terminal.

To solve the above issue, we implement the recommendation engine as an agent which is independent of the user's terminal and the video server. The recommendation engine gets the video player's information from the user's terminal(client). Since the agent is independent of the video server, the agent can be deployed close to the client to suppress the communication delay between client and agent. Thus, the agent can conduct the recommendation without the information lag while the recommendation engine does not consume the calculation resource on the client.

Fig. 1 shows an overview of our implementation. We use the reference player of the MPEG-DASH called *Dash.js* as the video player. To implement the agent-client communication, we add the interface to the Dash.js. The interface sends the player's state to the agent, then receives the recommendation result. According to the result, the client shows the recommendation through the user interface, then the user decides the bitrate on the video player.

To implement the communication between agent-client communication, we apply the WebSocket. WebSocket is a common way for bidirectional communication on the web application. Thus, the additional computation cost for the client is mainly caused by the sending/receiving message by WebSocket at the client/agent interface. We evaluate this additional computation cost in the next section and show that the additional cost is low enough.

V. Evaluation

In this section, we evaluate how the proposed recommendation system works on the real video player. First, we show that the proposed recommendation algorithm avoids the quantum Zeno effect by selecting the timing to recommend. Then, we show the effectiveness to implement the recommendation engine as an agent. That is, we confirm that additional computation cost on the user's terminal is low, and the communication delay can be suppressed.

A. Experimental Setting

Before we show the evaluation result, we explain the setting for the evaluation. In this evaluation, the video streaming is conducted over the recommendation system described in section IV.

We use the video file which is prepared by the DASH Industry Forum for the demonstration of the reference player Dash.js. The video has 10 profiles whose bitrate is ranged from 254 kbps to 14931 kbps and the segment length is 4 s. More detail about the video file is described its MPD file [15].

To verify that the recommendation is appropriately conducted when the environment changes, we manually drop the network throughput during the streaming by the network

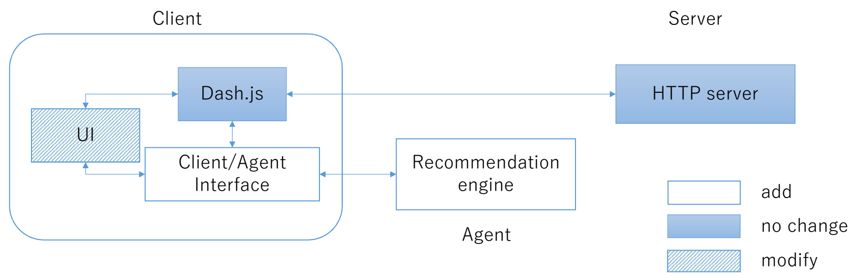


Fig. 1. implementation of the recommendation system in the MPEG-DASH

emulator. First, the network throughput is set to 10 Mbps. After 30 seconds video playing, the network throughput is dropped to 4 Mbps.

To show the effect by considering the cognitive model, we compare the proposed recommendation method with a recommendation method which does not consider the user's cognitive state. That is, the method conducts the recommendation to the user when the current bitrate differs from the optimal bitrate.

Assuming that the user follows the quantum decision-making model, we use the quantum decision-making model to decide the bitrate instead of the actual user.

B. Avoiding the Quantum Zeno Effect

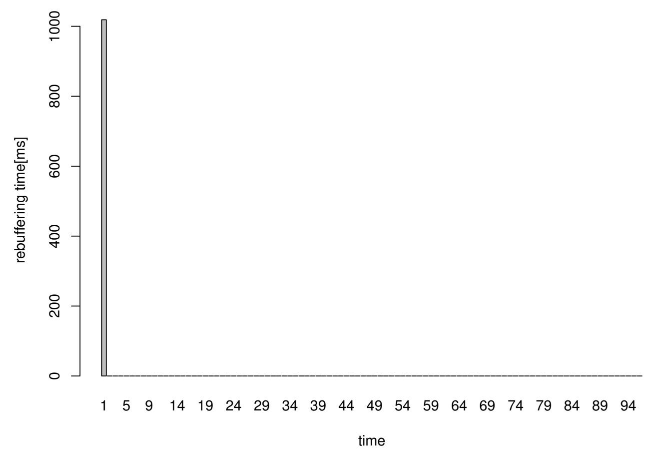
Even when the network throughput decreases, the user may still think that the current bitrate is suitable since the user does not have enough evidence for the degradation of the throughput. In this situation, the user selects the wrong profile with high probability unless the recommendation is postponed until the user's cognitive state is updated. Thus, we verify that our recommendation algorithm can avoid such cognitive bias by considering the user's cognitive model.

Fig. 2 shows the duration of rebuffering, that is, the how long the video streaming stopped at the time. Fig. 2(a) is the result of video streaming with our proposed method, and Fig. 2(b) is the result of a simple recommendation method.

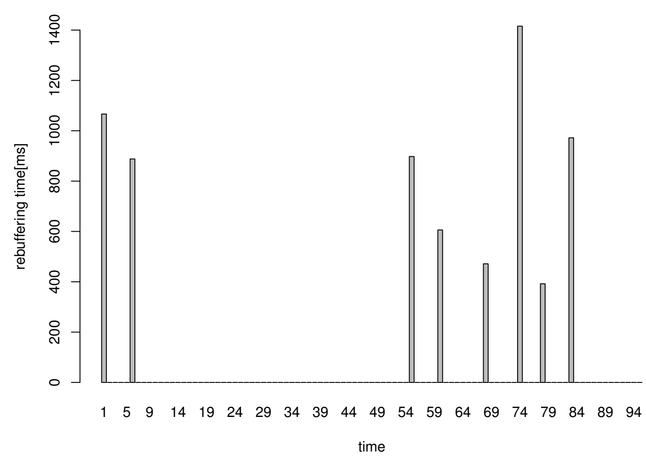
At the first time slot, the video streaming is stopped because the video player loads several segments to play the video smoothly. Thus, the rebuffering occurs for both the recommendation methods.

After throughput degradation at time 30, both methods try to recommend the low bitrate video profile to avoid the rebuffering. However, the simple recommendation cannot change the user's mind (quantum decision-making model) and the rebuffering occurs frequently as a result. This is because the recommending the low bitrate simply when the current bitrate does not suitable to the current network situation causes quantum Zeno effect. Although the user's mind does not completely change to the new situation, the simple recommendation method recommends the user to change the bitrate. Thus, the user tends to choose the current bitrate, and this decision makes the user have high confidence to his/her choice.

In our recommendation method, how the user reacts to the recommendation is predicted by the quantum decision model.



(a) Recommendation with Quantum Decision-Making



(b) Simple Recommendation

Fig. 2. Duration of the rebuffering at each time

Thus, the recommendation engine waits to recommend until the user selects the desirable bitrate with high probability. As a result, the user changes the bitrate by the recommendation before the rebuffering occurs.

C. Agent's Delay by Computation and Communication

Since the recommendation is conducted by the agent, the recommendation is no longer appropriate to the current state on the video player if the calculation and communication delay is too long. Thus, we verify that these overheads are small enough by measuring the time.

Tab. I shows the measured time for the proposed recommendation system. *computation on agent* represents the time spent to execute the recommendation algorithm to decide whether the recommendation should be conducted at the time. In this experiment, the agent has Intel Core i7-6600U and 8 GB RAM. *communication between agent and client* means the time between sending the player's information and getting the response from the agent on the video player. In this experiment, the client and agent are placed on the same computer as different processes. Thus, the measured communication delay is mainly caused by the processing of the message by the WebSocket. In an actual situation, there is also propagation delay on the network.

TABLE I
TIME REQUIRED FOR THE RECOMMENDATION ENGINE

	time[s]
computation on agent	0.03
communication between agent and client	0.17

From the table, the overhead by introducing the recommendation engine seems to be small. Comparing to the common segment duration 2–4 s [1, 15], the total delay of the recommendation 0.2 s is enough short. Even considering the additional propagation delay, the recommendation can be conducted during playing one segment. Thus, the recommendation engine can respond to the message from video player before the video stopping even is the message has been sent when the last segment in the buffer has been started.

VI. CONCLUSION

In this paper, we implement a new bitrate recommendation system for the user watching a video streaming by MPEG-DASH. In our system, the recommendation engine calculates the best timing to show the recommendation for the user by using the user's cognitive model. According to the quantum decision-making, the user tends to select the same choice if the recommendation is frequently conducted. Based on the prediction from the cognitive model, the proposed recommendation engine waits to the recommendation until the user selects the desirable bitrate with high probability. We implement the recommendation engine as an agent which is independent of the video player and video server. By deploying the agent close to the user's terminal, the agent obtains the latest information about the streaming while there is almost no additional computation cost on the user's terminal. Through the experimental evaluation, we show that our proposed method can induce the user to select the desired bitrate. As a result, the proposed method can avoid the rebuffering when the network throughput drops while the simple recommendation cannot avoid the rebuffering because of the user's bias. Also, we show that the overhead of introducing the recommendation agent is low enough with the standard segment duration.

Our future work includes the evaluation of the system in the edge computing environment. Fitting the model parameters with the actual user's log is also tackled in future work.

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