

Estimation of Multidimensional QoE of Multi-View Video and Audio (MVV-A) IP Transmission

Toshiro Nunome

Department of Computer Science and Engineering,
Graduate School of Engineering,
Nagoya Institute of Technology, Nagoya 466–8555, Japan
Email: nunome@nitech.ac.jp

Shuji Tasaka

Interdisciplinary Engineering Laboratory,
Nagoya Institute of Technology, Nagoya 466–8555, Japan
Email: tasaka@nitech.ac.jp

Abstract—In this paper, we study a real-time estimation method of QoE of Multi-View Video and Audio (MVV-A) IP transmission. The method utilizes application-level QoS parameters of video which can be measured in real time. At first, we perform an experiment with various types of average load, playout buffering time, and additional delay to the network. In the experiment, we employ two contents and two user interfaces for viewpoint change. We assess QoE multidimensionally and then carry out linear regression analysis in order to obtain regression lines for estimating QoE. We use the QoE metrics as the dependent variables and employ the application-level QoS parameters as the independent variables. From the comparison of measured values and estimated ones, we notice that real-time estimation of QoE is feasible in MVV-A IP transmission.

Index Terms—multi-view video and audio, QoE estimation, linear regression analysis, multidimensional assessment

I. INTRODUCTION

In the conventional television and in the current Internet streaming services, the users cannot freely choose the view (e.g., the viewpoint, angle, and direction) which they want to watch. Instead, they are forced to look at the same view given by the sender, even if they would prefer to watch another view of the same content, program, or event. In order to avoid this inconvenience, *MVV (Multi-View Video)* [1] has been developed.

In MVV, the users can choose one video from multiple video streams of the same content taken by multiple cameras from different positions. MVV systems can be applied to wide areas such as entertainment, sports, sightseeing, and education among others. MVV can be a base system of FTV (Free-viewpoint TV) [2], in which the users can select the viewpoint freely without the limitation of cameras' positions.

As the conventional television enhances its field from broadcasting to IPTV [3], MVV IP transmission attracts people's attention. One of the main issues in MVV transmission is the viewpoint change delay, which is the time from the moment the client sends a request for viewpoint change until the instant a new viewpoint is output at the client. In addition, when the server sends multiple video streams simultaneously in order to reduce the viewpoint change delay, the total bitrate increases as the number of viewpoints increases. Furthermore, synchronization among multiple video streams is also an important research issue.

The ultimate goal of the network services is to provide high *QoE (Quality of Experience)*, which represents the overall acceptability of an application or service, as perceived subjectively by the end-users [4]. In order to enhance QoE, it is important to monitor the QoE perceived by the users and manage the network services on the basis of the QoE.

There have been many studies regarding MVV systems. However, most of the studies focus on the coding techniques such as *MVC (Multi-view Video Coding)* and assess the effectiveness with the throughput and *PSNR (Peak Signal to Noise Ratio)*, which measures spatial quality of video. Thus, there is few studies which assess the effect of network delay and its jitter on QoE.

In [5], Kurutepe *et al.* present a client-driven multi-view video streaming system by transmitting a small number of views selected according to his/her head position. In addition, lower quality versions of some other views are also prefetched for concealment in case the current user's viewpoint differs from the predicted viewpoint. They evaluate the proposed system in terms of PSNR and the prediction error of the head position.

Cheung *et al.* have addressed the problem of designing a frame structure for interactive multiview streaming [6]. They propose an algorithm to encode the video stream for interactive view switching with low transmission cost by means of an optimal selection of I-, P-, and "merge" frames. They assess the efficiency in terms of the transmission cost.

ITU-T Rec. G.1080 [7] defines QoE requirements for IPTV services. However, this recommendation does not refer to the QoE in MVV systems. Thus, it is not clear what are dominant factors in affecting QoE of MVV IP transmission and how to assess them. In addition, it is also unknown what can enhance the QoE.

When showing the object to the users through the MVV system, we expect them to be interested in changing the viewpoint according to the object's movement. In [8] and [9], the authors perform QoE assessment of MVV-A, which is MVV accompanied by audio, with the ability of viewpoint change by a subjective experiment. They then analyze the effect of load traffic, packet delay, playout buffering time, and user interfaces on the QoE in a multidimensional way.

In QoE management, real-time assessment (monitoring) of QoE plays an important role. However, note that real-

time measurement of QoE is practically impossible, since the network operator cannot ask the users to report their perceptual quality in real time. This leads to an increasing demand for methods of estimating QoE by using automatically measurable lower-level QoS parameters such as packet loss ratio and delay jitter.

In [10], Tasaka and Ito propose a QoE estimation method from the application-level QoS parameters which represent temporal quality of audio and video streams. In [11], Tasaka and Watanabe propose an estimation method which employ spatial quality of video in addition to temporal quality of audio and video. However, these studies consider stored media transmission of single view video and audio, and then the characteristics of MVV-A are not considered. Furthermore, the studies deal with just a single QoE measure, i.e., a scalar value.

In this paper, we study an estimation method of multi-dimensional QoE for MVV-A IP transmission by means of application-level QoS parameters which can be measured in real time. In MVV-A, as we discussed earlier, the viewpoint change delay is one of the main issues. Thus, we introduce the viewpoint change response as a factor of multidimensional QoE. We conduct a subjective experiment to obtain measured values of multidimensional QoE and application-level QoS. We calculate the regression lines to predict QoE by means of linear regression analysis. We then confirm the feasibility of real-time monitoring of QoE.

The rest of the paper is structured as follows. Section II introduces a real-time estimation method of QoE. Section III outlines methods of the experiment we performed. Section IV describes methodology of QoE assessment. We present results of the QoE estimation in Section V, and Section VI concludes this paper.

II. REAL-TIME ESTIMATION OF QOE

In this paper, we utilize multiple regression lines that predict QoE measure values from application-level QoS parameter values. The reason why application-level QoS parameters have been selected as the independent variables for the estimation is that the application-level QoS can represent the temporal structures of audio and video¹.

The information unit for transfer between the application layers is referred to as the *MU* (*Media Unit*). A video MU is usually defined as a video frame and an audio MU as a constant number of audio samples.

As a first step of the study on QoE estimation in MVV-A, we employ the *MU loss ratio* and the *average MU delay* as the application-level QoS parameters for QoE estimation. The parameters can be assessed in real time and reflect the temporal structures of audio and video. The MU loss ratio is the ratio of the number of MUs not output at the recipient to the number of MUs transmitted by the sender. The lost MUs include discarded MUs owing to playout buffering control for media synchronization. The average MU delay means the average time in seconds from the moment an MU is generated until

¹Note that QoS parameters at the end-to-end and lower levels do not reflect the media types treated because of the principle of the layered network architecture.

TABLE I
APPLICATION-LEVEL QoS PARAMETERS.

application-level QoS parameter	notation for audio	notation for video
average MU delay [ms]	D_a	D_v
MU loss ratio [%]	L_a	L_v

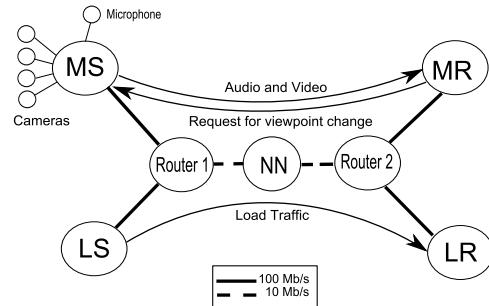


Fig. 1. Experimental system.

the instant the MU is output. The notations of the parameters are shown in Table I. It is our future study to estimate QoE with other application-level QoS parameters.

III. EXPERIMENTAL METHOD

A. Experimental system

Figure 1 shows the experimental system. MS is the server of the MVV-A application, and MR is the client. Four cameras and a microphone are connected to the server. Both router 1 and router 2 are Riverstone's RS3000. NN, which is a PC, is laid out between the routers.

The server captures the video of each camera. At the same time, the audio is captured by the microphone. The server sends the audio and video of a selected viewpoint to the client as two separate UDP packet flows. The client receives these packets and outputs the audio and video decoded from them. The client can choose one viewpoint from the four cameras by sending a request with a UDP packet.

The specifications of the audio and video are shown in Table II. We employed a simple scheme of playout buffering control at the client to absorb network delay jitter and set the buffering time to 60 ms, 100 ms, and 140 ms. If all the packets of an MU are not correctly received in time for output, the MU is not output.

NN delays packets going through routers 1 and 2 by using NIST Net [12]. By adding this delay, we can examine the effect of network delay on the QoE in the MVV-A system. The delay in the computer NN was set to one of the three constant values: 0 ms, 100 ms or 300 ms.

On the other hand, LS is the server of the load traffic, and LR is the client. LS generates UDP packets of 1472 bytes each with exponentially distributed interval and sends them to LR. The average bit rate was set to 7.2 Mb/s, 7.4 Mb/s, and 7.6 Mb/s.

TABLE II
SPECIFICATIONS OF AUDIO AND VIDEO.

	audio	video
coding method	G.711 μ -law	H.264
picture size [pixels]	-	704 \times 480
picture pattern	-	I
encoding bit rate [kb/s]	64	2000
average MU rate [MU/s]	25	25
duration [s]	20	

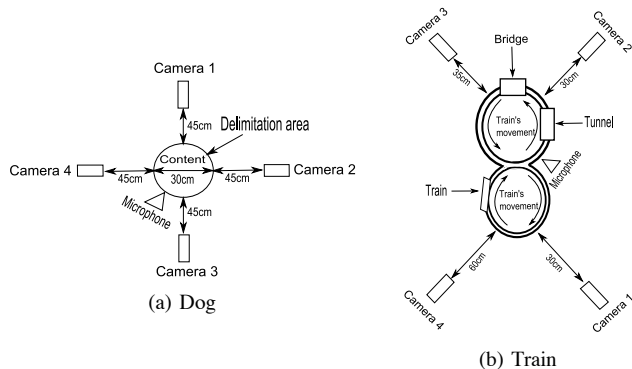


Fig. 2. Camera arrangements.

B. Contents and viewpoint change interfaces

In this assessment, we employ two types of contents and two viewpoint change interfaces as in [9].

Figure 2 shows the positions of the cameras and the microphone connected to MS for two contents that were employed. We refer to the content in Fig. 2(a) and that in Fig. 2(b) as “Dog” and “Train”, respectively.

As the object in Dog, we employ a dog doll which moves with battery. When the switch of the doll is turned on, the doll walks a few steps forward and barks with moving its tail while walking backwards. Later, the doll starts to walk forward again, but in a different direction; it moves in the counterclockwise direction.

In Train, we use a toy train which moves with battery. When the train is turned on, it moves continuously on the rail. The arrows inside the two circles in the center of Fig. 2(b) show the direction of movement of the train.

We used two different user interfaces. Each interface is shown as a small window on the display. The user can move this window to a desired position and can change the viewpoint by using the mouse. With the first one, the user can change the viewpoint by selecting the camera number, as shown in Fig. 3(a). The second one lets the user change the viewpoint by using the camera’s direction, according to the camera that is currently being watched, as shown in Fig. 3(b). In this paper, we refer to the first interface as “Interface 1” and to the second one as “Interface 2”.

Prior to this experiment, the assessors received instructions when watching the contents. In Dog, the assessors were instructed to follow the dog doll’s face. In Train, the instruction was to follow the train. We gave these instructions to the assessors so that we can measure the level of fulfillment of each interface with which the assessors accomplish the

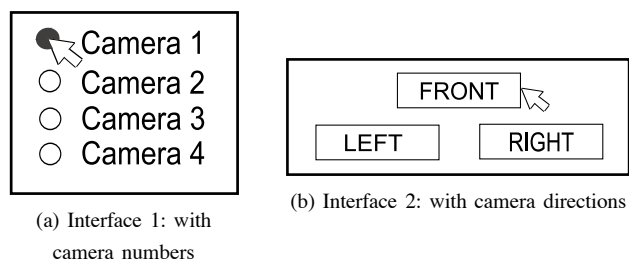


Fig. 3. User interfaces for viewpoint change.

TABLE III
ADJECTIVE PAIRS.

ID	adjective pair
AV1	the video is smooth - the video is interrupted
AV2	the audio is smooth - the audio is interrupted
I1	the viewpoint change response is fast - the viewpoint change response is slow
UI1	the interface is useful - the interface is not useful
MVV1	the system is reliable - the system is not reliable
MVV2	the system is convenient - the system is inconvenient
MVV3	I want to use the system - I do not want to use the system
MVV4	the system fulfills my expectations - the system does not fulfill my expectations
CO1	I can follow the content’s movement - I cannot follow the content’s movement
UF1	I feel relaxed - I feel impatient
UF2	I am not irritated - I am irritated
O1	excellent - bad

instruction.

IV. QOE ASSESSMENT METHOD

We employed 17 male students as assessors. Their age ranges from twenty through thirty.

We refer to an object for evaluation as a *stimulus*, which is an audio-video stream output at the receiver in each experimental run. For each combination of the content and the user interface, the assessor evaluates 30 stimuli including three dummies in a random order.

In this paper, we employ the *SD (Semantic Differential) method* [13] for subjective QoE assessment. This method was proposed by Osgood as a method of measuring meaning.

In the SD method, how to select pairs of polar terms used for the assessment is important. In order to select the polar terms, we performed preliminary tests analyzing different criteria regarding the audio-video streams (AV), the interactivity (I), the user interface (UI), the MVV-A system (MVV), the content (CO), user’s feelings (UF), and the overall satisfaction (O). When we could not find any appropriate adjective in order to evaluate a particular criterion, we adopted a verb instead. After the tests, we chose the criteria shown in Table III.

Note that the experiment was performed with the Japanese language. This paper has translated the used Japanese terms into English. Therefore, the meanings of adjectives or verbs written in English here may slightly differ from those of Japanese ones.

For each criterion, a subjective score is measured by the *rating scale method* [14]. In the method, an assessor classifies

the stimuli into a certain number of categories; here, each criterion is evaluated to be one of five grades. The best grade (score 5) represents the positive adjective (the left-hand side one in each pair), while the worst grade (score 1) means the negative adjective. The middle grade (score 3) is neutral.

When assessing the subjectivity quantitatively, it is desirable to use at least an *interval scale*. In order to obtain an interval scale from the result of the rating scale method, we first measure the frequency of each category with which the object for evaluation is placed in the category. With the *law of categorical judgment* [14], we can translate the frequency obtained by the rating scale method into an interval scale. However, since the law of categorical judgment is based on several assumptions, we have to confirm the goodness of fit for the obtained scale. For a test of goodness of fit, we conduct Mosteller's test [15]. Once the goodness of fit has been confirmed, we use the interval scale as the QoE metric, which is therefore called the *psychological scale* [16].

V. ESTIMATION RESULTS OF QOE

We calculated the interval scale for each criterion. Then, we carried out the Mosteller's test. As a result, we have found that the test with a significance level of 0.01 can reject the hypothesis that the observed value equals the calculated one in some criteria. Thus, we checked stimuli which give large errors of Mosteller's test and removed them in order not to reject the hypothesis. We then use the interval scale obtained by this operation as the psychological scale.

Since we can select an arbitrary origin in an interval scale, for each criterion, we set the minimum value of the psychological scale to the origin.

In the experiment, the MU loss ratio of audio is less than 1 % for all the experimental conditions, and then most of assessors hardly notice the degradation of audio. Thus, in this paper, we estimate QoE from the application-level QoS parameters for video.

A. Calculation of regression lines

In this paper, we calculated the regression lines for smoothness of the video (AV1), viewpoint change response (II), and overall satisfaction (OI) among the criteria because they show the major characteristics of MVV-A.

In each regression line, U means the estimated value of the psychological scale, and its superscript shows the pair of content type and viewpoint change interface. For example, $dog1$ represents that the user sees Dog with Interface 1, and $train2$ means that he/she watches Train with Interface 2. In addition, the subscript of U implies the criterion. Also, let R^{*2} denote the contribution rate adjusted for degrees of freedom.

1) *Viewpoint change response*: We present the regression line of viewpoint change response for each pair of content type and viewpoint change interface with the MU loss ratio of video L_v [%] and the average MU delay for video D_v [ms] in Eqs. (1) through (4).

$$U_{I1}^{dog1} = 3.874 - 2.446 \times 10^{-3} \times D_v - 7.323 \times 10^{-2} \times L_v \quad (R^{*2} = 0.838) \quad (1)$$

$$U_{I1}^{dog2} = 3.810 - 2.073 \times 10^{-3} \times D_v - 6.624 \times 10^{-2} \times L_v \quad (R^{*2} = 0.903) \quad (2)$$

$$U_{I1}^{train1} = 3.511 - 1.239 \times 10^{-3} \times D_v - 6.033 \times 10^{-2} \times L_v \quad (R^{*2} = 0.828) \quad (3)$$

$$U_{I1}^{train2} = 3.720 - 1.397 \times 10^{-3} \times D_v - 8.224 \times 10^{-2} \times L_v \quad (R^{*2} = 0.894) \quad (4)$$

From the equations, for both contents, the contribution rate with Interface 2 is higher than that with Interface 1. This is because Interface 2 is more intuitive than Interface 1, and then the deterioration of application-level QoS can affect QoE directly.

In addition, the regression lines for Dog have larger constant terms than those for Train. Thus, the psychological scale value for Dog tends to be higher than that for Train. This is because Dog moves slower than Train, and then the user does not so sensitive for viewpoint change response with Dog as that with Train.

2) *Smoothness of video*: The smoothness of video is mainly affected by the MU loss of video. Thus, we calculated the regression lines with the MU loss ratio of video. We present the regression lines for each pair of content and user interface in Eqs. (5) through (8).

$$U_{AV1}^{dog1} = 3.248 - 9.593 \times 10^{-2} \times L_v \quad (R^{*2} = 0.849) \quad (5)$$

$$U_{AV1}^{dog2} = 3.286 - 8.650 \times 10^{-2} \times L_v \quad (R^{*2} = 0.896) \quad (6)$$

$$U_{AV1}^{train1} = 3.155 - 7.220 \times 10^{-2} \times L_v \quad (R^{*2} = 0.828) \quad (7)$$

$$U_{AV1}^{train2} = 3.351 - 9.267 \times 10^{-2} \times L_v \quad (R^{*2} = 0.935) \quad (8)$$

We also find in these equations that the estimation accuracy depends on the content type and the user interface as we have found in the equations for the viewpoint change response.

3) *Overall satisfaction*: We calculated the regression lines of overall satisfaction for each pair of content and viewpoint change interface with the MU loss ratio of video and the average MU delay of video. However, for Train, the term of average MU delay is not significant with the significant level 0.05 because the train moves faster, and then the smoothness is more important for the assessors. We then calculated the regression lines for Train with only the MU loss ratio of video. Eqs. (9) through (12) show the regression lines.

$$U_{O1}^{dog1} = 3.398 - 1.231 \times 10^{-3} \times D_v - 8.796 \times 10^{-2} \times L_v \quad (R^{*2} = 0.851) \quad (9)$$

$$U_{O1}^{dog2} = 3.468 - 1.243 \times 10^{-3} \times D_v - 7.683 \times 10^{-2} \times L_v \quad (R^{*2} = 0.894) \quad (10)$$

$$U_{O1}^{train1} = 3.013 - 6.766 \times 10^{-2} \times L_v \quad (R^{*2} = 0.871) \quad (11)$$

$$U_{O1}^{train2} = 3.299 - 9.141 \times 10^{-2} \times L_v \quad (R^{*2} = 0.908) \quad (12)$$

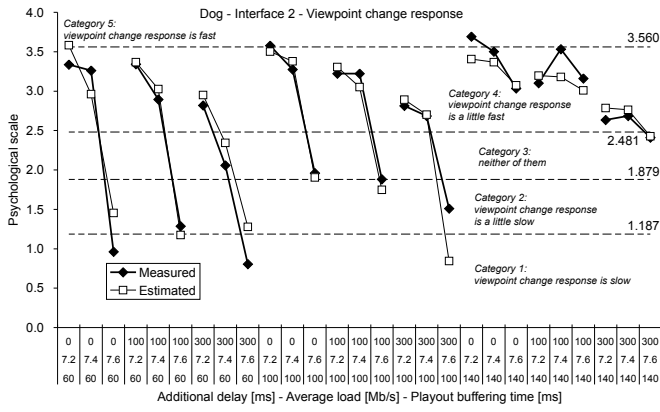


Fig. 4. Viewpoint change response for Dog with Interface 2.

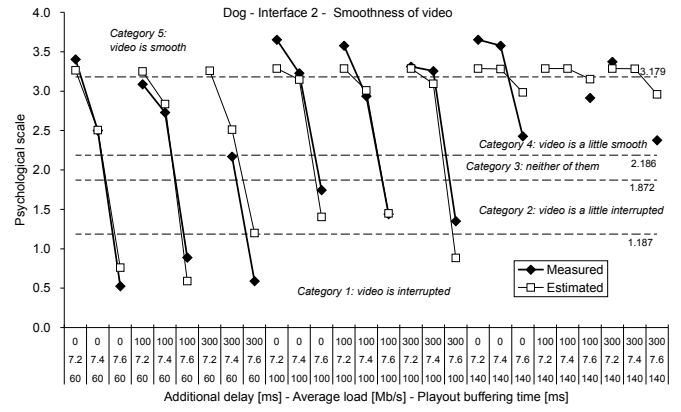


Fig. 6. Smoothness of video for Dog with Interface 2.

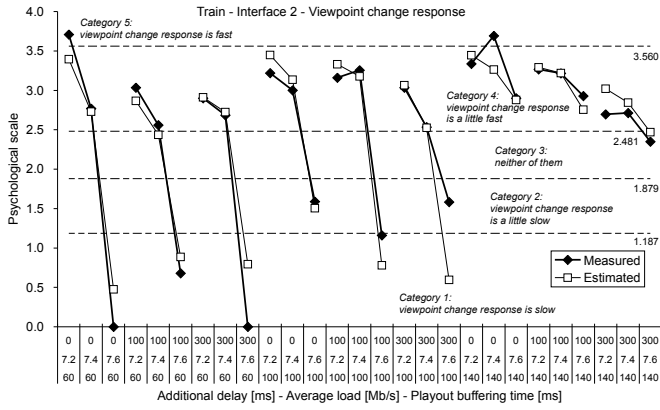


Fig. 5. Viewpoint change response for Train with Interface 2.

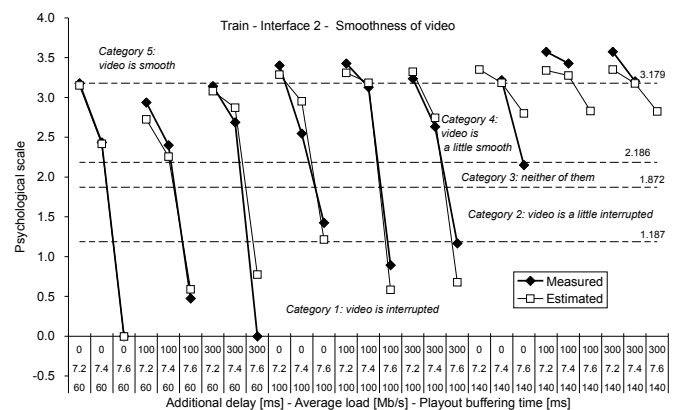


Fig. 7. Smoothness of video for Train with Interface 2.

We again notice that the contribution rate of each equation is high. Thus, the equations can estimate the psychological scale with high accuracy.

B. Assessment of accuracy

Figure 4 plots the estimated values obtained by Eq. (2) along with the measured ones for viewpoint change response (I1) in the case of Dog with Interface 2. Figure 5 shows the estimated values obtained by Eq. (4) and measured ones in the case of Train with Interface 2.

For the smoothness of video (AV1), we show the estimated values obtained by Eq. (6) and measured ones for Dog with Interface 2 in Fig. 6. The estimated values obtained by Eq. (8) and measured ones for Train with Interface 2 is shown in Fig. 7.

Figure 8 plots the estimated values obtained by Eq. (10) along with the measured ones for overall satisfaction (O1) in the case of Dog with Interface 2. Figure 9 shows the estimated values obtained by Eq. (12) and measured ones in the case of Train with Interface 2.

The abscissa in Figs. 4 through 9 presents the combination of additional delay in NN [ms], the average load [Mb/s], and the playback buffering time [ms]. These figures plot the

measured and estimated values of psychological scale for each combination of the three parameters. Note that the measured values deleted by the Mosteller's test are not shown in these figures. In the figures, the upper boundaries of Category 1 to Category 4 are plotted as straight broken lines parallel to the

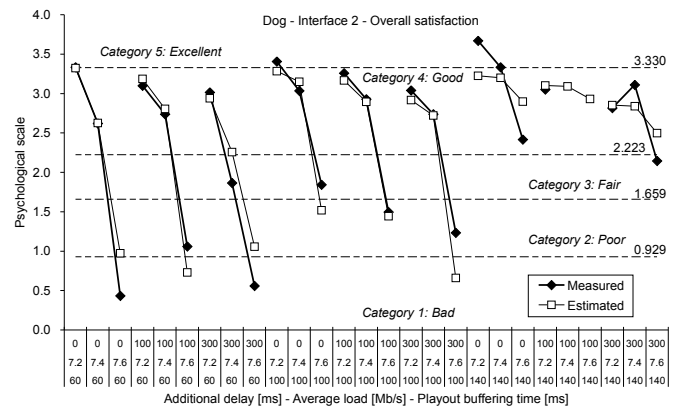


Fig. 8. Overall satisfaction for Dog with Interface 2.

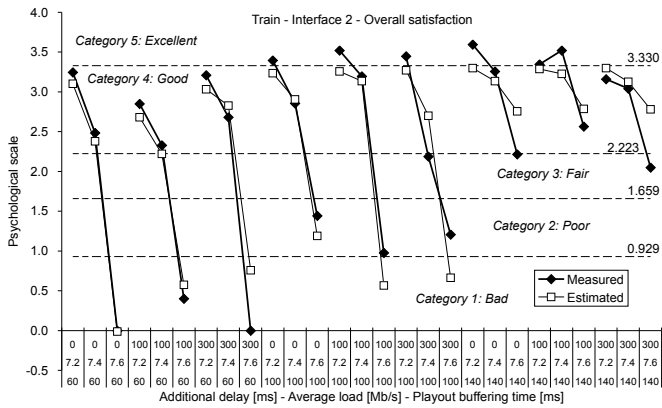


Fig. 9. Overall satisfaction for Train with Interface 2.

TABLE IV
CORRELATION COEFFICIENTS BETWEEN MEASURED VALUE AND ESTIMATED ONE.

content	interface	overall quality	viewpoint change	smoothness of video
dog	1	0.930	0.922	0.925
	2	0.950	0.954	0.949
train	1	0.936	0.917	0.914
	2	0.955	0.950	0.968

abscissa. Note that the lower bound of Category 1 is $-\infty$, and the upper bound of Category 5 is ∞ .

Furthermore, Table IV displays correlation coefficients between estimates and measured values.

We see in Figs. 4 and 5 that the psychological scale values for viewpoint change response for both contents can be estimated by means of the linear multiple regression analysis with the MU loss ratio and the average MU delay. However, we notice that the error between the estimated value and the measured one becomes large when the playout buffering time is 140 ms.

By comparing Figs. 4 and 5, we find that the psychological scale value for Train is smaller than that for Dog in the case of small buffering time under heavy load condition. In addition, the estimation error becomes large in the case.

In Figs. 6 and 7, we find that the psychological scale values for the smoothness of video can be estimated with high accuracy with the MU loss ratio. As in the case of the viewpoint change delay, the estimation error becomes large when the playout buffering time is large; the independent variables employed in this paper may be insufficient in the case.

We notice in Figs. 6 and 7 that the psychological scale value for the smoothness of video increases as the playout buffering time increases. Thus, the playout buffering can improve the smoothness, and the estimation can represent the enhancement.

In Fig. 8, we find that the psychological scale value of overall satisfaction for Dog can be estimated with high accuracy with the MU loss ratio and the average MU delay. For Train in Fig. 9, the regression line with the MU loss ratio can also estimate the psychological scale value.

In addition, we notice in Table IV that the equations can estimate with almost the same high accuracy in both contents. From the above discussion, the feasibility of real-time QoE estimation of MVV-A IP transmission is clarified.

VI. CONCLUSIONS

In this paper, we show the feasibility of QoE estimation for multi-view video and audio (MVV-A) IP transmission with the application-level QoS parameters which can be assessed in real time. Among the multidimensionally assessed QoE, we treated overall satisfaction, smoothness of video, and viewpoint change response. We then calculated regression lines by the linear regression analysis. As a result, it is clarified that the QoE estimation with the application-level QoS parameters for video is feasible. In addition, the estimation accuracy depends on the content, user interface, and the playout buffering time.

Future work includes the evaluation of accuracy with other data set obtained by new experiment. In addition, estimation of the other QoE metrics is also future study.

ACKNOWLEDGMENT

We thank Erick Jimenez Rodriguez and Makoto Yamamoto for their support in the experiment. This work was supported by the Grant-In-Aid for Young Scientists of Japan Society for the Promotion of Science under Grant 23760332.

REFERENCES

- [1] I. Ahmad, "Multiview video: Get ready for next-generation television," *Proc. IEEE Distributed Systems Online*, vol. 8, no. 3, art. no. 0703-03006, Mar. 2007.
- [2] M. Tanimoto, "FTV (Free viewpoint TV) and creation of ray-based image engineering," *ECTI TRANSACTIONS on Electrical Eng., Electronics, and Communications*, vol. 7, no. 2, Aug. 2009.
- [3] ITU-T Rec. H.720, "Overview of IPTV terminal devices and end systems," Oct. 2008.
- [4] ITU-T Rec. P.10/G.100, Amendment 2, "New definitions for inclusion in Recommendation ITU-T P.10/G.100," July 2008.
- [5] E. Kurutepe, M. R. Civanlar, and A. M. Tekalp, "Selective streaming of multi-view video for head-tracking 3D displays," *Proc. IEEE ICIP 2007*, pp. III-77 - III-80, Sept./Oct. 2007.
- [6] G. Cheung, A. Ortega and N. -M. Cheung, "Interactive streaming of stored multiview video using redundant frame structures," *IEEE Trans. on Image Processing*, vol. 20, no. 3, pp. 744-761, Mar. 2011.
- [7] ITU-T Rec. G.1080, "Quality of experience requirements for IPTV services," Dec. 2008.
- [8] E. Jimenez Rodriguez, T. Nunome and S. Tasaka, "QoE assessment of multi-view video and audio IP transmission," *IEICE Trans. on Commun.*, vol. E93-B, no. 6, pp. 1373-1383, June 2010.
- [9] E. Jimenez Rodriguez, T. Nunome and S. Tasaka, "Multidimensional QoE assessment of multi-view video and audio (MVV-A) IP transmission: The effects of user interfaces and contents," *Proc. IEEE WAINA 2012*, pp. 91-98, Mar. 2012.
- [10] S. Tasaka and Y. Ito, "Real-time estimation of user-level QoS of audio-video transmission over IP networks," *Conf. Rec. IEEE ICC2006*, June 2006.
- [11] S. Tasaka and Y. Watanabe, "Real-time estimation of user-level QoS in audio-video IP transmission by using temporal and spatial quality," *Conf. Rec. IEEE GLOBECOM2007*, Nov. 2007.
- [12] "NIST Net Home Page," <http://snad.ncsl.nist.gov/nistnet/>.
- [13] C. E. Osgood, "The nature and measurement of meaning," *Psychological Bulletin*, vol. 49, no. 3, pp. 197-237, May 1952.
- [14] J. P. Guilford, *Psychometric methods*, McGraw Hill, N. Y., 1954.
- [15] F. Mosteller, "Remarks on the method of paired comparisons: III a test of significance for paired comparisons when equal standard deviations and equal correlations are assumed," *Psychometrika*, vol. 16, no. 2, pp. 207-218, June 1951.
- [16] S. Tasaka and Y. Ito, "Psychometric analysis of the mutually compensatory property of multimedia QoS," *Conf. Rec. IEEE ICC 2003*, May 2003.