A VIDEO CLASSIFICATION METHOD FOR USER-CENTERED STREAMING SERVICES

Yuka Kato
Advanced Institute of Industrial Technology
1-10-40 Higashiohi, Shinagawa-ku, Tokyo 1400011, Japan

Katsuya Hakozaki
The University of Electro-Communicaions
1-5-1 Chofugaoka, Chofu-shi, Tokyo 1828585, Japan

Keywords: Multimedia communications, user-centered streaming services, user perceptive video quality, video content, subjective assessment, rate control.

Abstract: The present paper analyzes the relationship between video content and subjective video quality for user-centered streaming services. In this analysis, we conduct subjective assessments using various types of video programs, and propose a method of classifying video programs into a number of groups that are thought by a large majority of users to have the same video quality. Control to a high level of user satisfaction can be performed by applying a different control method to each group obtained using the proposed method. In addition, we demonstrate the necessity of rate control according to video content by comparing a classification result based on vision parameters with the classification result based on the assessment result.

1 INTRODUCTION

With the recent increased availability of broadband Internet access, such as xDSL and FTTH services, streaming video services on the Internet have become more widely used. In order to provide such services with high-quality streaming videos, adaptive rate control of the network environment is needed because system users access streaming video content from various system environments and because network resources on which video data are transmitted are shared among numerous users. Therefore, we should consider video content and user preference of video quality, because user perceptive video quality differs greatly with these factors. Recently, several studies have examined rate control methods with reference to video content. These studies can be classified into the following two types:
(1) Studies using the meta-data of streaming videos
In these studies, content creators, producers or distributors give some descriptions of scene importance as meta-data beforehand, and a rate controls are based on these meta-data. For example, a rate control method using semantic scene importance, which a content distributor determines according to his/her subjective judgment, has been proposed(Ohta et al., 1997). MPEG-7(ISO/IEC, 2002) can be used to describe meta-data for these methods.
(2) Studies using the results of feature extraction
In these studies, streaming systems automatically extract video features, such as scene changes and the degree of motion complication, and perform suitable rate control for the features. For example, rate adaptation transcoding for H.263+ videos has been proposed(Lei and Georganas, 2002).

In type (1) methods, content distributors can specify the importance of video scenes, and fine-grained quality control with high accuracy can be achieved. User subjective video quality is thereby improved. However, these methods have a problem in that they are difficult to apply to streaming services on the Internet because assigning meta-data to video programs is a time-consuming task and because it is impossible to assign meta-data to live programs. Moreover, the meta-data are based on subjective judgments, which are not always consistent with universal user perceptive video quality according to video content. On the other hand, the type (2) methods can overcome such difficulties of meta-data description, because streaming systems automatically extract video features. However, the target features of these methods do not express the semantic scene importance, but rather visual features, such as the degree of motion intensity. Semantic importance for the same scene taken from a football game may differ between a live sports program and a sports news program.

Kato Y. and Hakozaki K. (2006).
A VIDEO CLASSIFICATION METHOD FOR USER-CENTERED STREAMING SERVICES.
In *Proceedings of the International Conference on Signal Processing and Multimedia Applications*, pages 200-207
DOI: 10.5220/0001569402000207

Therefore, in the present paper, we analyze the relationship between video content and subjective video quality for use-centered streaming services. In this analysis, we conduct subjective assessments by using various types of video programs and propose a method of classifying video programs into a number of groups judged by a large majority of users to have the same video quality. Control with a high level of user satisfaction can be achieved by applying different control methods to each group obtained by using the proposed method. We also demonstrate the necessity of rate control according to video content by comparing a classification result based on vision parameters with that based on the assessment result.

2 PREPARATION

2.1 Feature Description Parameters

In the present paper, we classify video programs that have various features according to the user's perception of video quality. Here, we describe the video features as parameters and classify a number of video programs based on these parameters. We therefore determine the feature description parameters in this section. Since our goal is rate control with describe video content, as well as the vision parameters, which generally describe video features. We use the following parameters in the present paper:

- Vision parameters: average bit rate, motion intensity and number of objects.
- Semantic parameters: genre, importance of video, importance of audio, importance of information and entertainment factors.

2.2 Quality Parameters

Next, we define the quality parameters, which are control targets in the present paper because the same control method is applied to each group. In general, rate control of streaming services is performed by changing the spatial information content (bit rate per frame), by changing the time information content (frame rate), or both. We therefore define three types of quality parameter: image quality, frame size (spatial information content), and frame rate (time information content). These are defined as user perceptive qualities that do not depend on the streaming codec type. There is a trade-off between spatial content and time content if we reduce the information of a suitable reduction is required for maximizing the user subjective video quality.

Considering actual coding (or transcoding), more detailed allocation is needed. Several studies have examined such allocation methods. For example, a scene adaptive bit-rate control method in MPEG video coding(Lee et al., 1997) (reduction of spatial information content), a method of dynamically dropping frames according to the system environment for MPEG-1 streaming systems(Cha et al., 2003) (reduction of time information content), and a bitrate control method based on macro-block quantization parameter assignment in MPEG videos(Keesman et al., 1995) (reduction of spatial information content) have been proposed. For the actual coding process, we need to map these parameters. In the present paper, however, we do not consider the mapping method because mapping depends on the corder implementation.

Table 1: Relationship between sensation and emotion.

	Burn	Smell	Auditory	Vision
Affection	10	8	4	2
	..	..	..	..
Cognition	2	4	8	10

2.3 User Preferences Regarding Video Quality

Next, we define quantitative user preferences for video quality. All senses, including vision (sight), are generally with some emotion (e.g., comfort of discomfort, like or dislike). For example, the relationship between sensation and emotion is proposed as shown in Table 1(Pieron, 1950). This table indicates that higher sensations, such as vision, have a more intellectual aspect and a higher degree of objectivity, but also a certain degree of subjectivity (emotional aspects). Thus, for vision, a high level of user satisfaction can be obtained by targeting common preferences among many users while at the same time considering individual preferences.

From this viewpoint, we define user preference of video quality using the three quality parameters. These parameters are combined to define a user preference vector $p(u_i, v_i) = (w_q, w_s, w_f)$, where w_q, w_s and w_f are the importances of image quality, the importance of frame size and the importance of frame rate respectively, and u_i is a user ID, and v_i is a content ID. Each element of the vector is the weight of each quality parameter, i.e., $w_q + w_s + w_f = 1$.

3 RELATIONSHIP BETWEEN VIDEO CONTENT AND SUBJECTIVE VIDEO QUALITY

In this section, we use the quality parameters determined in the previous section to perform subjective assessment by paired comparison(Guilford, 1954), which is a psychometric method. Based on the results, we then conduct a cluster analysis of sample videos and classify the videos into a number of groups. In the present paper, our goal is to clarify the effects of the parameters on the subjective video quality for each of the respective groups. We therefore analyze these main factors. Here, we define the subjective video quality as the level of user satisfaction with respect to video quality.

3.1 Subjective Assessment

3.1.1 Experimental Methods

In this section, we investigate the degree of the effects of the quality parameters on subjective video quality. Several evaluation methods of user satisfaction have been proposed, including a subjective quality estimation method using neural networks(Lin and Mersereau, 1999). However, the evaluation accuracy of audio and video quality is low because determination of the absolute degree of audio or video quality is difficult. In order to obtain reliable results for such items, a method of paired comparisons can be used. Using this method, test subjects can easily evaluate video quality. Therefore, the present paper applies the method for subjective assessment.

Methods of paired comparisons can be classified into two types. The first type, which includes Beadley's method and Thurstone's method, expresses the comparison results by ranking. The second type is Scheffe's method, in which the results are expressed as scores. In this present paper, we express the comparison results as scores and analyze the results by assuming various structures of these scores, i.e. we adopt Scheffe's method. In addition, we use Nakaya's modified method(JUSE, 1973), in which each test subject is assigned all combinations of trials.

The experimental procedure is described in detail below. We provided 30 sample videos having various program features, i.e., various themes, styles and content, for example. A list of these sample videos is shown in Table 2. We selected the sample videos to reflect various viewing purposes in order to analyze the relationship between the video content and subjective video quality. The video features of these sample videos are described by the feature description parameters defined in Section 2 These parameter values are also listed in Table 2. Motion intensity is represented on a scale from 1 to 5 (in which larger numbers indicate more intensive motion). The number of objects is represented on a scale from 1 to 3 (in which larger numbers indicate a greater number of objects). Finally, the importance of semantic parameters is represented on a scale from 1 to 3 (in which larger numbers indicate higher importance).

Table 3: Quality parameter values for the experiment.

	Quality	Rate	Size
Original	100	30 fps	640×480
Slight degradation	27	10 fps	384×256
Medium degradation	15	3 fps	192×128
Severe degradation	10	1 fps	96×94

Next, we prepared 10 test videos for the experiment by changing the three quality parameters in three grades. In general, degradation appearances of digital video quality by the same factor (e.g. packet loss) differ among different codec types and it is necessary to consider these effects on subjective evaluation values. In the present paper, in order to eliminate these effects, we prepared the video under the condition that sufficient system resources exist. Quality parameter values for the experiment are listed in Table 3. In the table, video quality is denoted as image degradation ratios.

The number of test video is 10 for each sample program. In this experiment, we made pairs of test videos for each program and had test subjects evaluate which video was preferable and the degree of preferability with respect to subjective video quality. The subjects rated 45 pairs, such as a video with slight degradation of frame size and a video with a medium degradation of image quality, on a scale raging from -3 to 3 (i.e. seven-grade) for each program (See Table 4). Lower grades denote lower subjective evaluation values. Each test video was made in advance and was watched by the subjects for approximately twenty seconds on a 19-inch LCD monitor connected to a PC. We determined the experimental conditions based on ITU-R Recommendation BT.500(ITU-R, 2000). The distance between the test subject and the monitor was 60 cm, and the number of light sources in the experimental room was one. The measured intensity of illumination was 20 lux at the viewing point. The experimental procedure for comparing video streams, which consisted of watching and assessing streams, is shown in Fig. 1. In this figure, A and B compared video streams, and gray images are displayed for one second between A and B and for three seconds at the end of the sequence.

In this case, we did not consider the comparison order and asked all subjects to compare ordered pairs once, because spatial comparisons, for example of colors and shapes, were performed in this experiment, and afterimages may not have existed. The number of subjects was six (five male and one female), and 9,450 sets of data were obtained.

3.1.2 Experimental Results

This evaluation results can be summarized in a table having 10 degradation parameters as the vertical and horizontal rows, and the grades as its elements. An

Table 2: Sample programs for the experiment and feature description parameters.

No.	Genre (content)	Ave. bps	Motion intensity	Number of objects	Importance of video	Importance of audio	Importance of info.	Entertainment factors
1	News (accident)	985	1	1	1	2	3	1
2	News (sports)	1245	4	3	2	2	3	1
3	News (weather)	1014	1	2	1	2	3	1
4	News (general)	1110	1	2	2	2	3	1
5	Documentary (frescos)	1420	3	3	2	2	3	2
6	Vaudeville (vaudeville)	1309	3	2	1	2	1	3
7	Vaudeville (comedy)	1397	4	2	2	2	1	3
8	Vaudeville (quiz)	1283	2	1	1	2	1	3
9	Vaudeville (talk)	975	3	3	2	3	1	3
10	Drama (comedy)	1087	3	2	2	2	1	3
11	Drama (medical)	942	2	2	2	2	1	3
12	Drama (foreign)	1020	3	2	2	2	2	3
13	Drama (period drama)	1373	5	1	2	2	1	3
14	Animation (action)	1063	4	1	3	1	1	3
15	Animation (general)	1071	2	1	2	2	1	3
16	Movie (action)	987	4	1	3	2	1	3
17	Movie (war)	1181	5	1	3	2	1	3
18	Movie (SF)	855	1	2	3	2	1	3
19	Movie (musical)	779	3	1	3	3	1	3
20	Sports (baseball)	1253	4	2	3	1	1	3
21	Sports (marathon)	1331	5	1	2	2	1	3
22	Sports (boxing)	1320	4	3	3	1	1	3
23	Sports (rally)	1300	5	1	3	1	1	3
24	Music (pop music)	1147	2	3	2	3	1	3
25	Music (classic)	962	3	2	1	3	1	2
26	Music (traditional)	1124	2	2	1	3	1	3
27	Music (video clip)	1399	5	3	3	3	1	3
28	Hobby (cooking)	1179	3	2	2	2	3	2
29	Information (health)	1179	2	2	2	2	3	2
30	Education (English)	949	2	2	2	3	3	1

Table 4: Quality rating for the experiment.

Grade	Quality
3	Excellent
2	Very good
1	Good
0	Fair
-1	Poor
-2	Bad
-3	Extremely bad

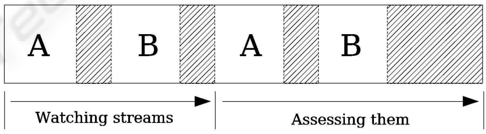

Figure 1: Experimental procedure.

example of the evaluation values for Program 1 for one test subject in shown in Table 5.

In this case, for example, the grade of (S2, Q1) is 3. This means that the video of Q1 is three grades better than that of S2. Thus, by using the total amount of the Q1 line, we can numerically express how much better, with respect to total grade, the video of Q1 is compared to other videos. In this example, the total grade of the video of Q1 is 9. In the same way, we calculated the grade of each parameter for each program. In the present paper, we define a subjective quality vector for each program as the average of the grades of all test subjects. This vector is represented by the quality parameters defined in Section 2.

3.2 Cluster Analysis

In this section, we calculate the Euclidean distances in ten-dimensional space between the experimentally obtained data and conduct cluster analysis. Cluster analysis is a method of collecting similar items from a sample set according to similarities among the items and classifying the items into a number of homogeneous clusters. These methods are roughly classified into two types: hierarchical clustering, which obtains a dendrogram as a result, and non-hierarchical clustering, which divides the sample data into a predetermined number of groups. In this analysis, we adopted hierarchical clustering because the number of groups was not determined. In addition, we adopted the Ward method to obtain manageable clusters. Figure 2 shows a dedrogram obtained by cluster analysis.

Table 5: An example of the experimental result (Program 1).

	O	Q1	Q2	Q3	S1	S2	S3	F1	F2	F3
O	–	0	0	-1	-2	-3	-3	0	0	0
Q1	0	–	0	-1	-2	-3	-3	0	0	0
Q2	0	0	–	0	-2	-3	-3	0	0	0
Q3	1	1	0	–	-1	-3	-3	1	1	1
S1	2	2	2	1	–	-2	-3	2	2	2
S2	3	3	3	3	2	–	-1	3	3	3
S3	3	3	3	3	3	1	–	3	3	3
F1	0	0	0	-1	-2	-3	-3	–	0	0
F2	0	0	0	-1	-2	-3	-3	0	–	0
F3	0	0	0	-1	-2	-3	-3	0	0	–
Total	9	9	8	2	-8	-22	-25	9	9	9

O: Original
Q1: Slight degradation of image quality, Q2: Medium, Q3: Severe
S1: Slight degradation of frame size, S2: Medium, S3: Severe
F1: Slight degradation of frame rate, F2: Medium, F3: Severe

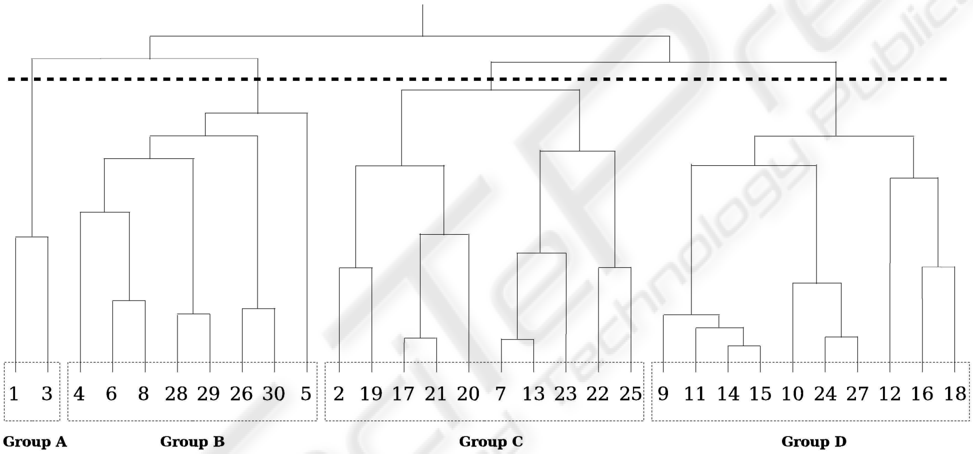

Figure 2: Dendrogram obtained by cluster analysis.

As the number of cluster increases, a detailed analysis can be carried out, but it becomes difficult to pick out factors representing each cluster because the number of elements in a cluster is small. In the present paper, we divided the programs into groups at the dotted line shown in Fig. 2, and constructed four groups, Group A through D, because the number of quality parameters, which are the control targets, is three and the suitable number of groups is from three to five. The features of each group are described as follows:

- **Group A** contains News (accident) and News (weather). In these programs, the importance of information is high and the entertainment factor is small. Thus, the importance of video is not so high.
- **Group B** contains News (general), Documentary (fresco), Vaudeville (vaudeville), Vaudeville (quiz), Hobby (cooking), Information (health) and Education (English). With the exception of the vaudeville programs, these programs are watched in order to gather information, and so the importance of information is high for these programs. The quality levels of video and audio must be sufficient so as not to interfere with information gathering. Vaudeville programs with little motion and with small numbers of objects are contained in the group. This is because the entertainment factors of these programs are high, but neither the importance of video nor the importance of audio is high.
- **Group C** contains News (sports), Vaudeville (comedy), Drama (period drama), Movie (war), Movie (musical), Sports (baseball), Sports (marathon), Sports (boxing), Sports (rally) and Music (Classic). In these programs, the entertainment factor and the importance of video are high. Programs having high motion intensities, including all sports

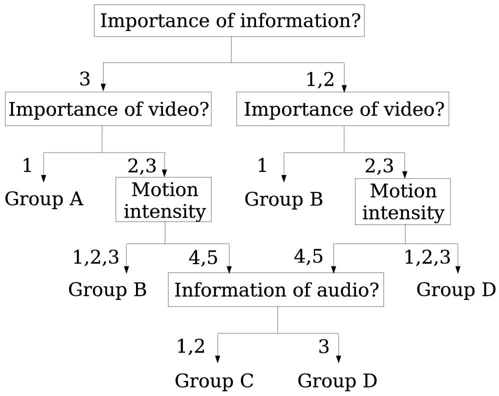

Figure 3: Classification process.

relate programs, are included in this group.

- **Group D** includes Vaudeville (talk), Drama (comedy), Drama (medical), Drama (foreign), Animation (action), Animation (general), Movie (action), Movie (SF), Music (pop music) and Music (video clip). The entertainment factors of these programs are high, but the importance of video is low compared to the programs in Group C. Music programs, for which the importance of video is relatively high, are included in this group. Although there are some exceptions, general dramas and video programs with low importance of motion are contained in the group.

Using these results, we designed a method which to classify the video programs into the above four groups. Four factors, which are the importance of information, the importance of video, the importance of audio and motion intensity, were used. The classification process is shown in Fig. 3. All programs except Animation (action), Movie (action), Movie (musical) and Music (classic) can be appropriately classified by this rule. In this case, we assumed that video features are given to each program as described in Table 2 in advance. However, these features can be given automatically to a certain extent using program genres. For example, news programs may have high importance of information and low entertainment factors, and movie programs may have high entertainment factors. Although there are some programs that need to be considered individually, such as sports news, feature description according to program genres makes automatic classification possible.

3.3 Relationship between Content and Subjective Video Quality

In order to apply the results of the previous section to actual quality control, in this section, we investigate the quantitative relationship between video content and subjective video quality.

First, we normalized the quality parameters used in the experiment, as shown in Table 6, for multiple linear regression analysis. The results of the multiple linear regression analysis are described below. In these equations, y, x_1, x_2 and x_3 represent the subjective quality value (which expresses the degree of user satisfaction of video quality), the normalized value of image quality, the normalized value of frame rate and the normalize value of frame size, respectively. The coefficient of determination (r^2) and F-statistic (F) are also shown.

Group A: $y = -0.02{x_1}^2 + 2.5x_1 - 0.04{x_3}^2 + 6.1x_3 - 248.3$ $\quad (r^2: 0.965, \quad F: 4.8, 4.6, -, -, 45.3, 85.2)$

Group B: $y = -0.02{x_1}^2 + 2.4x_1 - 0.03{x_2}^2 + 4.3x_2 - 0.05{x_3}^2 + 7.1x_3 - 372.3$
$(r^2: 0.916, \quad F: 6.0, 6.3, 40.7, 64.9, 100.6, 76.2)$

Group C: $y = -0.02{x_1}^2 + 2.7x_1 - 0.04{x_2}^2 + 6.6x_2 - 0.04{x_3}^2 + 6.1x_3 - 474.2$
$(r^2: 0.928, \quad F: 9.4, 10.9, 104.7, 204.6, 94.7, 172.5)$

Group D: $y = -0.04{x_1}^2 + 4.5x_1 - 0.05{x_2}^2 + 7.5x_2 - 0.04{x_3}^2 + 6.1x_3 - 468.4$
$(r^2: 0.920, \quad F: 28.8, 31.4, 171.3, 269.4, 100.5, 178.7)$

Since all of the coefficients of determination are greater than 0.9, these estimations are highly accurate. These F-statistics indicate the degree to which the quality parameters contribute to y estimation, and a large value of F indicates a large contribution (more precisely, F is the value for the test of significance in adding the parameter to the explanatory variables). Under practical streaming environments, there are various constraints of quality control, such as limitation of available quality parameters. In such cases, efficient quality control can be achieved by selecting parameter values that maximize the subjective quality value y under the constraints.

4 APPLICATION TO RATE CONTROL METHODS

In this section, we apply the analysis results obtained in the previous section to an actual encoding system and demonstrate the implementation process of the proposed method on practical streaming servers. This encoding system is TMPGEnc(TMPGEnc,), which is a software encoder. We provided MPEG-1 videos by using TMPGEnc for subjective assessment. TMPGEnc enables us to set various quality parameters including image quality, frame rate and frame size to target videos so that we can obtain encoded videos with various video qualities. At this time, the relationship between these quality parameters and the bitrate of encoded videos can be roughly expressed by

Table 6: Normalization of the quality parameters.

	Measured			Normalized		
	Image quality	Frame rate	Frame size	Image quality	Frame rate	Frame size
Original	100	30 fps	640×480	100	100	100
Slight degradation	27	10 fps	384×256	27	33	32
Medium degradation	15	3 fps	192×128	15	10	8
Severe degradation	10	1 fps	96× 94	10	3	3

Table 7: Numerical examples.

Programs	kbps	y	x_1	x_2	x_3
News (accident)	500	62	58	59	77
Vaudeville (vaudeville)	500	105	54	70	70
Sports (boxing)	500	112	48	79	70
Movie (action)	500	170	51	72	72
News (accident)	300	62	56	29	76
Vaudeville (vaudeville)	300	86	31	64	66
Sports (boxing)	300	82	26	75	68
Movie (action)	300	136	30	67	65
News (accident)	100	47	36	10	70
Vaudeville (vaudeville)	100	32	10	48	59
Sports (boxing)	100	3	10	61	47
Movie (action)	100	43	10	57	50

the following equation:

$$B = 0.0766 \times {x_1}^{0.732} \times {x_2}^{0.677} \times {x_3}^{0.703}$$

where x_1, x_2 and x_3 are normalized quality parameters, as indicated in Table 6, and B is the bitrate (kbps). By using this equation and the relationship between subjective video quality and the quality parameter values obtained in the previous section, we can calculate a set of parameter values x_1, x_2, x_3 for the maximum subjective quality value under the condition of fixed bitrate B.

Numerical examples are shown in Table 7. Target videos are News (accident) in Group A, Vaudeville (vaudeville) in Group B, Sports (boxing) in Group C and Movie (action) in Group D. Here, we show sets of quality parameter values and subjective quality values, where the bitrates are 500 kbps, 300 kbps and 100 kbps. Here, x_1, x_2 and x_3 are also normalized values. These results indicate that optimal parameter sets are different in each group, especially in the case of low bitrates. This influence is large for tasks such as video transmission and storing videos on disks.

In actuality, there may be few cases in which all of the quality parameters can be changed without any restriction, e.g., frame size is fixed on a mobile terminal. Even in such cases, the same procedure can be used for obtaining a set of the parameters using some fixed values. Here, let us consider the case in which the frame size is fixed as $x_3 = 33$, i.e., the frame size is 384×256. In Group A, $y = 23.0$ at both $(x_1, x_2, x_3) = (82, 100, 33)$ and $(x_1, x_2, x_3) = (45, 18, 33)$, but the bitrate is 500 kbps in the former case and 100 kbps in the latter case. In this case, we can reduce the bitrate by 20 % by changing the set of quality parameter values. As another example, in Group B, $y = 0.55$ and $y = 2.46$ at $(x_1, x_2, x_3) = (88, 93, 33)$ and $(x_1, x_2, x_3) = (82, 47, 33)$, respectively, but the bitrate is 500 kbps in the former case and 300 kbps in the latter case. In this case, we can reduce the bitrate by 60 %.

5 DISCUSSION

In this section, we compare a classification result obtained based on only vision parameters (not according to video content) and a classification result obtained based on the assessment result (according to video content), as mentioned in the previous section. We conducted cluster analysis for the same 30 programs used in the previous section by using the three types of vision parameters (average bps, motion intensity and number of objects) listed in Table 2. Figure 4 shows a dendrogram obtained by this analysis. We divided the programs into groups at the dotted line shown in the figure and constructed the following four groups:

- **Group 1**: News (sports), Documentary (fresco), Vaudeville (vaudeville, comedy, quiz), Drama (period drama), Sports (baseball, marathon, boxing, rally) and Music (video clip)
- **Group 2**: News (accident, weather), Vaudeville (talk), Drama (medical, foreign), Movie (action), Music (classic) and Education (English)
- **Group 3**: Movie (SF, musical)
- **Group 4**: News (general), Drama (comedy), Animation (action, general), Movie (war), Music (pop music, traditional), Hobby (cooking) and Information (health)

There are a number of common features shared between the group described in Section 3 and described in Section 5 For example, both the programs in Group 1 and those in Group C appear to have a feature of intensive motion. However, for the most part, the classification result based on the subjective assessment is very different from that based on only vision parameters. As a result, we found that subjective video

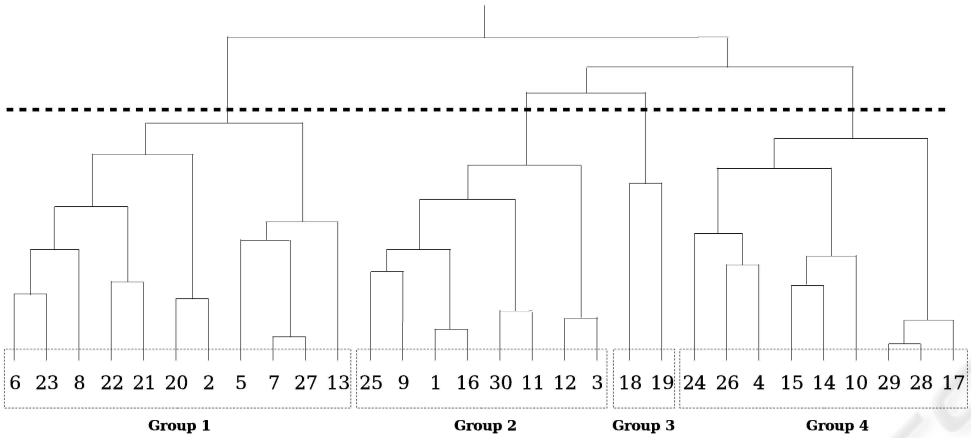

Figure 4: Dendrogram obtained by cluster analysis.

quality is affected by not only vision parameters, but also semantic parameters.

Moreover, an important point to note is that vision parameter values change with time, whereas semantic parameter values do not change within a program. Streaming services are continuous media, and it is generally difficult to perform rate control following such vision parameter changes. By using semantic parameters, which do not change within a program, for control, subjective video quality may be improved and more effective control might be achieved.

6 CONCLUSION

In the present paper, we analyzed the relationship between video content and subjective video quality for user-centered streaming services. In this analysis, we conducted subjective assessment using various kinds of video programs and clarified common perceptive video quality for several users. Based on the results, we proposed a method of classifying video programs into a number of groups judged by a large majority of users to have the same video quality. We also showed the necessity for rate control according to video content by comparing a classification result based on vision parameters with a classification result based on the assessment result. In the future, we will conduct a subjective assessment on a large number of test subjects (from 20 to 30) and will determine the values of feature description parameters as objective data.

ACKNOWLEDGEMENTS

This work was supported in part by the Grant-in-Aid for Scientific Research (No. 15700034) of the Japan Society for the Promotion of Science.

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