GA-based feature selection for QoE estimation using EEG during video viewing

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SUMMARY In recent years, Quality of Experiment (QoE) becomes an important factor for video viewing users and service providers, thus QoE-based video delivery control methods have been getting a lot of interests. In order to use the user's QoE for video delivery control, it is necessary to measure the QoE for the individual in real time. In this paper, we present a support-vector-machine-based QoE estimation method for a video viewing user by using the user's EEG. We extracted over 400 features from the EEG measurements, and we showed that the number of features did not need to be so large for the estimation of QoE. We also showed that the feature selection based on the genetic algorithm (GA) could improve the accuracy of QoE estimation by an average of 6% compared to a random feature selection.
key words: *QoE estimation, EEG, Genetic Algorithm, SVM*

1. Introduction

Video streaming services such as YouTube, Netflix, and Hulu and remote web conferencing systems such as Zoom and Cisco WebEx became extremely popular, and the number of users continues to increase every year. Research on improving the quality of experience (QoE) of users in video streaming delivery (henceforth referred to as "video delivery"), which is common to these services, have been very important for both users and service providers. In recent years, much interest has been focused on QoE-based methods for controlling quality in video delivery. Many existing studies focus on video quality (i.e. video resolution and frame rate) to estimate QoE of users[1], [2], but QoE of users is complicated due to not only external factors such as video quality, communication quality, viewing environment, and content itself, but also internal factors such as the current mood of a user and the personal taste of the video. In addition, in order to use the estimated QoE to control the video delivery, it is necessary to obtain the QoE of a user who is watching videos in a real-time manner. To solve these technical problems, we establish a method for estimating QoE using biometric information of a user, which can be obtained in real time due to advances in measurement equipment.

In recent years, several studies have been published that use the Electroencephalogram (EEG) to estimate QoE of users [3]–[5]. In this paper, as one of the biometric information, we use the EEG to estimate the QoE of video viewing users. Since our goal is to realize a video delivery control method based on the QoE estimated from user's biometric information, it is necessary to reduce the computational time of QoE estimation. We use a support vector machine (SVM), which is a supervised learning model, to estimate QoE, and for the reduction of the computational time, we use a small number of features. In our previous work, we confirmed that the accuracy of emotion estimation can be improved by selecting the features extracted from the EEG with genetic algorithm (GA). To implement QoE-based delivery control, we focused on detecting situations in which users' QoE decreases. Therefore, in this study, we extract 490 features from EEG measurements, but we use a small number of features for QoE estimation so that the computational time is small. We show that the feature selection based on the GA can improve the accuracy of QoE estimation.

The remainder of this paper is organized as follows. In Section 2, we explain the experiments we conducted to collect the data set for the estimation of QoE. In Section 3, we present our QoE estimation method. In Section 4, we show the evaluation results of our proposal. Section 5 gives the conclusion of this paper.

2. Data collection

To implement and evaluate a method for estimating the QoE of a video viewing user, we conducted an experiment to collect EEG during video viewing. Our experiment received approval from Osaka University Research Ethics Committee and permission from the head of our research institution. 20 healthy students from our University participated in the experiment. We prepared 11 video clips, and for each clip, 5 different qualities were prepared by modifying the bitrate and framerate from the original quality; two of the five qualities were downrated to 4 fps and 2 fps, and two of the five qualities were downrated to 350 kbps, 250 kbps, and the remaining one was played back in its original quality (>900 kbps). The video quality was changed using ffmpeg.

The bitrate change occurred after the start of each video clip in stages every 15 seconds between 15 seconds and 90 seconds from the start of the video playback, in order to reduce the effect of viewing the previous video clip. We randomly selected 10 of the 11 videos and the quality of each video was chosen so that there were two identical qualities. These video clips were played in a random order. After viewing each video clip, we asked how they felt about watching the video viewing. Participants replied with one of the following responses: Good, Normal, or Bad. These responses are used as a label for supervised learning as explained in the later section.

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EEG data were measured using EPOC+1 and recording software, EmotivPro (Emotiv [6]). EPOC+ has 14 symmetrical sensor electronodes, which are AF3-4, F7-8, F3-4, T7-8, P7-8 and O1-2 of the international 10—20 system. The resolution and the sampling rate of EPOC+ are 14 bit and 128 Hz, respectively. The recording of the EEG started at the same time as the video was played back and stopped after the video was finished. For QoE estimation, we only use the EEG from 15 seconds to 90 seconds after the start of the video playback, where the subject's QoE is likely to change significantly because during that period, the quality of the video changes.

Fig. 1 EPOC+ which used for recording EEG in the experiment.

3. QoE Estimation Method

We propose a method to estimate the QoE decline due to changes in video quality, as shown in Figure 2. We construct an SVM-based classifier. Following sections explain the methods for constructing the QoE classifier using EEG data; a preprocessing method of the EEG, a feature extraction method from the EEG, a feature selection method using a GA, and a classification method.

3.1 Preprocessing

A Butterworth bandpass filter was applied to remove irrelevant artifacts such as electromyogram (EMG) and power supply noises from the measured EEG raw data. We used MATLAB to apply the bandpass filter to EEG raw data. For subsequent feature extraction, the bandpass filter was applied in the four bands as shown in Table 1, where Fstop1 is the endpoint frequency of the first blocking band, Fstop2 is the starting frequency of the second blocking band, Fpass1 is the starting frequency of the passband, and Fpass2 is the endpoint frequency of the passband. Data contaminated by the subject's body movements and the disruption of communication during recording were excluded.

3.2 Feature Extraction

After removing the artifacts from the measured EEG using a bandpass filter, four kinds of features were extracted every 2-s non-overlapping window. The extracted features are Band power, Power Spectral Density (PSD), and Distributed Wavelet Transform (DWT), which have been commonly used in earlier studies [3], [7]. We used MATLAB to remove artifacts and also to compute these features. From PSD and level 2 to 4 components of DWT, four types of features are calculated; median, maximum, minimum and variance. We calculated Band Power, PSD and DWT features for each of the four frequency bands; 1) theta 4–8Hz, 2) alpha 8–12.5Hz, 3) beta 12.5–31Hz and 4) total 4–31Hz. In addition, the ratios of Band power from 1) to 3) and Band power from 4) were also calculated. We calculated each of features on the 14 channels of the EEG sensor, so the dimension of the total features is 490.

Table 1 Bandwidth of the Butterworth bandpass filter

Bandwidth	Fstop1	Fpass1	Fpass2	Fstop2
total	3.8	4	30	31
θ	3.8	4	8	8.2
α	7.8	8	12.5	12.7
β	12.3	12.5	30.5	31.7

3.3 Feature Selection

We limit the number of features to be used for QoE estimation, and we used a GA to find a good set of features. A GA is a meta-heuristic algorithm inspired by the process of natural selection, where the optimal individual is selected by selecting highly adapted individuals from the population and repeating the mating and mutation processes. We used a GA to explore the best combination of features for training the classifier. We used DEAP library in Python to implement a GA. The number of features to be selected was evaluated at 3, 5 and 10, respectively. For Comparison, random selection of 3, 5 and 10 features out of 490 are also evaluated.

Individuals of the GA in our proposal were represented as a permutation of integers from 0 to 489, where each integer corresponded to a type of feature. The fitness of an individual was defined as the average accuracy of the three-part cross-validation by an SVM with a Radial Based Function. For calculating the fitness, the features from the first to the third, fifth and tenth genes in individuals were used. The number of individuals and generations of the GA was set to 300 and 1000, respectively. And the mutation and crossing probabilities of the GA were set to 0.01 and 0.6, respectively, and the mutation probability was raised to 0.5 every 100 generations to prevent convergence to a local solution. The selection function used the tournament system. In the tournament system, a certain number of individuals are randomly selected from the population and the one with the highest fitness is selected for the next generation. The crossover function used the partial matching crossover method. Partial matching mating is a method of mating in which a gene for mating is randomly selected from two individuals and the genes are rearranged so that the sequence of the selected gene is the same as that of the other individual.

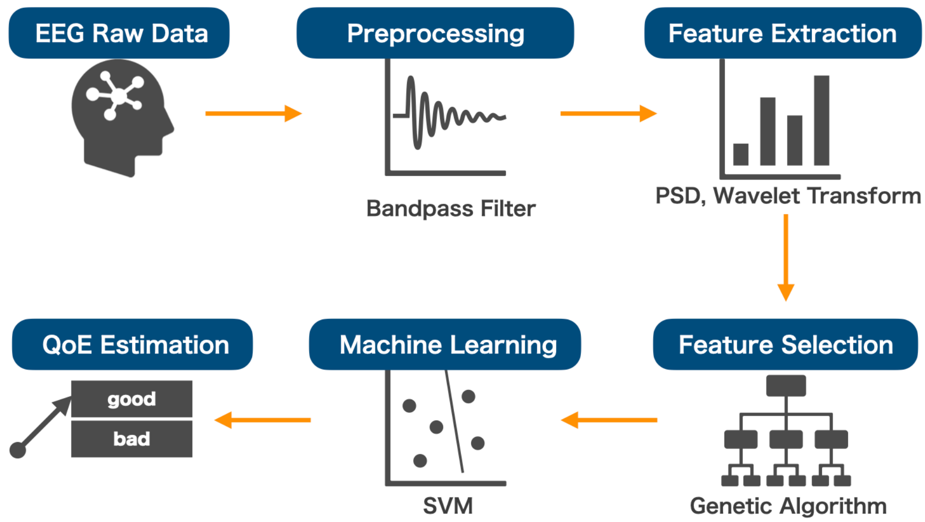

Fig. 2 Overview of QoE estimation method using EEG.

The mutation function used a translocation method in which the gene arrangement within an individual was randomly switched.

3.4 Classification Method

As a baseline classification method, we used an SVM with a Radial Based Function (RBF) kernel as a classifier. The RBF Kernel has two parameters; C determines the penalty of misclassified data and γ determines the width of the RBF kernel. We used scikit-learn library in Python to implement an SVM. The kernel parameters were set to $C = 1.0$, $\gamma = 1/490$.

To estimate QoE decline events, only Good and Bad data were used in the training. Due to a bias in the number of labels, the data of 12 participants were available. We trained the SVM for each participant and used the average of the 12 participants' accuracies for evaluation. We divided the data from the 10 trials into test data and train data, so that the label types were evenly distributed.

4. Result

We evaluated the performance of the QoE classifier regarding the accuracy for different feature selection methods and different numbers of features. Figure 3 presents the box plot of the accuracies using different number of features and the feature selection methods. As shown in Fig. 3, the GA-based selection outperformed the random selection with high accuracies in more than half cases at every number of features. However, at some subjects, the GA-based selection has lower accuracies than the random selection.

This may be due to the fact that some individuals have characteristics that make them prone to overlearning. For example, in cases where a user tends to react much differently depending on the content of a video, if the classifier is adapted too much to the content of the train data, it may not be able to respond to the content of the test data and the accuracy becomes worse. Therefore, more analysis is needed considering the characteristics of the content in order to improve the accuracy of our method.

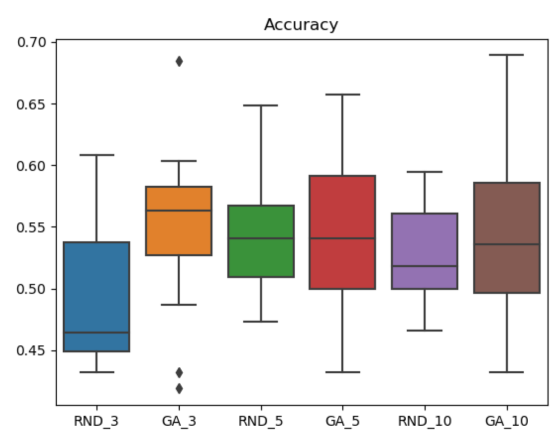

Fig. 3 Box plot of accuracy with each number of features and each method of feature selection. RND/GA represents kinds of feature selection methods, the numbers represents the number of features used in training.

5. Summary

Estimating the QoE of video viewing users is an important issue for video application service providers. In this paper, we propose a method for estimating the QoE from users' EEG data. Using the subject's EEG data during video viewing and QoE responses after video viewing, we trained the QoE classification model. We evaluated the accuracy of the estimation using a relatively small number of features, and showed that the accuracy was 6% better than that of the random selection. Our future work is to improve the accuracy and to construct a rate control method considering user's individual QoE.

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