Advertisement effectiveness estimation based on crowdsourced multimodal affective responses

Genki Okada
Chiba University
Chiba, Japan
g-okada@chiba-u.jp

Kenta Masui
Chiba University
Chiba, Japan
k_masui@chiba-u.jp

Norimichi Tsumura
Chiba University
Chiba, Japan
tsumura@faculty.chiba-u.jp

Abstract

In this paper, we estimate the effectiveness of an advertisement using online data collection and the remote measurement of facial expressions and physiological responses. Recently, the online advertisement market has expanded, and the measurement of advertisement effectiveness has become very important. We collected a significant number of videos of Japanese faces watching video advertisements in the same scenario in which media is normally used via the Internet. Facial expression and physiological responses such as heart rate and gaze were remotely measured by analyzing facial videos. By combining the measured responses into multimodal features and using machine learning, we show that ad liking can be predicted (ROC AUC = 0.93) better than when only single-mode features are used. Furthermore, intent to purchase can be estimated well (ROC AUC = 0.91) using multimodal features.

1. Introduction

The diversification of video content provided on the Internet has progressed, and viewing it is becoming a daily habit. Moreover, in the communication between companies and users, video content is becoming accepted. Against this backdrop, the video advertising market continues to grow more quickly than the previous year, and it has become the driving force behind the growth of the Internet advertising market as a whole. In the US, the costs of the Internet advertising market exceeded those of television advertising in 2017. In Japan, the size of the video advertisement market in 2017 reached 137.4 billion JPY, which is 163% that of the previous year, and is expected to increase from now on. By 2021, 1.9 billion people worldwide will watch online videos and are expected to watch 3 trillion minutes of videos each month. It can be predicted using simple calculations that, globally, each person will watch more than 1,500 hours of online videos per month on average.

The goal of video advertisement is to get the target layer to recognize products and services (awareness), ask them to consider making a purchase (consideration), and ultimately achieve sales (action). The important and interesting criteria that measure the achievement of these goals are ad liking and purchase intent. Recently, these criteria can not only be measured using costly questionnaires but also can be predicted from viewers' facial expressions and physiological responses [1][2][3][4]. Although facial expressions have been shown to predict liking, which is a relatively simple emotion, purchase intent, which is relatively ambiguous, cannot be predicted as accurately. To improve the prediction accuracy of purchase intent, it is useful to analyze physiological responses such as heart rate, which are effective for ambiguous emotion estimation, and to use multimodal features combined with facial expressions. In addition, Japanese people have brief facial expressions [5], so it is necessary to understand the relationship between facial expressions in the Japanese and these metrics.

Traditionally, video advertising consumer tests, whether using questionnaires, facial reactions, or physiological responses, have been performed in laboratory environments. Studies in laboratory environments have many advantages such as the ability to measure physiological responses and muscle movements with high accuracy. However, the subjects might be influenced by irrelevant factors such as the existence of the experimenter and the discomfort of the experimental environment. Moreover, computer-based machine learning and pattern analysis are highly dependent on the number of training samples. In particular, the diversity and complexity of naturalistic and spontaneous emotional expressions means that a large quantity of data is required for effective learning. This is because individual differences, such as cultural and gender differences, can be substantial. Recently, studies to analyze natural facial reactions using crowdsourcing have attracted attention because data collection is performed very efficiently using the Internet. Crowdsourcing means "outsourcing" tasks to an unspecified number of individuals in a "crowd." Remote measurements using the Internet can be collected far more efficiently and more diverse participants from groups with different backgrounds can be used than in a laboratory environment.

In this paper, we estimate the effectiveness of the emotional content of advertisements within the same scenario that media is normally used by using online data collection and contactless measurement methods of facial expression and physiological responses. First, we collected a significant number of videos of Japanese faces watching video advertisements via the Internet. Next, facial expressions and physiological responses such as heart rate and gaze were remotely measured by analyzing the facial videos. Finally, by combining the measured responses as multimodal features and using a support vector machine (SVM), ad liking and purchase intent were estimated.

2. Related work

2.1. Facial expression

Numerous studies have been demonstrated that facial behavior conveys basic emotional information. Moreover, some of these expressions are consistent throughout all cultures [6][7][8][9][10]. Furthermore, expression is continuous and dynamic, and it is possible to express how emotions change over time. However, in recent years, Girard collected a large number of smile responses, a globally common facial expression, and showed that there are cultural and geographical differences in the expression of smiles [5]. Of them, Japanese people have a weak smile and short expression time, so emotion estimation from facial expression only might be more difficult than in other countries. Friesen compared the behavior of the face of 25 Japanese and 25 American college students during stressful movie viewing [11]. The result, called a display rule, showed that Japanese masked negative emotions with a positive expression in the presence of authority [12]. Teixeira *et al*. showed that inducing emotion is important for reducing the frequency of "zapping," or skipping advertisements, and concentrate the attention of viewers of online video advertisements [1].

2.2. Heart Rate

In the study of physiological psychology, it is known that there is a strong correlation between a physiological response caused by the autonomic nervous system and a human emotional state. Furthermore, physiological signals are less affected by social and cultural differences [13]. We can estimate the original emotions that people are trying to hide or that cannot be recognized even by themselves. In recent years, the ability to measure heart rate without contact has been developed and various applications are expected. Poh *et al*. measured heart rate using the independent component analysis (ICA) of RGB signals of facial images photographed using a webcam [14]. McDuff *et al*. further analyzed heart rate variability (HRV) to detect participant stress with 85% accuracy [15]. Okada *et al* measured heart rate from the RGB facial images of participants watching a video that evokes the five basic emotions, and estimated each emotional state with an accuracy of 94% by analyzing HRV [16]. Variability in heart rate has been used to capture the arousal and attention of ad viewers. This was demonstrated by studying the reactions of participants who watched television advertisements inserted between two situation comedies to simulate a more realistic viewing experience [2].

2.3. Gaze

Eye movements are controlled by six extraocular muscles and involve involuntary movements as well as spontaneous movement. Yonezawa *et al*. showed that the staying time of the gaze on the image of a face that is judged to be attractive is longer than one that is considered unattractive [17]. Venkatraman showed a significant correlation between advertisement preference and gaze ratio [3]. Eyeballs also have involuntary micromovements called microsaccades, even when the gaze is fixed. This involuntary eye movement reflects the state of the attention induced by the external stimulus and potential attention without gaze change [18].

2.4. Multimodal features

In recent years, recognition accuracy has been improved by combining not only single-mode features but also features from multiple modes in machine emotion recognition. Kapoor *et al*. presented one of the first examples of multimodal features in emotion estimation using physiological response and facial behavior to predict frustration [19]. Mansoorizadeh *et al*. recognized basic emotions by combining facial expressions and speech features. They obtained better accuracy than when only single-mode features were used [20]. Monkaresi *et al.* estimated engagement with higher accuracy when multimodal features consisting of facial expressions and noncontact heartbeat measurements were used [21]. Pham *et al*. used a combination of contact-based photo plethysmography (PPG) sensing and remote facial expression analysis to predict a viewer's attention, engagement, and sentiment when watching video advertisements on smartphones [4]. They found that facial expression analysis is more effective with strong emotions such as joy or anger, while the PPG channel is more beneficial for subtle reactions and emotions. Moreover, the PPG and facial expression features are complementary. Burzo *et al*. showed that it is possible to effectively predict changes in human affect using four different modalities consisting of visual facial behaviors, thermal imaging, heart rate measurement, and verbal descriptions [22].

2.5. Crowdsourcing

Many video advertisement consumer tests, including the studies described above, were conducted in a laboratory environment. Research in laboratory environments have many advantages such as the ability to measure physiological responses and muscle movements with high accuracy, but there are also many problems. Participants might be influenced by factors unrelated to the stimuli under study, such as the presence of the experimenter and the discomfort of the experimental environment. Therefore, such a problem can be avoided by performing an experiment without using a sensor that makes participants uncomfortable in a context other than the laboratory environment. Teixeira *et al*. extended the study that showed that joy is one of the conditions stimulating viewer's retention in commercials [1] by collecting viewer responses on the Internet [23]. McDuff *et al*. modeled the relationship between the large-scale analysis of facial responses to video content measured on the Internet and advertisement effectiveness [24]. As a result, they showed that ad liking and change in purchase intent can be accurately predicted from facial reactions acquired by webcams.

3. Data acquisition by crowdsourcing

Figure 1 shows the online data collection framework.

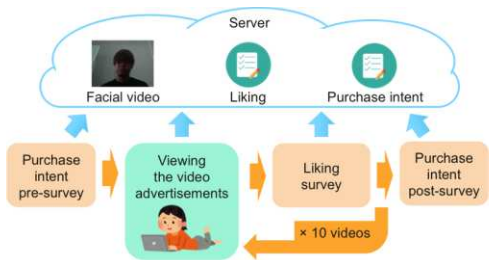


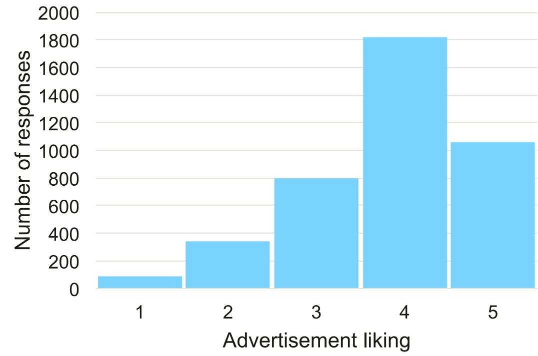
Figure 1. Online data collection framework

The facial video and self-reports were collected via the Internet. First, participants were asked to agree to the use of the webcam and the recording of the facial video. Next, as a baseline of purchase intent, they answered the following question:

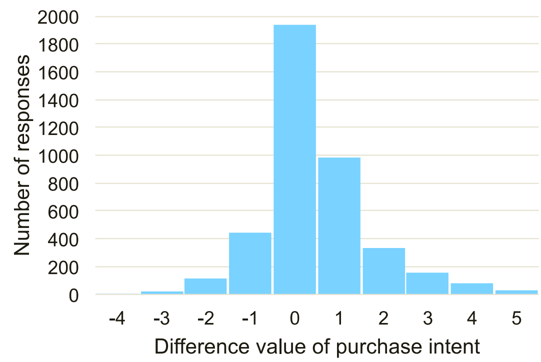
How likely are you to purchase this product, now?				
5	4	3	2	1
Likely to purchase		Neutral		Not likely to purchase

If participants did not know the product, they could indicate this rather than entering an evaluation.

Prior to watching the video advertisements, they viewed their webcam stream to check the position of the face (in the middle of the display) and the brightness (sufficiently bright). Wearing a hat or mask, eating, drinking, and using a mobile phone were not allowed.



(a)



(b)

Figure 2. Results of the evaluation: (a) ad liking and (b) purchase intent

After checking the stream, participants watched the video advertisement and subsequently answered the following question:

How much did you like the advertisement that you just watched?				
5	4	3	2	1
Very much		Neutral		Not at all

This process was repeated ten times. To minimize primacy, recency, and the carry-over effect, 10 advertisements were randomly selected out of 40.

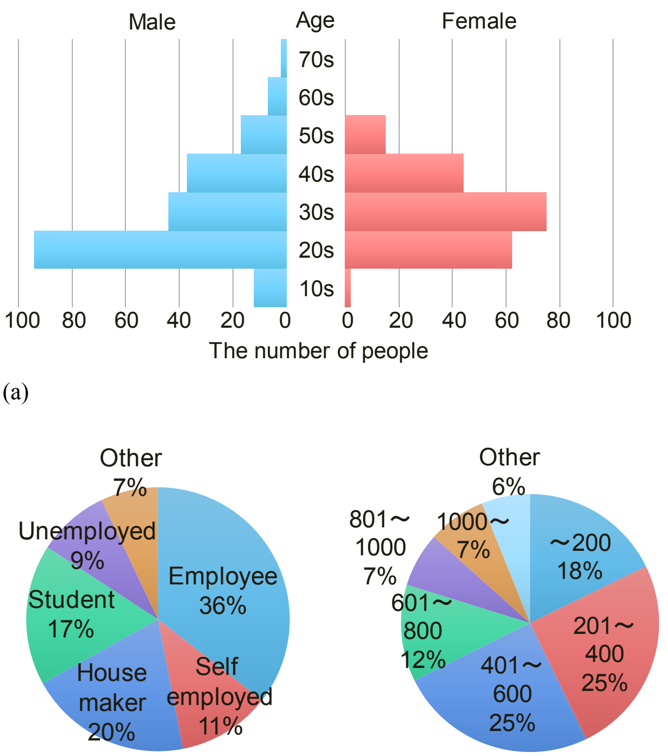
After viewing all the video advertisements, they responded again to the question about the product to calculate the difference in value of purchase intent. In addition, the comfort and behavior of participants were evaluated by the following respective questions:

How comfortable did you feel during the experiment?				
5	4	3	2	1
Very comfortable		Neutral		Very uncomfortable

Did you react differently than when you saw the advertisement in a situation that is not this experiment?		
3	2	1
Very differently	A little differently	No differently

Of the viewers, 24% reported that they felt "very comfortable," 49% felt "comfortable," 23% felt "neutral," 3% felt "uncomfortable." Moreover, 61% reported "no differently," 36% reported "a little differently," and 3% reported "very differently." Figure 2 shows the result of the evaluation. These aggregate results suggest that the reactions of viewers recorded while they viewed video advertisements were natural.

The video advertisements used for experiments were broadcast in Japan between 2014 and 2017. The average length of the video was 31.25 s and its standard deviation was 1.13 s. Each advertisement was watched by an average of 108 subjects. The videos were advertisements for eight products from the categories of alcohol, drink, food, confectionery, or daily items. We focused on products that might be bought frequently rather than those that require long-term purchase decisions such as cars.



(a)

(b) (c)

Figure 3. Distribution of the participants: (a) age and gender, (b) job, and (c) annual income (million JPY)

In this study, 411 Japanese people participated and 4,108 facial responses were collected over a short period of about 3 weeks. Figure 3 shows the distribution of participants. Using crowdsourcing, we were able to collect the data from participants with a wide range of ages, genders, locations, occupations, household compositions, and income, which helped reduce the influence of self-selection bias. At least 76% of the viewers were users of the product category being advertised. Subjects took about 30 min to complete the experiment, and when the work was approved, they earned 500 JPY. Not all participants visiting the task page had a webcam nor agreed to record the facial videos, and, in either case, the experiment was terminated. Approximately 88% of the participants who visited the task page had webcams, and of these 88%, about 98% agreed to record facial responses. In addition, of the more than 13,000 people who visited the recruitment page, the proportion of visits to the task page was about 4%.

4. Multi-modal features

4.1. Facial expression

To calculate the facial expression feature, first, 68 face parts were detected from each frame of the recorded facial video using Kazemi and Sullivan's method [25]. Figure 4 shows the detected face parts.

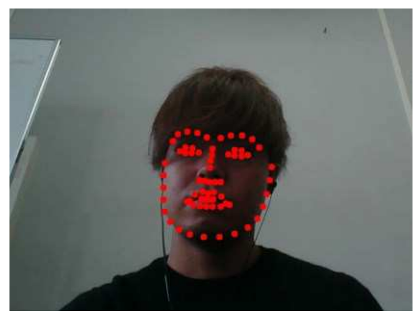


Figure 4. Example of detected face parts

In addition, we calculated the histogram of oriented gradients (HOG) features of the detected face region. Using the coordinates of the facial parts and the HOGs, 17 action units (AUs) shown in Table 1 are detected by a linear kernel with support vector regression. The time mean value, standard deviation, maximum value, minimum value, median value and entropy of each AU are calculated as a feature of facial expression.

Translation and rotation of the face were also calculated as features. Translation and rotation represent the relative movement of the face with respect to the camera and have three degrees of freedom. Translation is the movement of the coordinates in the X-, Y-, and Z-axes in three-dimensional (3D) coordinates. Rotation indicates rotation of the head around the axes roll, pitch, and yaw axes. Translation and rotation are estimated by projecting the 3D coordinate points of the head model onto the image plane using a perspective projection transformation and minimizing the reprojection error (the sum of squares of the distance between the detected point and the projected point). For simplicity, we approximate the optical center as the

AU	Description
1	Inner brow raise
2	Outer brow raise
4	Brow lower
5	Upper lid raise
6	Cheek raise
7	Lid tighten
9	Nose wrinkle
10	Upper lip raise
12	Lip corner pulling
14	Dimpler
15	Lip corner depression
17	Chin raise
20	Lip stretch
23	Lip tighten
25	Lips parting
26	Jaw drop
45	Blink

Table 1. AUs

center of the image and the focal length as the width of the image, and assume that radial distortion does not exist. To calculate reprojection error, the detected ends of the left and right eyes, nose apex, left and right ends of the mouth, and jaw tip are used. Finally, the average value, standard deviation, maximum value, minimum value, median value, entropy, skewness, and kurtosis of the estimated translation and rotation are calculated to form the facial expression feature.

4.2. Heart Rate

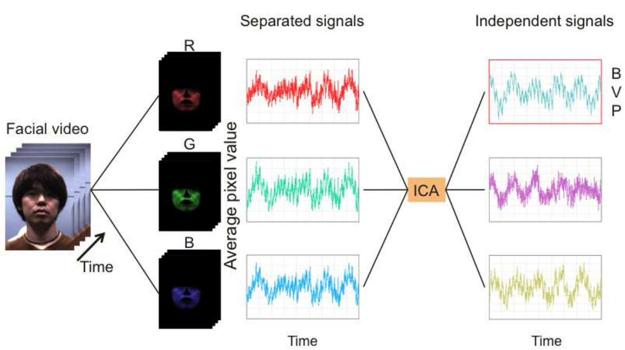


Figure 5. Remote heart rate measurement

Heart rate was measured remotely using the original method based on Poh et al.'s method [14]. Figure 5 shows the flow of the remote heart rate measurement. First, the skin region extracted using the mask image created by removing the eyes, nose, and mouth based on the coordinates of the detected contour of the face and face parts is taken as the region of interest (ROI). The ROI is divided into red, green, and blue channels, and the spatial average of each channel is calculated. Temporal changes in the spatial average of each channel are detrended using a smoothness prior approach [26]. Then, ICA based on the joint approximate diagonalization of eigenmatrices (JADE) algorithm [27] is used for the detrended signals. A band pass filter is applied to the output signals of the ICA to reduce noise. Unlike the conventional method [14], an adaptive multibandpass filter is used in which the pass bands are the width of the highest peak within the range of 0.75–3.00 Hz and the peak width of the second harmonic. Because the blood volume pulse (BVP) signal is more periodic than the other signals, a signal including the spectrum with the highest peak in the frequency domain is selected as the BVP signal. ICA outputs three signals, which includes the BVP signal. The interbeat intervals (IBI) are calculated by interpolating the selected signal to 50 Hz using a cubic spline function and detecting the peak using a moving window.

HRV, which is the variability of the continuous IBI, is controlled by the sympathetic and parasympathetic nerves of the autonomic nervous system. The function of the autonomic nervous system can be evaluated by analyzing IBI in the time domain and nonlinearly.

The time domain method can be easily executed because it directly analyzes the IBI. The average and standard deviation of IBI and the average and standard deviation of the heart rate calculated by dividing 60 by the average IBI is the most easily obtainable index. The standard deviation of IBI reflects the overall change while the root mean square of the successive difference reflects the short term variation. Furthermore, NN50, which is the number of IBIs for which the successive difference is 50 ms or longer, and the pNN50, which is the relative number of NN50 to the total number of consecutive IBIs, are also used as indicators of the parasympathetic nerve. In addition to these statistical features, geometric indicators can be obtained by analyzing the histogram of the IBI [28]. RRtri is a value obtained by dividing the integral value (total number of IBIs) of the histogram of the IBI by the maximum value of the histogram. TINN (the triangular interpolation of the NN interval histogram) is obtained by calculating the base of the triangle approximated by the IBI histogram.

Because the cardiac control system is very complex, it is reasonable to assume that nonlinear mechanisms affect heart rate variability. Nonlinear methods using Poincaré plots are commonly used to analyze heart rate variability. Poincaré plots are graphs showing the correlation between consecutive IBIs. The shape of the plot is used as an indicator and is generally quantified by applying an ellipse to the plot. The standard deviation in the minor axis direction represented by SD1 reflects short-term fluctuations due to respiratory sinus arrhythmia. The standard deviation in the long axis direction represented by SD2 is an index showing long-term fluctuation.

4.3. Gaze

We used the coordinates of the detected face parts to detect eye areas including the eyelids, iris, and pupil. When the positions of the eyes and the pupil are detected, the gaze vector of the eye is individually calculated for each eye. We calculate the intersection of the eyeball sphere with the ray emitted from the camera's origin toward the center of the pupil in the image plane. This gives us the position of the pupil in 3D coordinates. A vector from the 3D eyeball center to the pupil position is the estimated gaze vector. This is a quick and accurate method for human-independent gaze estimation in webcams.

5. Classification

Classification is performed by an SVM using the calculated features and labels. The radial basis function (RBF) is used as the kernel function. To create a generalizable model, learning and classification were carried out by K-fold cross-validation. In the K-fold cross-validation, the sample group is divided into K parts. One of them is a test case and the remaining $K - 1$ are training cases. In the cross-validation, each sample group is verified K times as a test case. The average of the K evaluations obtained in this way is obtained and a single estimate is calculated. During the validation, parameter K was 10. The RBF SVM parameters γ and C were selected by using Bayesian optimization to minimize 10-fold cross-validation loss.

5.1. Labeling

The labels used were obtained by the crowdsourcing participants' survey answers. For both purchase intent and ad liking, the data are divided into two groups to create a two-class classification problem .

5.1.1 Purchase intent

To label the purchase intent for the products of each video advertisement, we calculate the difference in the responses to the pre-survey and post-survey question ("How likely are you to purchase this product, now?"). The data are divided into two classes, those with differences greater than 0 and those with differences equal to or less than 0.

5.1.2 Liking

To label the liking for each video advertisement, we divided the data by the response to the question immediately after viewing each video advertisement ("How much did you like the advertisement that you just watched?"). The data are divided into two classes, those with responses greater than 3 and those with responses equal to or less than 3.

5.2. Oversampling

The number of samples in each class is not uniform, as shown in Figure 2. Handling such imbalanced data can markedly reduce the classification accuracy. Therefore, we solved this imbalance problem by oversampling using Synthetic Minority Over-Sampling Technique (SMOTE) [29]. First, an instance is selected from the minority class and the k nearest neighbor instances are extracted. Then, new instances are added randomly between the k nearest neighbor instances and the selected instance. As a result, the classes were balanced in size.

5.3. Feature selection

Too many features with respect to the number of class or samples to be classified might reduce classification accuracy due to noise-like or redundant features. Excluding such features and selecting only useful ones not only improves classification accuracy but also improves processing speed and readability. In this study, because the quantity of data was huge, reduction of calculation cost was prioritized. Therefore, ReliefF [30] was used for feature selection. ReliefF outputs the weight of each feature in relation to the inputs including the features normalized to the range of [0, 1] in each feature and the corresponding class values. First, the weights of all features are initialized to 0 and the following steps are repeated for all instances. The distances from one instance selected from the input feature to the k nearest neighbor instances in the same class and to the k nearest neighbor instances in other classes are calculated. One instance is selected from the input features and the distance from the k nearest neighbor instances in the same class and the distance to the k nearest neighbor instances in the other class are calculated. The Manhattan distance is used for distance calculation. The weights of each feature are updated by subtracting the average value of the distances in the same class and adding the average value of the distances in the other classes. Finally, the weights are iteratively calculated for all the output instances. In general, 10 is considered to be the optimal value for k. In this study, we selected the features whose output weights were positive for the estimation.

6. Results and discussion

6.1. Purchase intent

Figure 6 shows the receiver operating characteristic (ROC) curve for the purchase intent estimation, which is obtained by changing the threshold of SVM. Figure 7 shows the area under the curve (AUC) of the ROC. We compared the estimation performance of single-mode and multimodal methods.

Figure 6. ROC curve for purchase intent estimation: FE = facial expression, HR = heart rate, and G = gaze

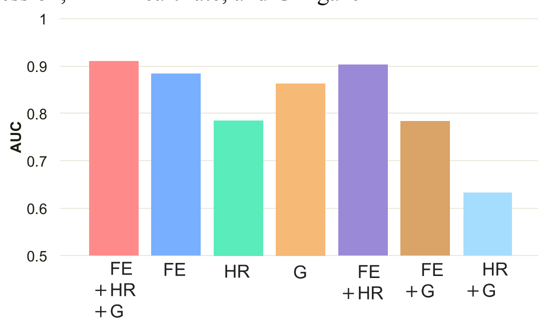


Figure 7. AUC for the ROC for purchase intent estimation. Abbreviations are the same as in Figure 6

The estimation accuracy was the highest (ROC AUC = 0.91) when features acquired from all three modes were used. In addition, when using features calculated from the two modes of facial expression and heart rate, the classification accuracy (ROC AUC = 0.90) was equivalent to that obtained by combining the features from all modalities.

6.2. Ad Liking

Figure 8 shows the ROC curve for the ad liking estimation obtained by changing the threshold of the SVM. Figure 9 shows the AUC for the ROC. We compared the estimation performance for single mode and multimodal features.

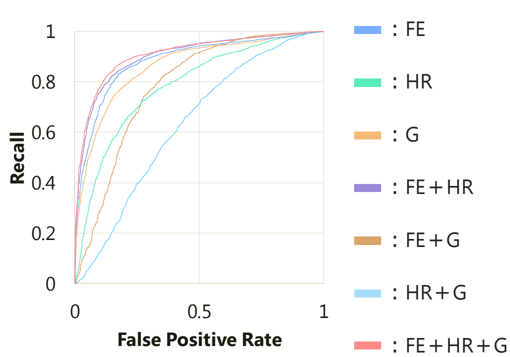


Figure 8. ROC curve for ad liking estimation. Abbreviations are the same as in Figure 6

Figure 9. AUC of the ROC for ad liking estimation. Abbreviations are the same as in Figure 6

Similar to the purchase intent estimation, the estimation accuracy was the highest (ROC AUC = 0.93) when feature values acquired from all three modes were used. Even when using features calculated from only facial expressions, facial expressions and heart rate, or facial expressions and gaze, ad liking was estimated with high accuracy (ROC AUC = 0.90, 0.91, and 0.93, respectively).

The difference between these results seems to support the finding of a previous study [4], which is that facial expression analysis is effective for stronger emotions such as ad liking while heart rate is more beneficial for subtle reactions and emotions such as purchase intent.

7. Conclusion and future work

We estimated advertisement effectiveness by acquiring and analyzing multimodal features from face reactions when a person views video advertisements. A large quantity of data was collected using crowdsourcing. First, by recruiting participants via the Internet, we collected 4,108 facial responses when viewing video advertisements. The distribution of participants was not biased with respect to age, gender, occupation, job, household composition, or household income, and self-selection bias could be reduced. Along with the face reaction, affective responses to video advertisements and products were collected by questionnaire as labeling in machine learning. Next, facial expression, heart rate, and gaze were measured from the collected facial video. For the facial expression measurement, we calculated the AU, which is an index of facial muscle movement as well as translation and rotation. For the heart rate measurement, the features were calculated by analysis in the time domain and nonlinear methods. The heart rate signals were measured using ICA. For gaze measurement, we analyzed the temporal changes in gaze of the left and right eyes and made it a feature. Then, we combined features calculated from each mode and estimated the ad liking and purchase intent. As a result, we show that combining features acquired from multiple modes leads to higher accuracy for both ad effects than then features obtained from only a single mode are used.

Future tasks are to elucidate the relationship between the acquired features and the content of the video advertisement. The goal of measuring advertisement effectiveness is to improve sales by improving the quality of the advertisement. Hence, it is very important to analyze the temporal changes in the content of the video advertisements and the viewer's emotional reaction. In addition, we estimated effects for short video advertisements in this study. However, if the measurement time is longer, the frequency and duration of the facial reactions may differ from the results of this study.

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