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TEMPERATURE ANALYSIS OF FACE REGIONS BASED ON DEGREE OF EMOTION OF JOY

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Abstract. *Various studies pertaining to facial-expression and emotion detection have been conducted from the perspective of emotion communication. We considered it is possible to discriminate between intentionally expressed and naturally evoked facial-expressions, as well as the magnitude of change in facial-expressions, by using temperature changes in the face. The objective was to classify the emotion of joy into intentionally expressed and naturally evoked facial-expressions, and analyze the relationship between the magnitude of change in facial-expression in the section where the facial-expression is expressed and the temperature change in the regions of interest on the face. The temperature change was larger for the degree of emotion than for the steady state. Additionally, the temperature change was larger for natural-facial-expression than for intentional-facial-expressions, and also for facial-expression than for the expressionless section. The magnitude of the temperature change and the average amount of temperature change could be used to discriminate between intentional- and natural-facial-expressions, or the degree of emotion.*

Keywords: Emotional arousal, Skin temperature, Degree of emotion, Infrared thermography, Face detection

1. Introduction.

Nowadays, with the enhancement of computer performance and decrease in cost, computer technologies are applied to various areas of people's lives, such as offices, education, and production. Previously, researchers have attempted to develop reasonable methods to enhance the interaction between humans and machines. However, most contemporary human-computer interaction systems are deficient in interpreting and understanding emotional information and lack emotional intelligence. Thus, it is difficult to precisely identify human emotional states and use this information for decision making and taking actions [1,2]. Therefore, the importance of human interaction in realizing seamless man-machine communication has increased. Various studies pertaining to facial-expression and emotion detection have been conducted from the perspective of emotion communication [3-16].

Nonverbal communication, such as facial-expressions, accounts for 65% of the total human communication [3]. Yet, humans may involuntarily or deliberately conceal emotions in facial-expressions [1]. Thus, it is possible that machines fail to recognize real emotions when using only facial-expression images [2]. On the other hand, physiological changes are controlled by the autonomic nervous and endocrine systems and not by subjective ideas [4]. One of the physiological changes is temperature change in the face [2]. Therefore, we consider that temperature change can be used to discriminate between intentionally expressed (intentional-facial-expression) and naturally evoked (natural-facial-expression)

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facial-expressions. Infrared thermography (IRT) is a non-contact, non-invasive technique for measuring the temperature of the face, regardless of lighting conditions [5-7]. Many studies have used IRT on the whole face, nose, and forehead, and it has been found that the nose region is particularly sensitive to temperature changes [9-11]. It has also been shown that temperature changes occur in the cheek regions [12,13], but few studies have focused on them. Because the cheeks tend to be reddish in color, blood flow changes occur. In addition, the cheek regions are larger than the nose region, which makes it easier to detect them. Thus, it is necessary to consider cheek regions as well. In addition, the more drastic the emotional change, the more significant the change in facial-expression will be in a normal situation. To perform subtle facial-expression recognition, it is necessary to identify the magnitude of change in the facial-expression (degree of emotion). Although there are many studies on discriminating multiple facial-expressions [5,8-12], they did not focus on a single expression to analyze the degree of emotion and the differences between intentional- and natural-facial-expressions. Therefore, the novelty of this study is that it focuses on a single facial-expression, and analyzes the degree of emotion and the difference between intentional- and natural-facial-expressions.

Previously, we analyzed the relationship between changes in facial temperature and emotions. Specifically, we clarified that temperature change occurred at the nose and cheeks (regions of interest (ROIs)) when emotions of joy are evoked [17,18]. Furthermore, to analyze a significant amount of data for temperature analyses in the ROIs, we developed a general-purpose face detection method [18] that uses both thermal and visible moving images. However, owing to the scarcity of data extracted from the emotion of joy, the relationship between the emotion of joy and the temperature change in the ROIs could not be analyzed in detail. The aim of this study is to distinguish the emotion of joy and examine its relationship with temperature change in the ROIs. In summary, we classify the emotion of joy into intentional- and natural-facial-expressions, and then analyze the relationship between the degree of emotion in the section where the facial-expression was expressed (facial-expression section) and the temperature change in the ROIs.

This paper consists of six sections. Section 1 describes the background, objectives, and related studies. Section 2 describes the data acquisition method used in this study and the facial detection and temperature analysis methods used on the ROIs. Section 3 describes the results that show differences between intentional- and natural-facial-expressions. Section 4 describes the results of the temperature analysis on the time series data of intentional-facial-expressions. Section 5 describes the consequences of temperature change on intentional- and natural-facial-expressions. Finally, Section 6 provides a summary of the conclusions and future prospects.

2. Materials and Methods.

First, we describe the data acquisition method. Next, we describe the analysis methods.

2.1. Data.

Figure 1 illustrates the data acquisition environment. Using an infrared thermal imaging device (R500EX-S: Nippon Avionics Co., Ltd.) [19] and a web camera (C922 Pro Stream Webcam: Logitech), the emotional arousal data of the participants were simultaneously acquired as thermal and visible moving images (640 × 480 pixels each, 30 fps). There were 11 participants labeled from A-K (age: in their 20s, 6 men and 5 women). Intentional- and natural-facial-expression data were obtained for three days (days 1-3). The data acquisition environment was as follows.

1) Room temperature: 24.9°C-25.6°C (participants A-E; intentional- and natural-facial-expression data), 18.7°C-22.5°C (participants F-K; intentional-facial-expression data), and 21°C-24.7°C (participants F-K; natural-facial-expression data).

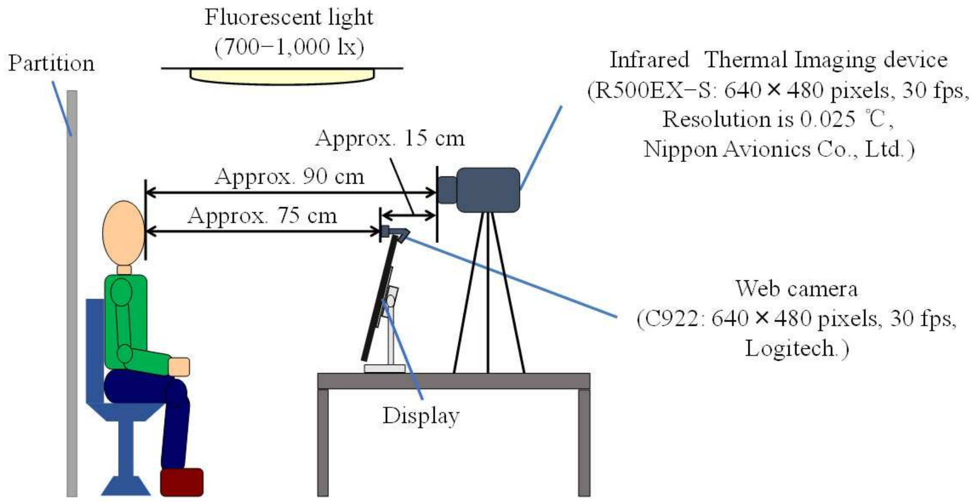


Figure 1. Data acquisition setup

2) Room humidity: 49.5%-60.9% (participants A-E; intentional- and natural-facial-expression data), 41.8%-57.6% (participants F-K; intentional-facial-expression data), and 49.3%-70.1% (participants F-K; natural-facial-expression data).

For participants A-E, both the intentional- and natural-facial-expression data were obtained on the same day; whereas for participants F-K, the data were obtained on different days. Given that the thermal and visible cameras have fields of view of different sizes, the positions in the real world corresponding to the corners of the thermal moving images were indicated using four markers on the partition behind the participant. The data used in this investigation were acquired in accordance with the ethical regulations concerning studies that involve human participants at Akita University, Japan.

2.1.1. *Intentional-facial-expression data.* The intentional-facial-expression data are thermal and visible moving images in which 10 s of "expressionless" and 5 s of "intentional-facial-expression" are alternately expressed. The intentional-facial-expression was classified into two types, i.e., "weak laughter" and "strong laughter" based on the degree of emotion of joy. For each participant, the data were obtained for six sections for "expressionless" and five sections for each of "weak laughter" and "strong laughter". In this paper, "expressionless" is defined as a state in which joy is not expressed, "weak laughter" as a facial-expression of snorting laughter, and "strong laughter" as a facial-expression of loud laughter. However, each participant had a different way of expressing facial-expressions.

2.1.2. *Natural-facial-expression data.* The natural-facial-expression data are thermal and visible moving images during the viewing of emotion-evoking videos [20-23], which last approximately 10 min. The participants themselves classified the degree of emotion of joy into four levels (i.e., "expressionless", "weak laughter", "medium laughter", and "strong laughter"). For the degree of emotion, in addition to the definitions described in Section 2.1.1, "medium laughter" is defined as a facial-expression that is between weak and strong laughter. In this study, "weak laughter" and "strong laughter" were used for examination.

2.2. **Analysis method.** First, the face detection method was used to extract face regions from grayscale thermal images. Next, the ROIs were set and temperature analysis was performed on them. Although there exist face detection methods based on learning and tracking [24], we employed an easy method that uses Dlib for face detection.

2.2.1. *Face detection method.* To analyze the temperatures in the ROIs, the face region in the grayscale thermal images was obtained using the face detection method that combines grayscale thermal and visible moving images [18]. Figure 2 shows the flow and overview of the method.

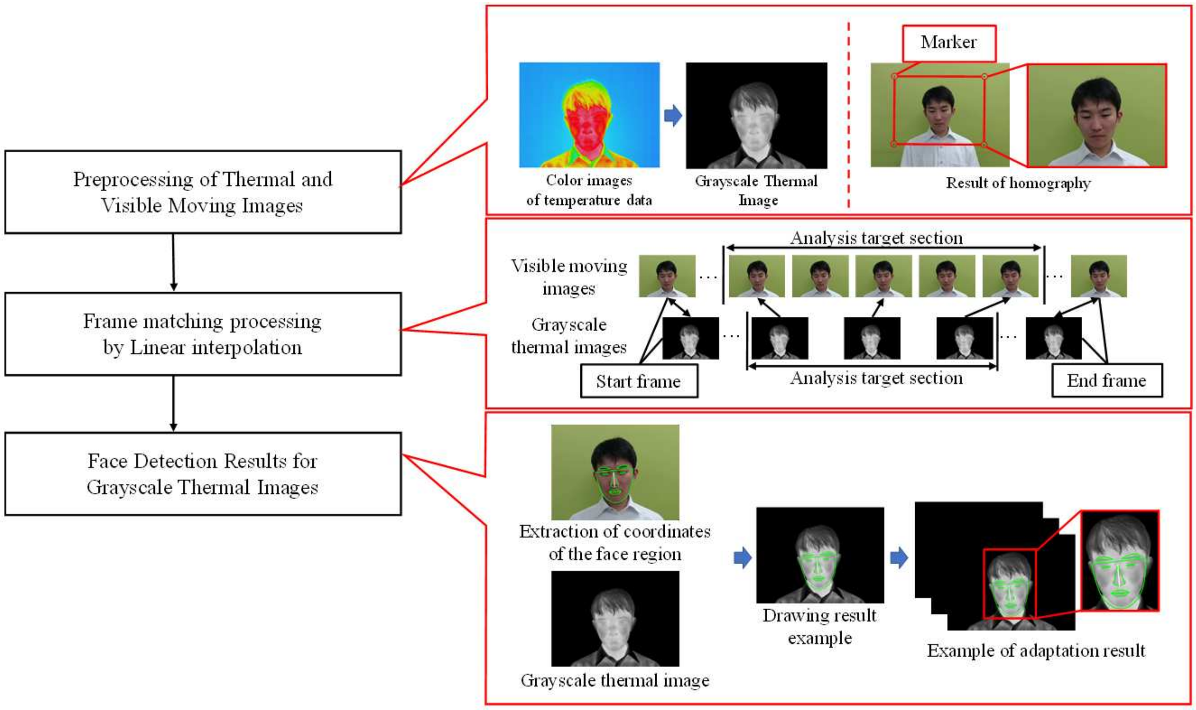


FIGURE 2. Flow and overview of the face detection method

2.2.1.1. *Preprocessing of thermal and visible moving images.* First, grayscale images (grayscale thermal images) were created using the temperature data of the thermal moving images. The pixel intensity was converted from 0 to 255, corresponding to the temperature ranges of 29°C-37°C (participants A-E) and 26°C-37°C (participants F-K). Second, visible videos partitioned at 30 fps underwent homography transformation [25] using the coordinates of the four markers such that they were of the same size as the grayscale thermal images. Finally, processing was conducted to match the number of frames of the grayscale thermal images using linear completion and correct them to the same frame index because the total number of frames in the grayscale thermal and visible moving images were different.

2.2.1.2. *Face detection results for grayscale thermal images.* First, face detection was performed on the visible moving images using the face detection function [26,27] included in the open-source library Dlib, and the coordinates of 64 facial points were acquired [28]. Finally, the acquired facial coordinates were plotted against grayscale thermal images with temporal correspondence.

2.2.2. *Temperature analysis method of ROIs.* To analyze the temperature in the ROIs in the face region acquired by the face detection method in Section 3, the amount of temperature change (ATC) was calculated.

2.2.2.1. *Setting the ROIs.* The ROIs were set as shown in the blue frame in Figure 3 for the grayscale thermal image of the first frame after face detection. The nose region is the area between the apex and root of the nose, and does not include the nostrils. The right and left cheek regions are the areas below the eyes and do not include the eyes, nose, and mouth. From the feature point between the nostrils obtained by Dlib, the red point on the nose was moved left 5 pixels along the x-axis and up 15 pixels along the y-axis, the red point on the right cheek was moved left 35 pixels along the x-axis and up 5 pixels along the y-axis, and the red point on the left cheek was moved right 35 pixels along the x-axis and up 5 pixels along the y-axis. The corresponding ROIs for the nose and cheeks were 10×30 pixels and 30×30 pixels, respectively. The feature point between the nostrils is used as the reference point, and each ROI is processed such that it follows the tilt of the face.

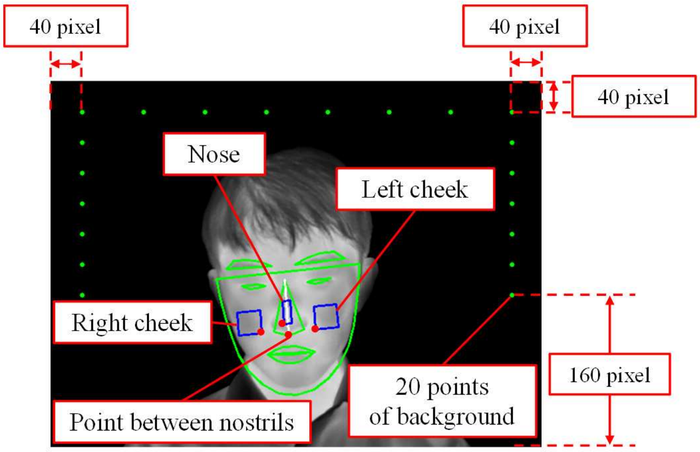


FIGURE 3. Example of 20 background points and ROIs

2.2.2.2. *Estimation of skin temperature difference.* First, to reduce the effect of temperature fluctuations in the room, the time series data of the skin temperature difference (STD) were calculated using the difference between the average temperature of each ROI and the average temperature of 20 background points. The green points in Figure 3 show an example of setting 20 background points. The 20 background points were set such that they were equally spaced. Next, to remove noise, a moving-average filter [29] was used to smoothen the STD time series data for the focus frame, and one frame before and after the focus frame.

2.2.2.3. *Estimation of amount of temperature change.* For the smoothed STD time series data, the ATC was calculated using the difference between the temperature of the frame of interest and that of 30 frames earlier.

3. **Significant Difference for Intentional- and Natural-Facial-Expressions.** The differences between the steady state and facial-expression sections of the 11 participants were investigated. Welch's t-test [30] was performed on the STD between the steady state and facial-expression sections of the intentional- and natural-facial-expression data for each participant. In this study, we also set the significance level to 5%, similar to the two-tailed Welch's t-test. The data used for the tests are described as follows.

1) Steady-state: the first 100 frames of the first expressionless section are the steady state.
2) Intentional- and natural-facial-expression data: all frames in each facial-expression section.

Figure 4 shows the results of investigating the significant differences in the facial-expression sections of the intentional- and natural-facial-expression data against for each ROI. The number of facial-expression sections with significant differences was more than 90.0% of the total number of facial-expression sections in the intentional- and natural-facial-expression data. Focusing on the "strong laughter" data of the intentional-facial-expression data, which has the highest percentage in Figure 4, participant G showed a temperature change of approximately 0.2°C in the positive direction compared to the steady-state section of the facial-expression data, wherein there was a significant difference. Therefore, the ROIs in the facial-expression sections of the intentional- and natural-facial-expressions data show a larger temperature change than those in the steady-state sections. This suggests that the STD in the ROIs is a useful index for discriminating between expressionless and joy.

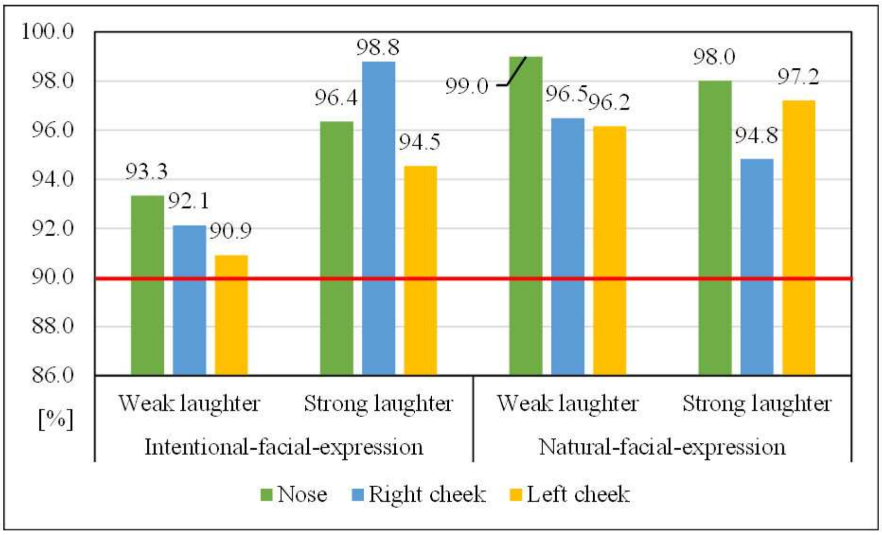
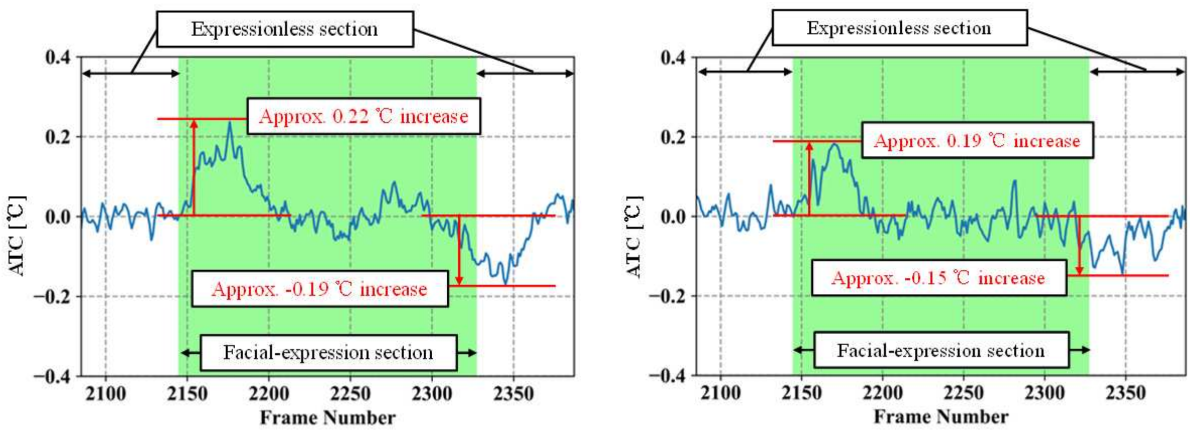


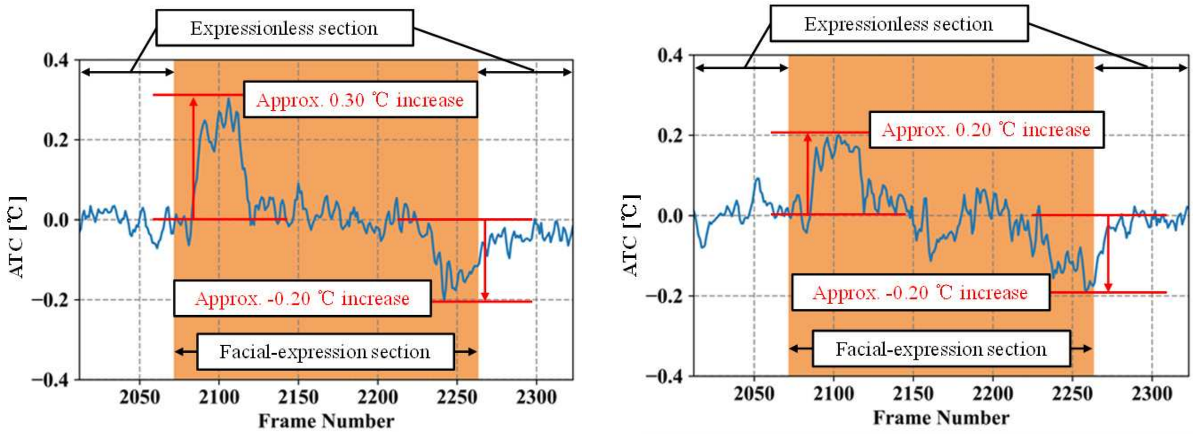
FIGURE 4. t-test result for the STD

4. **Analysis of Temperature Change in Intentional-Facial-Expression Data.** The intentional-facial-expression data of the 11 participants focused on the ATC at the right and left cheek regions. Figures 5 and 6 show the ATC of the right and left cheek



(a) Right cheek (b) Left cheek

FIGURE 5. Weak laughter (participant H, day 3)



(a) Right cheek (b) Left cheek

FIGURE 6. Strong laughter (participant H, day 3)

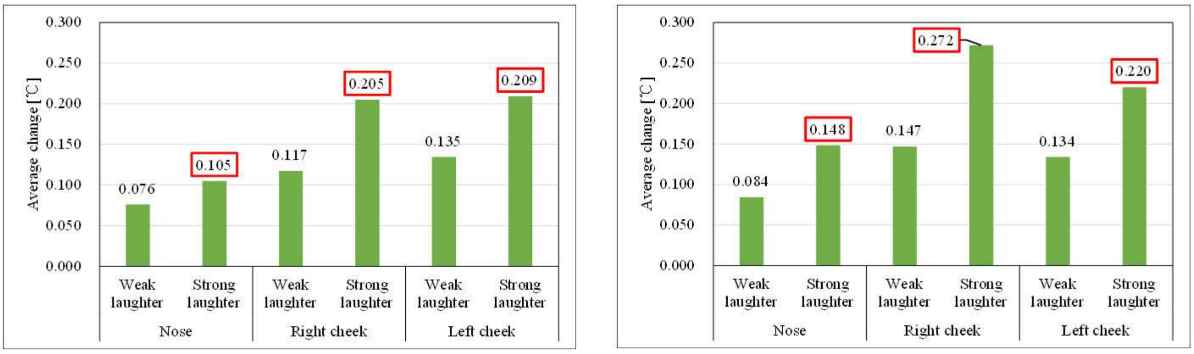
regions in one facial-expression section of weak and strong laughter, respectively (participant H, day 3). In Figure 5(a), the ATC changed by approximately +0.22°C and −0.19°C near the start and end frames, respectively. In Figure 5(b), the ATC changed by approximately +0.19°C and −0.15°C near the start and end frames, respectively. In Figure 6(a), the ATC changed by approximately +0.30°C and −0.20°C near the start and end frames, respectively. In Figure 6(b), the ATC changed by approximately +0.20°C and −0.20°C near the start and end frames, respectively. Similarly, in other participants, the ATC tended to increase in the positive and negative directions near the start and end frames, respectively. However, for the weak and strong laughter data of participant A on day 1, a different waveform was obtained. Specifically, the ATC was larger in the negative and positive directions near the end and start frames, respectively. It is considered that the results of participant A on day 1 were different from those of other data because the data were obtained after working under the hot sun.

In addition, we compared the weak and strong laughter of the intentional-facial-expression data. The ATC near the start frame of the facial-expression section was more significant in the strong laughter than in the weak laughter. These results suggest that in the intentional-facial-expression, the waveform of the ATC differs between the facial-expression and expressionless sections. Furthermore, it was suggested that the degree of intentional-facial-expression could be determined by comparing the ATC magnitudes near the start frame of the facial-expression section. Although few studies have focused on the cheeks, the results of this study revealed differences in the temperature changes of the cheeks depending on the degree of emotion; therefore, we believe that focusing on the cheeks is also effective.

5. **Analysis of Temperature Change in Intentional- and Natural-Facial-Expression Data.** First, the peaks that had a change of more than the threshold value in relation to the maximum ATC value in the expressionless and facial-expression sections of the 11 participants, as well as the average value of the ATC (average change) in the peaks of the expressionless and facial-expression sections were extracted. The threshold value was set at 77% for the expressionless section and 75% for the facial-expression section. The procedure for calculating the threshold value was as follows.

1) The threshold value was increased by 10% in the range of 20%-100%, the average change was calculated for each expressionless and facial-expression section, and the degree of emotion in each data type was acquired for each participant.
2) The values at which the calculated average change began to converge (convergence value) were obtained for each expressionless section and degree of emotion.
3) The average convergence value was obtained for each expressionless section and the degree of emotion of each participant was adopted as the threshold value.

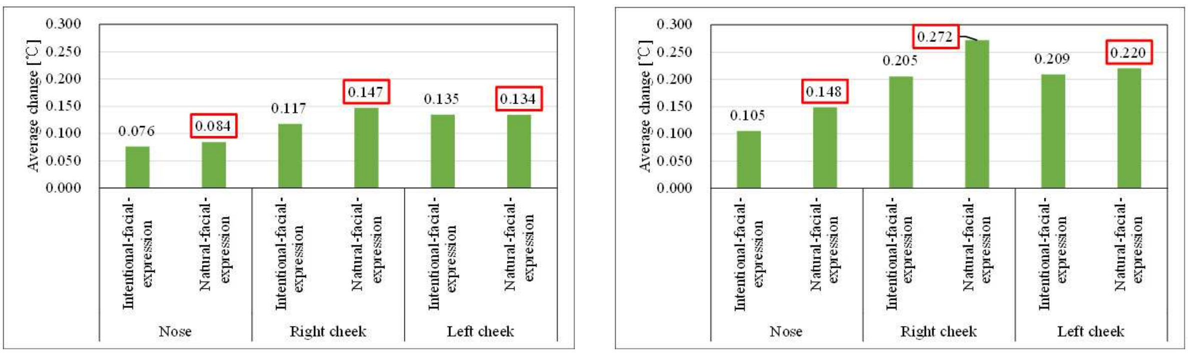
5.1. **Comparison of average change in weak and strong laughter.** Figure 7 shows the results of the average change calculation for weak and strong laughter. For both intentional- and natural-facial-expression data, the average change in each ROI was larger for strong laughter than for weak laughter. This suggests that it may be possible to discriminate between weak and strong laughter by comparing the average change.



(a) Intentional-facial-expression (b) Natural-facial-expression

FIGURE 7. Average change in weak and strong laughter

5.2. **Comparison of average change in intentional- and natural-facial-expression data.** Figure 8 shows the results of the average change calculation for the intentional- and natural-facial-expression data. For both weak and strong laughter, the average change in each ROI was larger for the natural-facial-expression data than for the intentional-facial-expression data. In particular, the right cheek region shows a larger difference in the average change for the intentional- and natural-facial-expression data than the nose and left cheek regions. This suggests that it may be possible to discriminate between intentional- and natural-facial-expression data by comparing the average change for the same degree

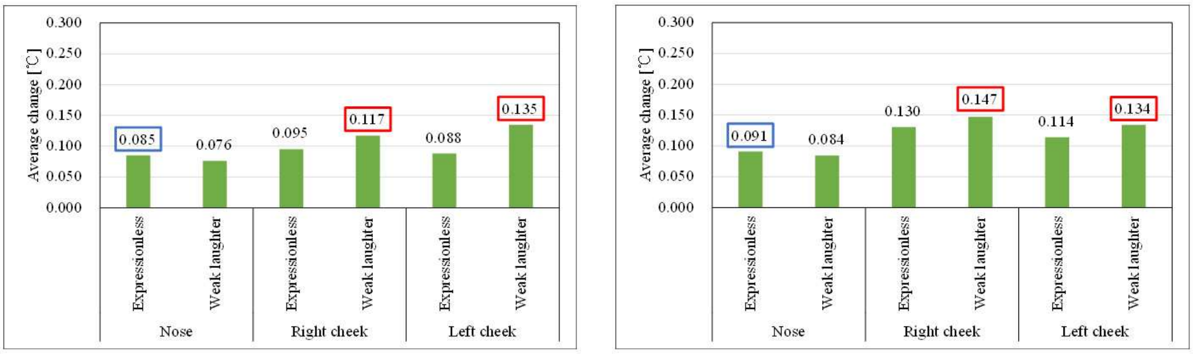


(a) Weak laughter (b) Strong laughter

FIGURE 8. Average change in intentional- and natural-facial-expression data

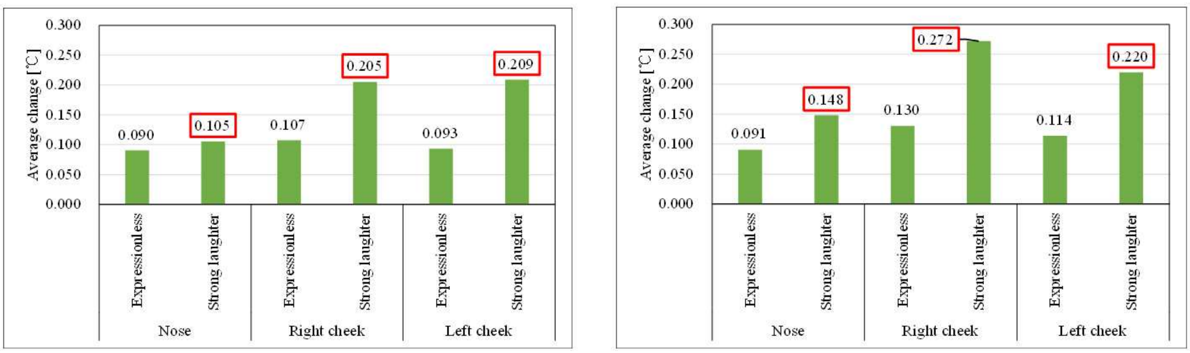
of emotion. Although previous studies have compared multiple facial-expressions to identify whether there is a temperature change in the nose, the present results clarify that there is a difference by classifying a single facial-expression into intentional- and natural-facial-expressions data and comparing the temperature change in the nose and cheeks. Therefore, we believe that it is effective to classify the data into intentional- and natural-facial-expressions, and compare their temperatures.

5.3. **Comparison of average change in expressionless and facial-expression sections.** Figures 9 and 10 show the results of the average change calculation for the expressionless and facial-expression sections, respectively. In Figure 9, the average changes in the intentional- and natural-facial-expression data for weak laughter are larger in the facial-expression section than in the expressionless section in the right and left cheek regions. The average change in the nose region is larger in the expressionless section than in the facial-expression section. In Figure 10, the average change in the intentional- and natural-facial-expression data for strong laughter is larger in the facial-expression section than in the expressionless section. In other words, the average change in the right and left cheek regions is larger in the facial-expression section than in the expressionless section, regardless of the degree of emotion. The average change in the nose region is larger in the expressionless section than in the facial-expression section for weak laughter. This



(a) Intentional-facial-expression (b) Natural-facial-expression

FIGURE 9. Average change in expressionless and facial-expression sections (weak laughter)



(a) Intentional-facial-expression (b) Natural-facial-expression

FIGURE 10. Average change in expressionless and facial-expression sections (strong laughter)

suggests the possibility of discriminating weak and strong laughter by focusing on the average change in the expressionless and facial-expression sections in the nose region.

6. **Conclusions.** The purpose of this study was to discriminate the emotion of joy and investigate its relationship with temperature change in facial ROIs in detail. Our first conclusion is that STD is a useful index for discriminating between an expressionless condition and joy. Second, the ATC of the intentional-facial-expression data tends to be different from that of the expressionless section before and after a facial-expression. Third, the degree of emotion in the intentional-facial-expression data may be distinguished by comparing the magnitude of temperature change near the start frame of the facial-expression section. Further, to discriminate the degree of emotion in intentional- and natural-facial-expressions, it may be useful to compare the average change. Lastly, to distinguish weak laughter, it may be beneficial to focus on the average change in expressionless and facial-expression sections in the nose region.

It has not yet been possible to detect the facial-expression sections from the waveform of the temperature change in the ROIs. Therefore, it is necessary to find effective features for detecting the facial-expression sections from the waveform of temperature change.

Finally, future studies should focus on time series data and examine the relationship between the degree of emotion, order of expressionless, and temperature change.

This research is expected to be applied to communication robots, wherein the robots can recognize intentional- or natural-facial-expressions data from the change in human facial temperature.

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