Improvement of Lip Extraction Method Using Interpolation Method

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Abstract

Feelings of amusement improve the quality of life (QOL). However, in the authors' previous studies, it was revealed that the variance value of lip movement increases when people feel amusement. Therefore, it is important to extract the lip shape accurately and automatically for quantifying amusement feelings and the QOL in daily life. A lip shape extraction method using a feedforward neural network and correction method using a shadow-removing method for the lip shape extraction method (previous method) was proposed. The previous method can accurately extract the lip shape and solve the problem that the lip is extracted excessively from the shadow around the lip. However, the previous method has the problem that the entire lip area is not extracted because of the shadow or highlights. In this work, improvement of the lip extraction method using an interpolation method is proposed. In the experiments conducted, the proposed method was less susceptible to lighting and provided more-satisfactory lip area extraction than the previous method.

Keywords: lip, human interface, feedforward neural network.

1. Introduction

In recent years, such problems as increasing costs of nursing care and medical expenses in the super-aging society in Japan have intensified. Maintaining and improving people's quality of life (QOL) can solve these problems in the super-aging society in Japan. Therefore, people have started taking into consideration the QOL to solve the problems⁽¹⁾. However, it is known that feeling amused improves the QOL. In previous studies, it was revealed that

the variance value of lip movement increases when people feel amusement⁽²⁾. The psychological change is delicate. Therefore, it is important to extract the lip shape accurately for quantifying the amusement feeling and QOL.

As conventional methods, a face feature points extraction method using Convolutional Neural Network (CNN)⁽³⁾, and face detection method using Recurrent Neural Network (RNN) and CNN⁽⁴⁾. These methods can extract the lip feature points from face image. Furthermore, a face parts extracted method based on machine learning using face shape vector, face image, and trained function⁽⁵⁾ were proposed by other research groups. However, many training data are needed for machine learning. In addition, the lip extraction method based on the face shape vector cannot extract the lip shape when part of the face is hidden.

A lip shape extraction method using a feedforward neural network (FFNN)⁽⁶⁾ and a correction method using a shadow-removing method for the lip shape extraction method⁽⁷⁾ (previous method) was proposed. The previous method can accurately extract the lip shape using a few amount training data, and can extract lip shape even if part of the face is hidden. Furthermore, the previous method solves the problem that the lip is extracted excessively from the shadow around the lip. However, in the previous method, the entire lip area is not extracted. The reason is that the features of the lip and skin become similar because of the shadow or highlights.

In this work, improvement of the lip extraction method using an interpolation method (proposed method) is proposed. The proposed method can extract lip area is not extracted using the previous method. The proposed method, the previous method and the lip extraction method based on feature points were compared to clarify the usefulness of the proposed method.

Fig. 1. Data acquisition environment.

Table 1. Lighting environments.

	I	II	III
Lamp 1	Turn on	Turn on	Turn on
Lamp 2	Turn on	Turn off	Turn off
Lamp 3	Turn on	Turn on	Turn off
Illuminance	370lx–450lx	190lx–230lx	90lx–160lx

2. Data Acquisition

Image data of seven subjects' (A–G, all of Asian descent) pronunciation were taken using a web camera (Logicool C922 PRO STREAM WEBCAM) from the front in three kinds of lighting environment (I–III). The data acquisition environment is shown in Fig. 1, and the three kinds of lighting environment are shown in Table 1. A pronouncing command “o/fu/ro” (meaning “bath” in English) was used. The given command was used for two reasons.

- The word is familiar.
- Shadows tend to appear under the lower lip.

The data used in this study were acquired in accordance with the ethical regulations concerning studies involving humans at Akita University, Japan.

3. Proposed Method

3.1 Outline of the Proposed Method

As shown in Fig. 2, the proposed method consists of three processes. The first process is the lip shape extraction method using an FFNN. The second process is the correction method using a shadow-removing method. These two processes used the previous method for lip shape extraction. The third process is the interpolation process for the extracted lip shape. It can interpolate the unextractable lip area using the previous method.

Fig. 2. Overview of proposed method.

3.2 Lip Extraction Process

Lips were extracted using a lip extraction method⁽⁶⁾ based on an FFNN. First, the first frame was obtained from all frames for training the data. Second, the rima oris was extracted from the first frame. Third, features were extracted, six patterns each, from the lip and skin based on the rima oris for training the FFNN. Finally, the FFNN was trained, and the lip shape was extracted from all frames of one utterance using the trained FFNN.

3.3 Shadow-Removing Process

The shadow-removing process⁽⁷⁾ was executed based on the L^* (lightness value) of an $L^*a^*b^*$ color space⁽⁸⁾, because the shadow area had low lightness. First, the threshold was calculated based on the average L^* on the lip area. Next, the shadow areas were extracted from the lip area using the threshold. Finally, the shadow area was removed from the extracted lip area.

3.4 Interpolation Process for Extracted Lip Shape

The interpolation process consists of four processes (a)–(d).

(a) Contour pixel extraction process

Contour pixels of the lip were extracted from some lip pixels in the lip extraction image, based on the following criteria of lip contour, Class 1–4.

- Class 1: The lip pixels have skin areas in all pixels of the left and up directions.
- Class 2: The lip pixels have skin areas in all pixels of the left and bottom directions.

Fig. 3. Example of contour pixel extraction.

Fig. 4. Example of the contour pixel movement in Class 3.

- Class 3: The lip pixels have skin areas in all pixels of the right and up directions.
- Class 4: The lip pixels have skin areas in all pixels of the right and bottom directions.

Fig. 3 shows an example of the result for the contour pixels extracted.

(b) Moving process for contour pixels

Lip shape was interpolated by linking lip contour pixels. However, contours of the lip extracted correctly were interpolated to the wrong shape. Therefore, the contour pixels of the lip extracted were moved on the inside of the lip contours. Lip contour pixels in each class were moved using the following process, Class 1–4.

- Class 1: All lip contour pixels were moved by (1, 1) pixels.
- Class 2: All lip contour pixels were moved by (1, -1) pixels.
- Class 3: All lip contour pixels were moved by (-1, 1) pixels.
- Class 4: All lip contour pixels were moved by (-1, -1) pixels.

Fig. 4 shows an example of the contour pixel moving result.

(c) Linking process for contour pixels

Lip shape was interpolated by linking lip contour pixels classified in the same class. Fig. 5 shows an example of the linking process for contour pixels. First, x coordinate values of all contour points were calculated. Second, the differences (dis) between the maximum and minimum values of x coordinate values were calculated in each class. Third, the n th pixel (P_n) and pixels in the same class as P_n and within a distance of half dis pixels from P_n were linked. Finally, the

Fig. 5. Example of linking the contour pixels in Class 4.

Fig. 6. Example of lip shape interpolation (green line links the contour pixels).

above processing was performed for all classes.

(d) Interpolation process of lip shape

First, a binary image in which the lip area and connecting line were white pixels and other areas were black pixels was made. Next, black pixels between white pixels were reset to white pixels. Fig. 6 shows an example of the image before and after the interpolation process adaptation.

4. Evaluation Experiment

4.1 Mask Image and Evaluation Index

Mask images of the seven subjects' lip areas were created to compare the proposed method and previous method. Mask images were created by one operator based on the following lip criteria i)–iii).

- The area that exists in the mouth part of the face and is reddish.
- The area of the mouth corner.
- The area where the upper lip and the lower lip are in contact and rima oris.

F -score⁽⁹⁾ was used to compare of the proposed method with the previous method. First, *precision* and *recall* were calculated as per (1) and (2). Next, the F -score was calculated as per (3) using *precision* and *recall* values. The F -score can be used to evaluate classifier performance. The F -score is a value between 0.0 and 1.0, and the higher the value, the better the classifier's accuracy. TP is the number of pixels with which the lip is correctly classified as the lip, FP is number of pixels with

Table 2. Result of average F_{ave} .

Subjects	Proposed method	Previous method	Difference
A	0.9398	0.9027	0.0372
B	0.9477	0.8963	0.0514
C	0.9387	0.9123	0.0263
D	0.9276	0.8831	0.0445
E	0.9305	0.8897	0.0408
F	0.8780	0.7941	0.0838
G	0.9038	0.8828	0.0209
Average	0.9237	0.8802	0.0436

(a) Original. (b) Proposed method. (c) Previous method.

Fig. 7. Example of lip extraction result.

which the skin is incorrectly classified as the lip, and FN is number of pixels with which the lip is incorrectly classified as the skin.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$F\text{-score} = \frac{2 \times Precision \times Recall}{precision + Recall} \quad (3)$$

In addition, the proposed method was compared to the lip extraction method based on the face shape vector is implemented using the machine learning library dlib⁽¹⁰⁾. Officially distributed face detector⁽¹¹⁻¹³⁾ was used in the dlib. The dlib can get 20 lip feature points from face image. *Intersection-over-Union* (IoU)⁽¹⁴⁾ was used to compare of the proposed method with the dlib. IoU was calculated as per (4), and two rectangles was used for calculation of IoU . One is the rectangle that circumscribes the lip area of the mask image, while the other is one that circumscribes the lip area extracted automatically. “Area of overlap” is the logical AND of the two rectangles, and “Area of union” is the logical OR of the two rectangles.

$$IoU = \frac{Area\ of\ overlap}{Area\ of\ union} \quad (4)$$

4.2 Calculation of Evaluation Index

(a) Calculation of F-score

First, lip areas were extracted for seven subjects’ image

Table 3. Result of standard deviation F_{ave} .

Subjects	Proposed method	Previous method	Difference
A	0.0011	0.0112	-0.0101
B	0.0070	0.0175	-0.0105
C	0.0139	0.0378	-0.0239
D	0.0262	0.0411	-0.0149
E	0.0068	0.0175	-0.0106
F	0.0120	0.0397	-0.0276
G	0.0072	0.0098	-0.0026
Average	0.0106	0.0249	-0.0143

data using the proposed method and previous method. Second, the $F\text{-score}$ was calculated using the extracted lip area and the mask image. Third, the average value of the $F\text{-score}$ (F_{ave}) was calculated for each lighting environment of each subject. Finally, the average F_{ave} and standard deviation F_{ave} were calculated for each subject, and the results of the proposed method and previous method were compared.

(b) Calculation of IoU

First, lip areas and lip feature points were extracted using the proposed method and dlib from seven subjects’ image data, respectively. Second, the IoU was calculated using the mask image for lip area and lip feature points, respectively. Third, the average value of the IoU (IoU_{ave}) was calculated for each lighting environment of each subject. Finally, the average IoU_{ave} and standard deviation IoU_{ave} were calculated for each subject, and the results of the proposed method and dlib were compared.

5. Experimental Result

5.1 Evaluation Results of Average F_{ave}

Table 2 shows the calculation result of the average F_{ave} for each method. In all subjects, the average F_{ave} of the proposed method was higher than that of the previous method, and the best value was 0.9477. The proposed method can improve the average F_{ave} by 0.0436 on average. Fig. 7 shows an example of the resulting image. The results suggest that the proposed method is more useful for lip extraction than the previous method.

5.2 Evaluation Results of Standard Deviation F_{ave}

Table 3 shows the calculation result of the standard deviation F_{ave} for each method. In all subjects, the standard deviation F_{ave} of the proposed method was lower than that of the previous method. The results of the average F_{ave} becoming higher and the standard deviation F_{ave} becoming

Table 4. Result of average IoU_{ave} .

Subjects	Proposed method	Dlib	Difference
A	0.8927	0.9026	-0.0100
B	0.9099	0.8241	0.0858
C	0.9147	0.8564	0.0584
D	0.9134	0.9027	0.0107
E	0.8959	0.8664	0.0295
F	0.8174	0.8787	-0.0613
G	0.8617	0.8264	0.0353
Average	0.8865	0.8653	0.0212

Table 5. Result of standard deviation IoU_{ave} .

Subjects	Proposed method	Dlib	Difference
A	0.0197	0.0302	-0.0105
B	0.0106	0.0358	-0.0252
C	0.0019	0.0166	-0.0147
D	0.0263	0.0141	0.0122
E	0.0032	0.0307	-0.0274
F	0.0201	0.0430	-0.0229
G	0.0144	0.0394	-0.0250
Average	0.0137	0.0300	-0.0162

lower suggest that F_{ave} was improved in each lighting environment. The results suggest that the proposed method is useful for lip extraction and reduces the effects of lighting compared with the previous method.

5.3 Evaluation Results of Average IoU_{ave}

Table 4 shows the calculation result of the average IoU_{ave} for each method. In 5 out of 7 subjects, the average IoU_{ave} of the proposed method was higher than that of the dlib, and the best value was 0.9147. Furthermore, subject A's difference of the average IoU_{ave} was small. The results suggest that the proposed method is useful for lip extraction. On the other hand, subject F's average IoU_{ave} of the propose method is lower than the dlib because the lip shape extracted using an FFNN⁽⁶⁾ was over corrected by the shadow removing method⁽⁷⁾ in the proposed method. Therefore, by improving the shadow removing method, lip shape extraction accuracy is improved.

5.4 Evaluation Results of Standard Deviation IoU_{ave}

Table 5 shows the calculation result of the standard deviation IoU_{ave} for each method. In 6 out of 7 subjects, the standard deviation IoU_{ave} of the proposed method was lower than that of the dlib. The results of the average IoU_{ave} becoming higher and the standard deviation IoU_{ave} becoming lower suggest that proposed method can extract the lip shape with accuracy equal to or better than the dlib.

6. Conclusions

An interpolation method was proposed for the lip extraction method using an FFNN, and the accuracy of lip extraction was improved. The experiments demonstrated that i) the interpolation method could solve the problem of the previous method that the entire lip area is not extracted, ii) the proposed method is less susceptible to lighting than the previous method and can extract lip area more satisfactorily than the previous method, and iii) the proposed method can extract the lip shape with accuracy equal to or better than the dlib.

Acknowledgment

The authors would like to thank Japan Business Systems, Inc. for its assistance in conducting this study.

This study has been supported by JSPS KAKENHI Grant Number JP19K12909.

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