Facial Mimicry Analysis Based on 3D Morphable Face Models

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Abstract—**Facial mimicry is an important non-verbal communication that can promote favorable social behavior and positive relationships. As recent computer vision technologies have reached the level of human perception for processing facial information, the study of automated analysis of facial mimicry has attracted the attention of the Human Computer Interaction (HCI) society. In this study, we propose a system to evaluate the similarity of facial images based on the shape of the face derived from 3-Dimensional (3D) face data. Two different 3D face data were used in this study: a 3D Digital Character (3DDC) and the Surrey 3D Morphable Face Model (3DMFM). Our approach consists of the following steps: (1) landmark extraction from the facial image; (2) 3D shape fitting; (3) similarity analysis for the face point cloud. Our results show that the similarity between faces can be assessed by analyzing the non-rigid portions of the faces. The proposed system can be extended as a facial mimicry training tool to improve social communication.**

Keywords-mimicry; expression training; emotion; image processing.

I. Introduction

People often consciously or unconsciously mimic the facial expressions of their conversation partners. This type of non-verbal communication is important in providing additional information beyond verbal communication. This study extends our previous research on a facial mimicry training based on 3-Dimensional (3D) morphable face models [1]. Non-verbal communication refers to communication methods without using languages, such as gestures, facial expressions, tone of voice, eye contact, and posture. Unconscious mimicry increases affiliation, which helps to foster relationships with others [2].

Facial expressions involve signals of a larger communicative process, conveying the focus of attention, intention, motivation, and emotion. For instance, a smile with the corners of the mouth turned up to expose the front teeth may express joy. A frown, typically with the corners of the mouth turned down, forms an expression of disapproval. Some researchers believe that emotions are a universal construct. However, differences in culture can lead to differences in the absolute level of intensity of emotions [3].

The FACS (Facial Action Coding System), which is a set of facial muscle movements corresponding to displayed emotions, is a traditional measure for analyzing facial expressions [3]. The movements of individual facial muscles are encoded by FACS from slightly different instantaneous changes in facial appearance. Each action unit (AU) is described in the FACS manual.

Manual coding of video recordings of participants according to the units of action described by FACS takes a significant amount of time and effort. Automatic analysis of facial expressions has received a great attention from the computer vision community. Bartlett et al. (1999) made an early attempt to automate facial expressions using FACS by applying computer image analysis to classify the basic elements that comprise complex facial movements [4]. Using template matching to detect facial features, such as lips, eyes, brows and cheeks, Tian et al. (2000) developed an Automatic Face Analysis (AFA) system [5], which recognizes changes in facial expression into AUs.

Recent computer vision technology has made it possible to perform conventional face recognition processes such as face detection, face matching, facial feature extraction, and facial expression classification in real time. Baltrušaitis et al. (2018) developed an open source facial behavior toolkit, OpenFace 2.0. This toolkit uses a linear kernel support vector machine to detect facial expressions by detecting the unit of motion (AU) of the face [6]. iMotions [7] is a commercial tool for automatic analysis of facial expressions. The tool allows the user to select the FACET [8] or AFFDEX [9] algorithm for facial expression recognition.

In contrast to the growing interest in the application of automated facial expression analysis, there have been surprisingly few attempts to measure the similarity of facial expressions. In our previous work, we used a deformable 3D Digital Character (3DDC) to find the most similar shape to a given facial image [1]. The similarity of the faces was measured by calculating the relationship between the 3D point clouds obtained from each face.

In this study, we extend our previous work to evaluate the similarity of facial images based on the shape of the face derived from two different face data: a 3DDC [10] and the Surrey 3D Morphable Face Model (3DMFM) [11]. We fit these models to the corresponding facial images and derive the facial features that are important for similarity analysis.

The rest of this paper is organized as follows. Section II discusses known approaches to facial expression imitation. Section III introduces our proposed facial mimicry analysis system. Section IV shows our experiment results. Finally, Section V gives a short conclusion and highlights the most important outcomes of this paper.

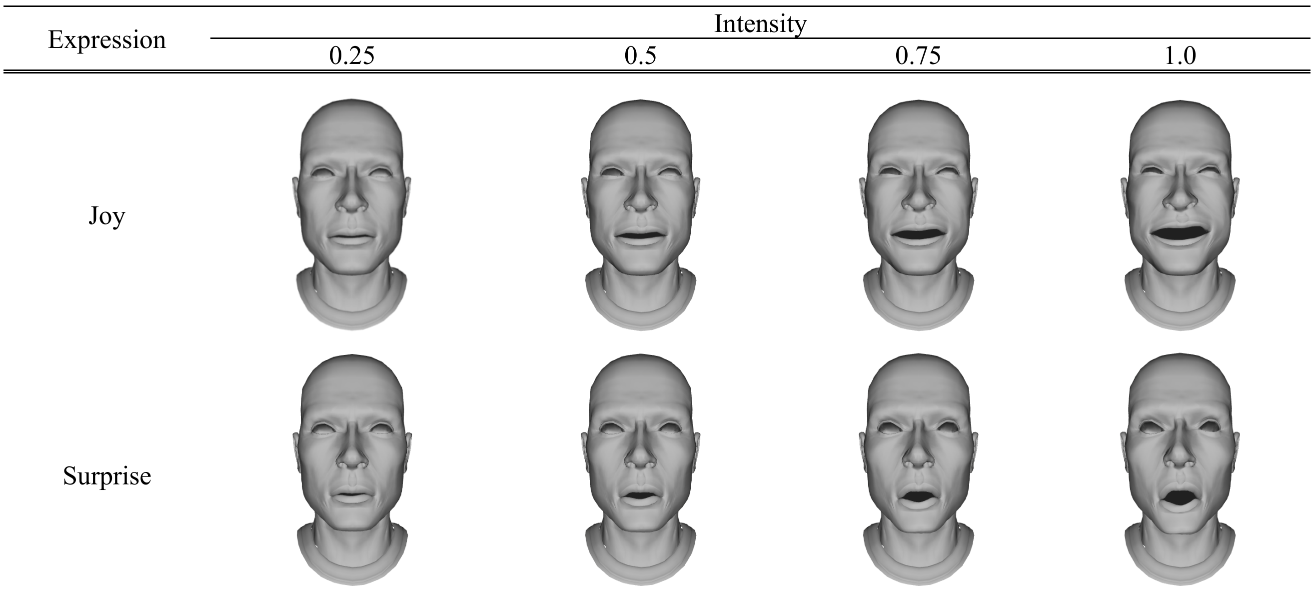

Figure 1. Some facial expressions generated using 3DDC.

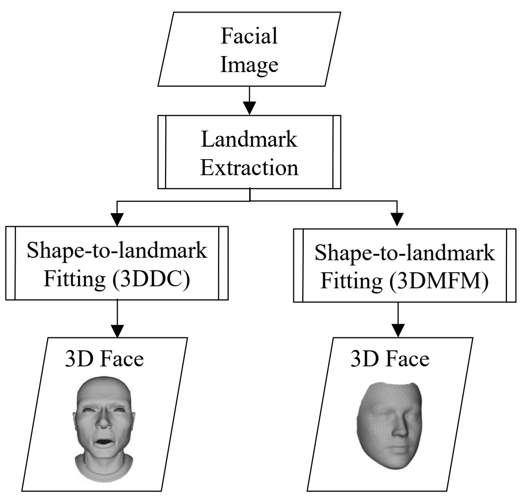

Figure 2. Generation of 3D face data for this study.

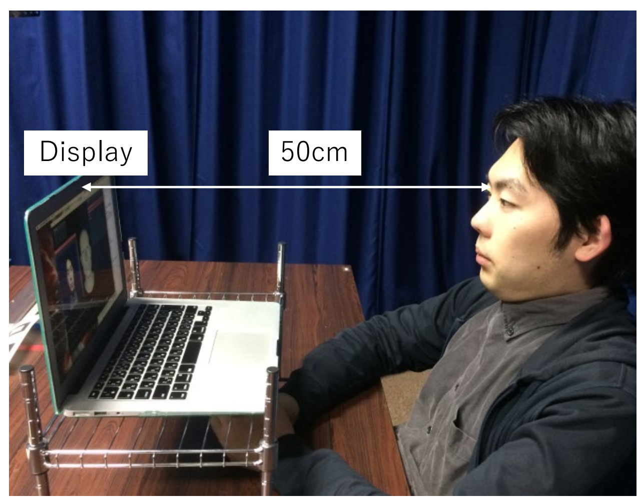

Figure 3. The experiment setup in this study.

II. Related Work

Measuring the degree of similarity between facial images is an important task in the field of face recognition. Many studies have used dimensional reduction techniques between feature representations to infer similarity. These studies include Eigenfaces [12] and Fisherfaces [13], which have been used in traditional face recognition.

An attempt to construct a facial similarity map was made by Holub et al. (2007). This map was calculated based on Triplets [14]. The resulting map demonstrated that the resulting map can effectively create a metric space that preserves notions of facial similarity.

The drawback of existing automatic facial expression recognition methods is that most of them focus on AU detection. Sadovnik et al. (2018) suggested that face recognition and face similarity are correlated, but the two are inherently different [15]. Since similarity in facial images can be recognized even when they are not the same person, there is a need to build a new dataset corresponding to the similarity of facial expressions. Vemulapalli and Agarwala (2019) built a large faces-in-the-wild dataset that labels facial expressions based on human visual preferences [16] and visualized the similarity of faces using t-SNE [17].

As described above, many studies have analyzed face similarity using 2-Dimensional (2D) facial images. However,

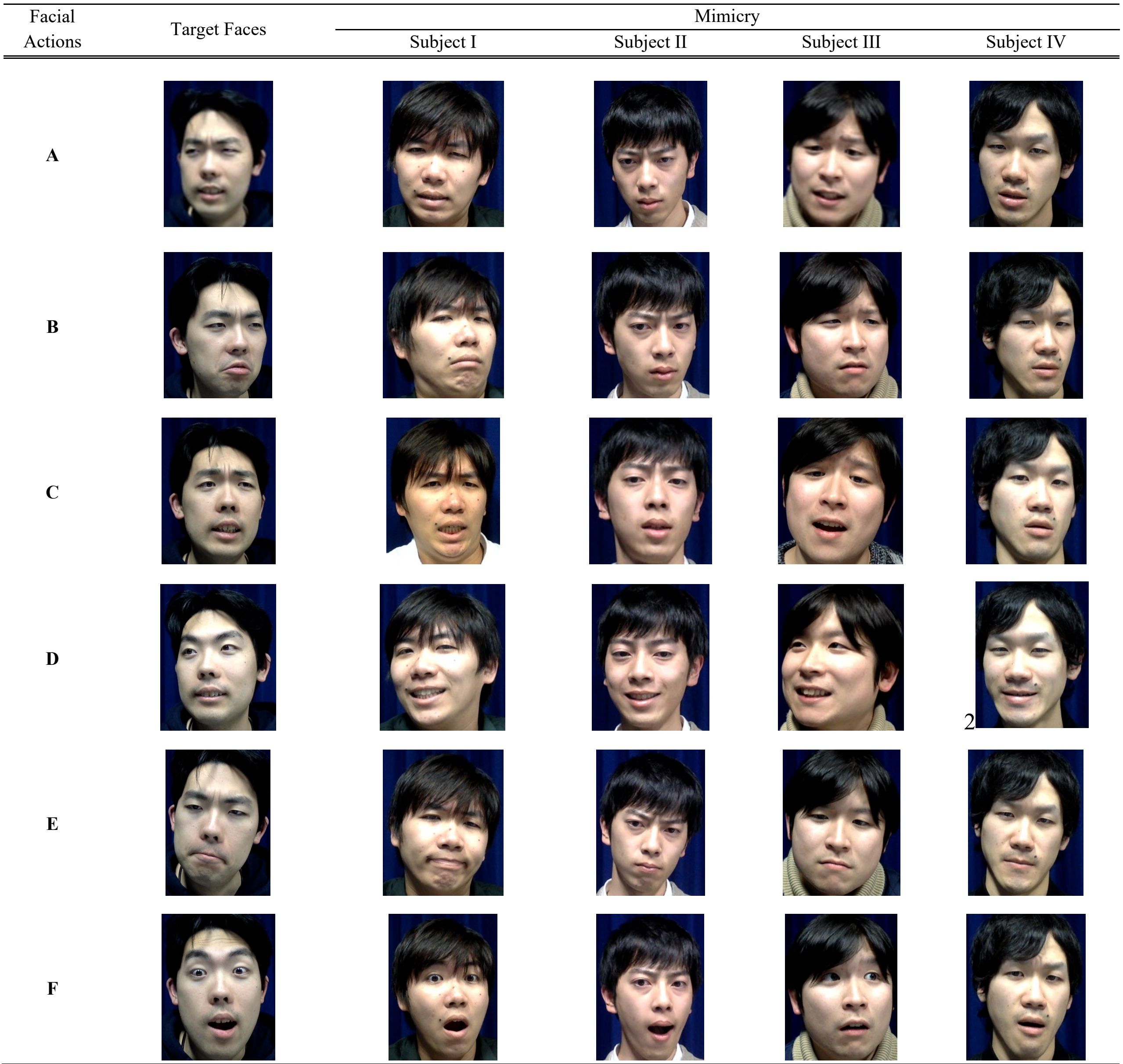

Figure 4. The target face and facial mimicry performed by each subject.

only few studies have used 3D facial images. Moorthy et al. (2010) extracted Gabor features from automatically detected fiducial points of texture images from the 3D face and demonstrate that these features correlate well with human judgements of similarity [18].

After Blanz and Vetter (1999) introduced a 3DMFM as a general face representation and a principled approach to image analysis [19], 3DMFM have incorporated into many solutions for facial analysis. 3DMFM generates a 3D face data from a given facial image and modifying the shape and texture in a natural way using its Principal Component Analysis (PCA) model of face shape and color information. Huber et al (2016) have made a publicly available 3DMFM, accompanied by their open-source software framework [11].

Another technique to generate an associate 3D face data from a given facial image is the deformation transfer. It is a well-recognized technique in computer graphics that creates expressive and plausible animations. Sumner and Popović (2004) proposed deformation transfer for triangle meshes, where the cloning process does not require the source and the target model to share several vertices or triangles [10]. Prima et al. (2020) demonstrated deformations of faces based on their expressions [1] as an initial attempt to measure similarity of pairs of 3D faces (Figure 1).

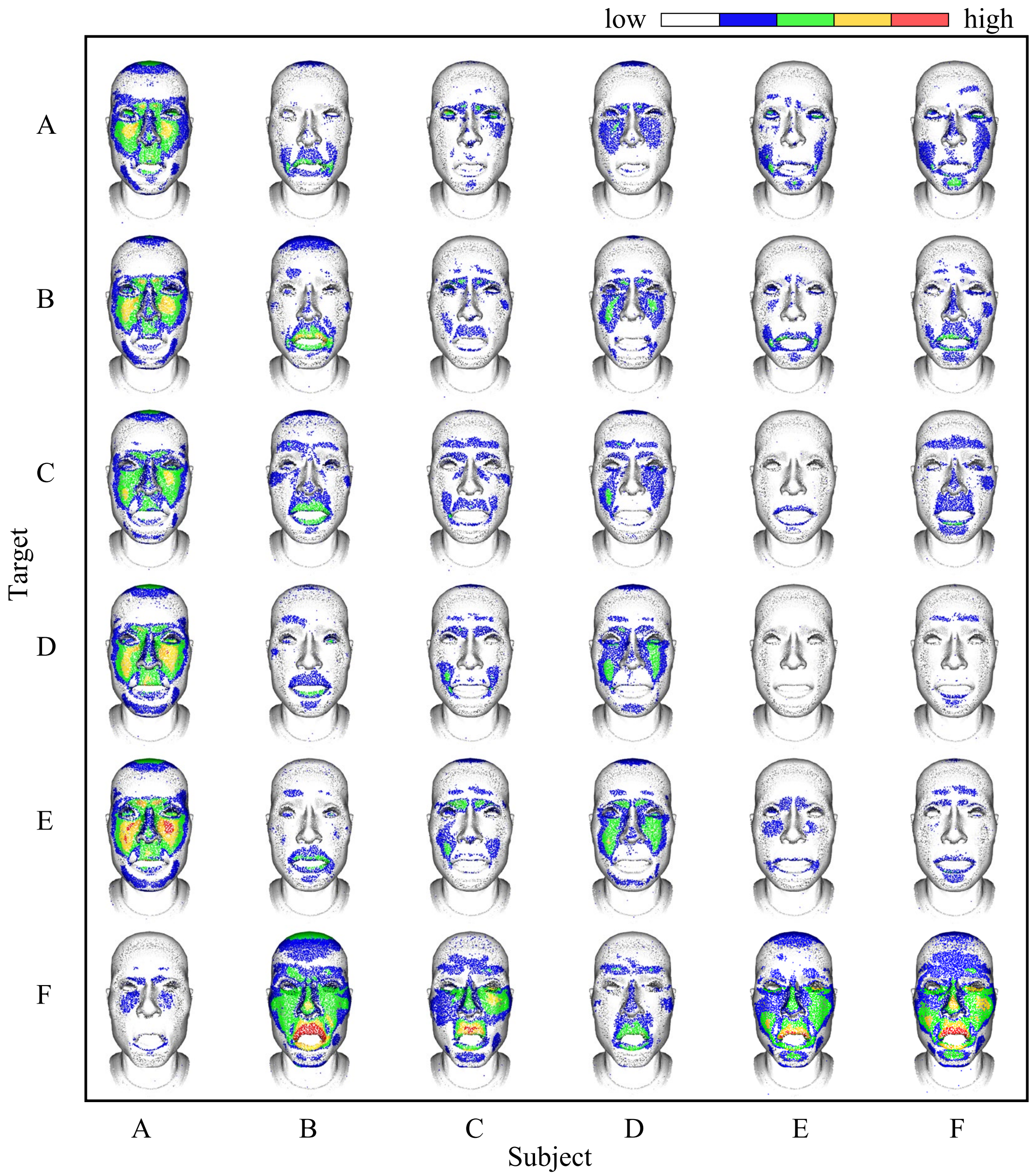

Figure 5. Differences in distance between the point clouds of 3DDC for the target face and the mimetic face of subject I.

To fit a 3D face data into a facial image, some points of the model need to be associated to the corresponding 2D landmark points in the facial image. Extracting landmark points from facial images can be done using automated facial landmarks tools, such as Dlib library [20]. Those 2D landmark points are mapped into the 3D face data using a shape-to-landmarks fitting method [21].

III. Facial Mimicry Analysis

Our attempt to analyze the facial mimicry of a pair of facial images takes three steps. The first step is to generate 3D face data from the facial images. The resulting 3D face data is then registered in a common 3D coordinate space. The second step is to sampling point clouds from the 3D face data. In the last step, we verify the similarity of the faces by analyzing the point clouds that correspond to each face. Each of these steps is described below.

1) *STEP 1: Generation of 3D Face Data*

Here, 3DDC and 3DMFM were generated from the input face images, respectively. Figure 2 shows the flow for generating the 3D face data in this study. At first, 68 facial landmark points were extracted from the face image using the Dlib library. The 3D face data was then fitted to these landmark points to generate 3D face data that represents the original face image. For the 3DDC, the shape-to-landmark

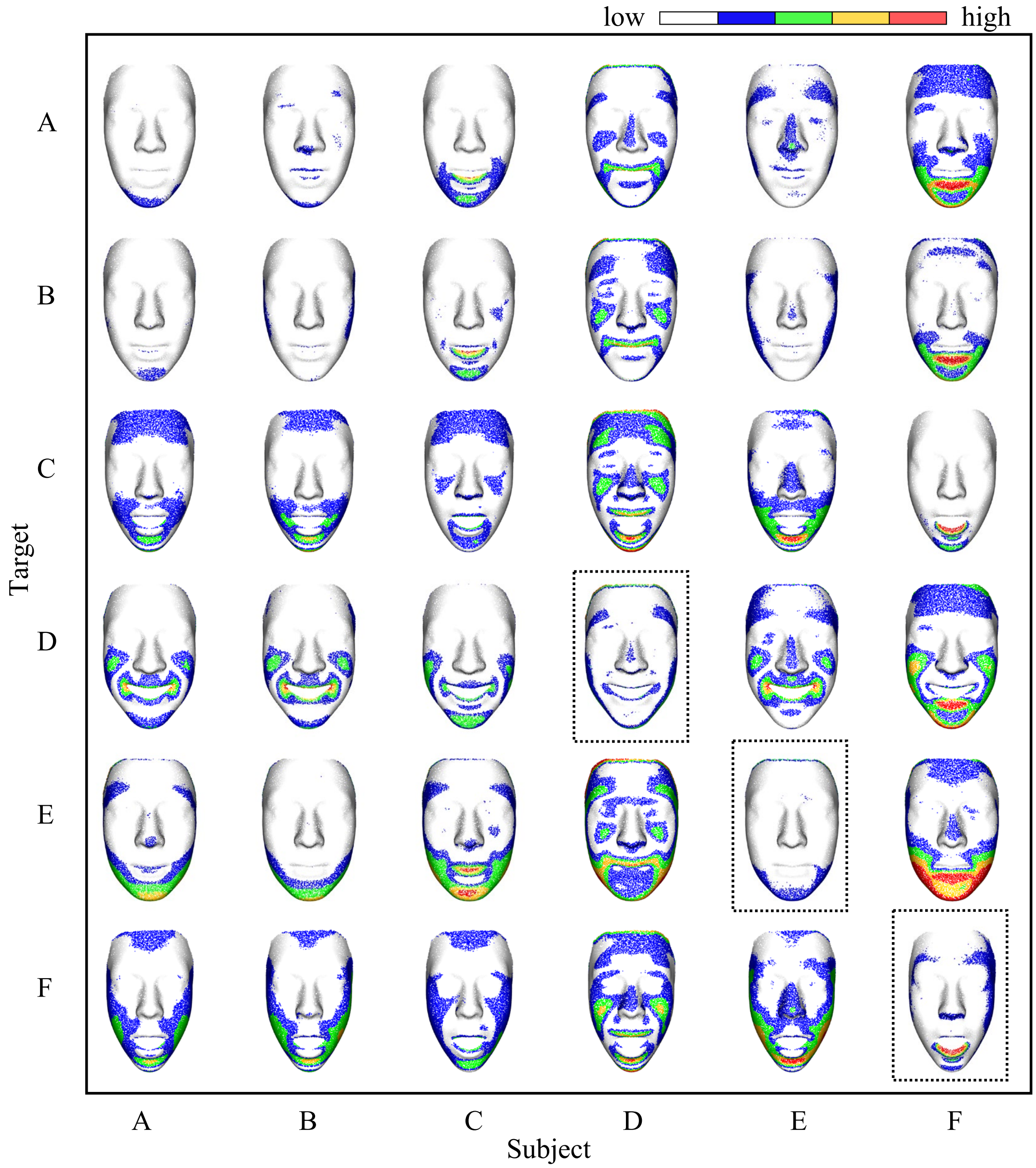

Figure 6. Differences in distance between the point clouds of 3DMFM for the target face and the mimetic face of subject I.

calculation was performed by solving the Perspective-n-Point (PnP) problem and deformation transfer [10]. The resulting rotation vector from the PnP were applied to the 3DDC so that the 3DDC was oriented the same as the input facial image. For the 3DMFM, pose estimation and shape fitting was performed using a lightweight 3DMFM fitting library, "eos" [22]. The generated 3D face data is saved in OBJ file format.

2) STEP 2: Point Cloud Extraction

We extracted point clouds from the resulting 3D face data obtained from the previous step. Open3D [23], an open-source library for analyzing 3D data, was used for this purpose. Sampling was done uniformly from the 3D surface based on the triangle area. Here, due to the different scales of 3DDC and 3DMFM, the sampling interval was adjusted to have the same number of sampling data from both face data.

3) STEP 3: Similarity Analysis

In order to analyze the similarity between facial images, the distance of each point on the original face was calculated to determine the distance to the target face. The internal functions of Open3D were used to calculate the distance. Here, the shorter the distance, the more similar the faces are.

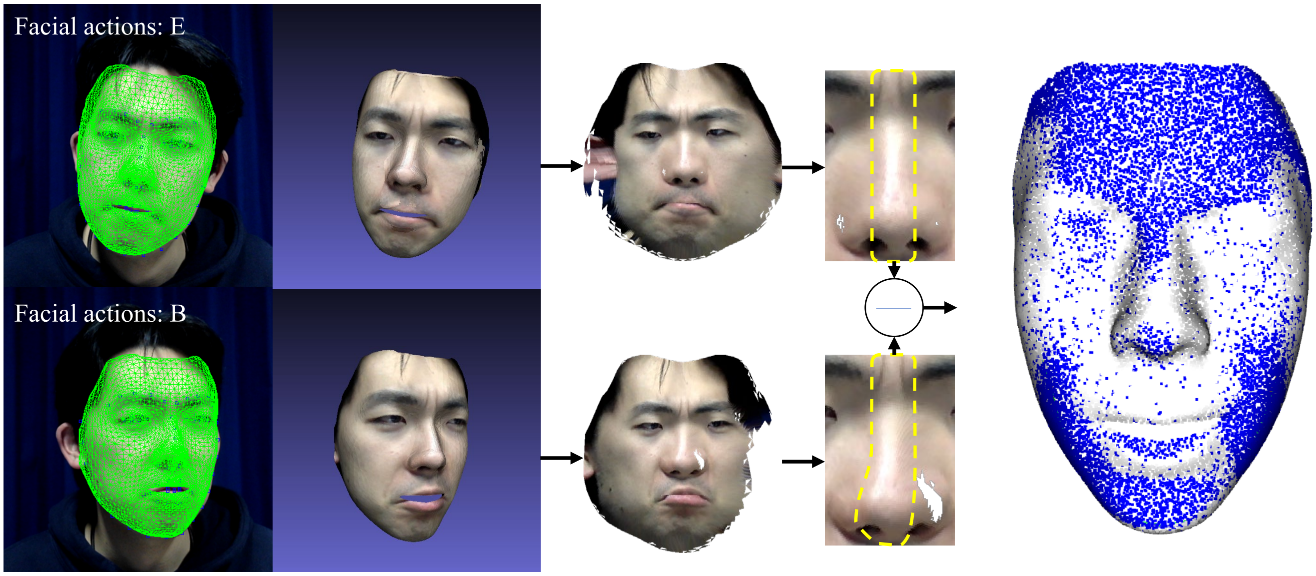

Figure 7. Distortions around the nose after the face frontalization.
(from left: 3DMFM aligned to the target face, face cropping, face frontalization (isomap), and distortion at the nose)

Considering that the non-rigid motion of the face is dominant when mimicking the opponent's face, we cropped the mouth and analyzed the correlation between the point clouds of this area.

IV. Result

Four male subjects (mean age 20.6 years) were recruited for the experiments. All subjects agreed to participate and signed the consent forms, to allow their data to be used in publications of this study. The room was set up with a table and stool for the subjects. On the table was a laptop computer that was used to display the target face to be mimicked by the subject. The monitor resolution was set at 1,440 × 900 and the refresh rate was 60 Hz. The subject was seated at approximately 50 cm from the laptop. Figure 3 shows the experimental setup in this study.

Subjects completed one practice block followed by six experimental blocks. For every block, a target face to mimic was displayed on the laptop. Subjects were asked to press the space button on the keyboard when they best imitate the target's face image. By pressing this button, the computer's built-in camera will take a picture of the subject's face. Finally, subjects were debriefed by the experimenter about the purpose of the study. Figure 4 shows the target face and facial mimicry performed by each subject. Subjects are imitating not only the facial expression of the target, but also the head posture of the target face.

1) Differences in distance between the 3D face data

3DDC and 3DMFM were used to generate 3D face data for target and mimetic faces. The difference in distance between the point clouds of 3D face data for the target face and the mimetic face of each subject was calculated. In order to be able to compare the two data correctly, we performed frontalization to each 3D face data in advance.

Figures 5 and 6 show the calculation results for 3DDC and 3DMFM of subject I, respectively. The colors indicate the degree of difference between the target face and the imitated face. Ideally, there will be the least difference between the two 3D face data in the right downward diagonal direction. In Figure 5, no facial actions yield the most similar (least different) results in that direction. However, in Figure 6, facial action: D, E, and F (dotted rectangles) were found to be the most similar between pairs, indicating subject I properly mimic the given three target faces.

In the case of the 3DDC face data, there are large differences in non-rigid areas such as the forehead, cheeks, eyebrows, and mouth. Similar results were seen in the 3DMFM face data, but the color distribution appeared to be less. Interestingly, there were significant differences at around the area of the nose, which is the rigid area. To figure out what caused these differences, we observed the 3D face data generated from the same person but in different head poses.

Figure 7 shows the 3D face data generated from the two target faces: B and E. As described in the previous section, we applied the initial 3DMFM to these faces using the shape-to-landmark method. However, after the 3D face data was frontalized, the difference in the shape of the nose are observable even in the same person's face. This suggests that the resulting frontalized face data contain some degree of distortion. Therefore, 3DMFM may not be supposed to generate 3D facial data with extreme head postures. This drawback also applies to 3DDC.

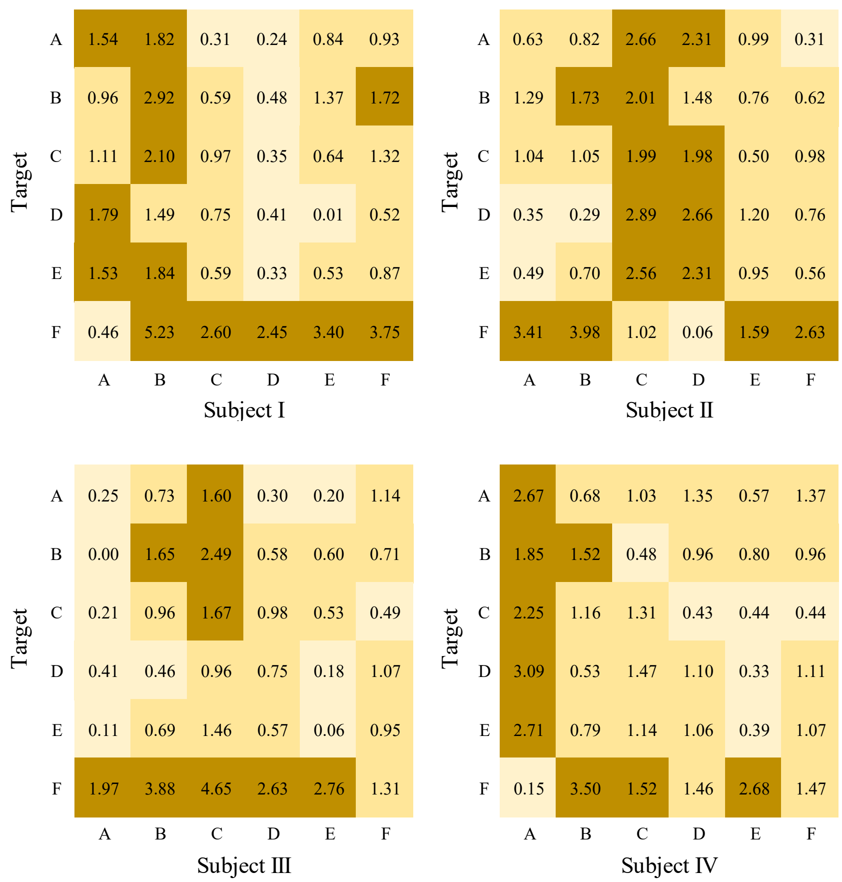

Figure 8. Differences in distance among 3DDC of the target faces and the mimetic faces of all subjects.

Figure 8 shows the difference in distance between the 3DDC of the subject faces and the 3DDC of the mimetic faces of all subjects. Similarly, Figure 9 shows the difference in distance between the 3DMFM of the subject faces and the 3DMFM of the mimetic faces of all subjects. Values were standardized to enable comparison among different data sources: 3DDC and 3DMFM. These values were colored in three levels to make them visually distinguishable. The values surrounded by dotted rectangles indicate the smallest difference between the presented face image and the imitated face image. To summarize, the 3DMFM sees that subjects I and III imitated the target faces of C, D and E, whereas, subject II imitated the target faces of B, C and E. Unfortunately, we were not able to see the suitability of facial mimicry in 3DDC just by calculating the difference in distance of the 3D face data. Overall, these results indicated that measuring the similarity between two 3D face data based solely on the differences between them is not sufficient.

2) Correlation Analysis between the 3D face data

For a more detailed analysis, we analyzed the similarity between two 3D facial data for point clouds in and around the mouth. Here, since the 3DDC is a complete head model, a 3D bounding box was needed to crop the mouth region. Open3D was used to perform this task.

Table I shows the correlations between the target face and the mimetic face in the mouth region of 3DDC for all subjects, whereas Table II shows the correlations in the mouth region of 3DMFM. In the 3DDC, the correlation was highest when the subject's facial expression was the same as that of the presenting face (values surrounded by a square on the diagonal). However, it might be difficult to assess facial mimicry solely based on this value because of the overall high values of the correlation coefficients in all data, as shown in Table I. On the other hand, the values of correlation coefficients obtained from the 3DMFM varied, but the correlation coefficients were found to be high when the target face's facial action were consistent with those of the subject. This finding indicates that 3DMFM is more suitable than 3DDC for evaluating facial mimicry.

3) Perceptual Judgment

In order validate the resulted facial mimicry performed by each subject, a 5-point Likert scale was used to gauge similarity. A value of 1 indicated that the two faces were completely dissimilar, while a value of 5 indicated that the two faces being compared were identical. Ten independent

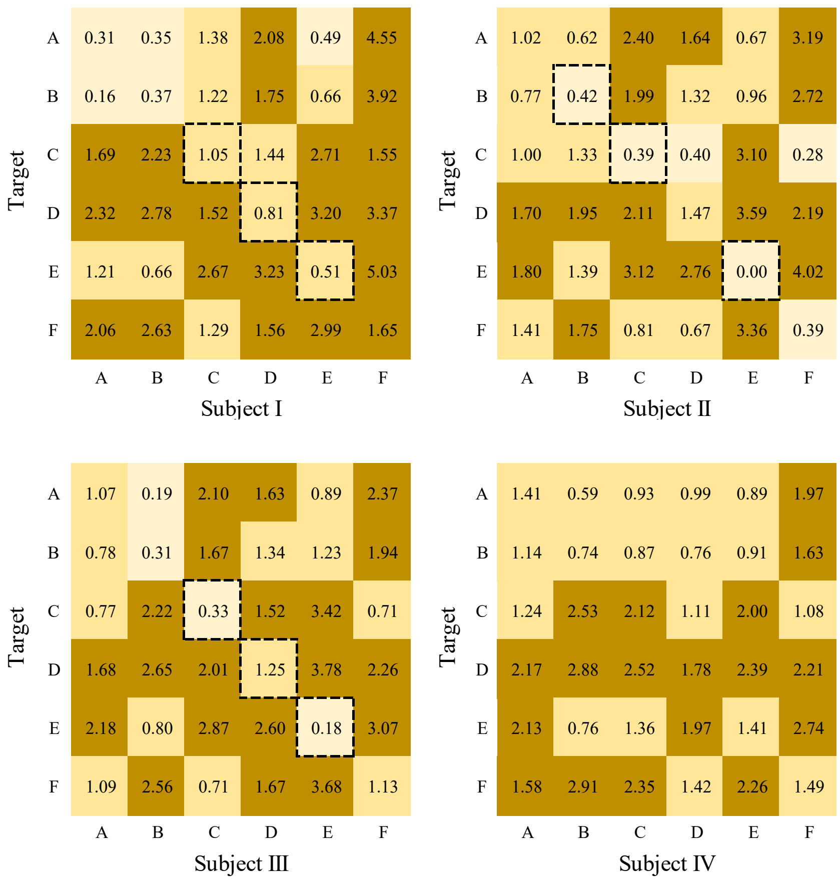

Figure 9. Differences in distance among 3DMFM of the target faces and the mimetic faces of all subjects.

raters were asked to rate the similarity between their faces and the presented faces shown in Figure 4. The raters were instructed to focus on the three areas of the eyebrows, eye shape, and mouth, which varied greatly.

To evaluate whether there was a difference in the mean score on the perceived similarity of pairs of faces, we conducted a one-way ANOVA. The means and standard deviations are shown in Table III. These results showed that there was a significant effect of the type of the facial action on the perceptual judgment level for the six conditions [$F(5, 234) = 2.25$, $p < 0.01$]. The target face and the face imitated by the subject were perceived to be similar, except for the facial action C.

V. Concluding Remarks

In this study, we extended our previous work to assess the similarity of pairs of 3D face data by using differences in the distance and correlation of point clouds in the 3D face data. The face data use in our study was generated using deformable 3-Dimensional Digital Character (3DDC) and the Surrey 3-Dimensional Morphable Face Model (3DMFM). We utilized the deformation transfer technique to clone the subject's facial movements into the 3DDC when mimicking a given facial image. The 3DMFM allows for a closer correspondence between the points, rather than only a set of facial feature points as in 3DDC.

To analyze the similarity of pairs of 3D face data, all 3D face data generated in this study were frontalized. We believed that comparison of faces can be made more effective by using a face-frontal view. However, while analyzing the experimental data, we noticed that some facial parts were distorted by this process. Therefore, we suggest that we need to be aware of this distortion when generating 3D facial data with extreme head posture.

Our experimental results show that measuring similarity using only the differences between point clouds of 3D face data is not sufficient. However, for the non-rigid part of the face, the similarity between the two 3D facial data can be measured by performing correlation analysis.

The proposed system can be extended as a face imitation training tool to improve social communication. Using this tool, users can practice imitating faces from photographs by referring to the differences in the reconstructed 3D facial data.

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TABLE I. CORRELATIONS BETWEEN THE TARGET FACE AND THE MIMETIC FACE IN THE MOUTH REGION OF 3DDC.

	Subject I					
Target	A	B	C	D	E	F
A	0.99	0.91	0.88	0.9	0.87	0.92
B	0.91	0.99	0.89	0.92	0.89	0.93
C	0.89	0.91	0.99	0.93	0.92	0.93
D	0.91	0.93	0.93	0.99	0.92	0.93
E	0.87	0.9	0.92	0.93	0.99	0.92
F	0.89	0.93	0.91	0.91	0.9	0.99

	Subject II					
Target	A	B	C	D	E	F
A	0.99	0.91	0.88	0.89	0.85	0.91
B	0.91	0.99	0.89	0.91	0.87	0.93
C	0.89	0.91	0.98	0.92	0.91	0.93
D	0.91	0.92	0.93	0.99	0.91	0.92
E	0.87	0.9	0.93	0.93	0.99	0.91
F	0.89	0.93	0.91	0.9	0.88	0.99

	Subject III					
Target	A	B	C	D	E	F
A	0.99	0.92	0.89	0.91	0.87	0.91
B	0.91	0.99	0.90	0.92	0.89	0.93
C	0.90	0.91	0.99	0.93	0.92	0.93
D	0.92	0.93	0.93	0.99	0.92	0.92
E	0.88	0.9	0.93	0.93	0.99	0.91
F	0.9	0.93	0.92	0.91	0.9	0.99

	Subject IV					
Target	A	B	C	D	E	F
A	0.99	0.91	0.9	0.9	0.85	0.91
B	0.91	0.99	0.90	0.91	0.88	0.93
C	0.89	0.90	0.99	0.93	0.91	0.93
D	0.91	0.92	0.94	0.99	0.91	0.92
E	0.87	0.90	0.93	0.93	0.99	0.91
F	0.89	0.92	0.92	0.90	0.89	0.99

TABLE II. CORRELATIONS BETWEEN THE TARGET FACE AND THE MIMETIC FACE IN THE MOUTH REGION OF 3DMFM.

	Subject I					
Target	A	B	C	D	E	F
A	0.99	0.67	0.71	0.68	0.6	0.66
B	0.67	0.99	0.68	0.76	0.74	0.59
C	0.74	0.66	0.99	0.69	0.6	0.77
D	0.68	0.73	0.71	0.99	0.69	0.62
E	0.61	0.76	0.61	0.73	0.99	0.44
F	0.76	0.68	0.79	0.68	0.56	0.97

	Subject II					
Target	A	B	C	D	E	F
A	0.99	0.68	0.73	0.69	0.64	0.72
B	0.67	0.99	0.70	0.77	0.76	0.66
C	0.75	0.68	0.99	0.69	0.64	0.78
D	0.68	0.74	0.73	0.99	0.72	0.68
E	0.60	0.75	0.65	0.75	0.99	0.53
F	0.77	0.70	0.78	0.68	0.6	0.99

	Subject III					
Target	A	B	C	D	E	F
A	0.98	0.69	0.71	0.7	0.65	0.64
B	0.66	0.99	0.68	0.74	0.77	0.56
C	0.75	0.68	0.99	0.73	0.64	0.75
D	0.68	0.74	0.71	0.99	0.72	0.6
E	0.58	0.75	0.62	0.70	0.99	0.41
F	0.77	0.71	0.78	0.72	0.6	0.96

	Subject IV					
Target	A	B	C	D	E	F
A	0.93	0.72	0.73	0.72	0.67	0.72
B	0.61	0.98	0.69	0.76	0.76	0.66
C	0.76	0.73	0.99	0.75	0.72	0.79
D	0.64	0.75	0.72	0.99	0.74	0.68
E	0.51	0.72	0.63	0.72	0.94	0.53
F	0.79	0.76	0.79	0.74	0.67	0.99

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TABLE III. THE MEANS AND STANDARD DEVIATIONS OF THE PERCEPTUAL JUDGEMENT.

	FACIAL ACTION					
	A	B	C	D	E	F
MEAN (STDEV)	2.9 (1.16)	3.3 (1.10)	2.2 (1.19)	4.2 (0.94)	4.0 (0.88)	3.8 (1.07)

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