

Generation of Facial Expression Map using Supervised and Unsupervised Learning

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1. Introduction

Recently, studies of human face recognition have been conducted vigorously (Fasel & Luetttin, 2003; Yang et al., 2002; Pantic & Rothkrantz, 2000a; Zhao et al., 2000; Hasegawa et al., 1997; Akamatsu, 1997). Such studies are aimed at the implementation of an intelligent man-machine interface. Especially, studies of facial expression recognition for human-machine emotional communication are attracting attention (Fasel & Luetttin, 2003; Pantic & Rothkrantz, 2000a; Tian et al., 2001; Pantic & Rothkrantz, 2000b; Lyons et al., 1999; Lyons et al., 1998; Zhang et al., 1998).

The shape (static diversity) and motion (dynamic diversity) of facial components such as the eyebrows, eyes, nose, and mouth manifest expressions. Considering facial expressions from the perspective of static diversity because facial configurations differ among people, it is presumed that a facial expression pattern appearing on a face when facial expression is manifested includes person-specific features. In addition, from the viewpoint of dynamic diversity, because the dynamic change of facial expression originates in a person-specific facial expression pattern, it is presumed that the displacement vector of facial components has person-specific features. The properties of the human face described above reveal the following tasks.

The first task is to generalize a facial expression recognition model. Numerous conventional approaches have attempted generalization of a facial expression recognition model. They use the distance of motion of feature points set on a face and the motion vectors of facial muscle movements in its arbitrary regions as feature values. Typically, such methods assign that information to so-called Action Units (AUs) of a Facial Action Coding System (FACS) (Ekman & Friesen, 1978). In fact, AUs are described qualitatively. Therefore, no objective criteria pertain to the setting positions of feature points and regions. They all depend on a particular researcher's experience. However, features representing facial expressions are presumed to differ among subjects. Accordingly, a huge effort is necessary to link quantitative features with qualitative AUs for each subject and to derive universal features therefrom. It is also suspected that a generalized facial expression recognition model that is applicable to all subjects would disregard person-specific features of facial expressions that are borne originally by each subject. For all the reasons described above, it is an important task to establish a method to extract person-specific features using a common approach to every subject, and to build a facial expression recognition model that incorporates these features.

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The second task is to verify the validity of categorizing emotions into six basic emotions: anger, sadness, disgust, happiness, surprise, and fear. In general, facial expressions rarely appear as a pure and solitary basic emotion, but they often appear as a mixture of various emotions. Moreover, the variety of motions of facial parts and forms is not unique; motions are diverse patterns of facial expression. Facial expressions are presumed to be classifiable into categories whose number is determined as optimal for each subject. Consequently, the categorization of facial expressions is attributed to a problem of classification into an unknown number of categories. Accordingly, it is necessary to establish a method for determining the optimal number of categories for each subject.

An ideal facial expression recognition system is expected to be capable of categorizing facial expressions into as many types as possible. For that purpose, it is desirable that a facial expression pattern be categorized with its operator's subjectivity excluded, and that the operator be able to attribute emotions uniquely to the categories. That is, because an emotion in one universal category might yield different patterns of facial expression in each subject, a system is expected to be capable of varying criteria for facial expression categorization according to the subjective interpretation of an operator.

For this chapter, we assume categorization of facial expression as a classification problem into an unknown number of categories. We propose a generation method of a person-specific Facial Expression Map (FEMap) using the Self-Organizing Maps (SOM) (Kohonen, 1995) of unsupervised learning and Counter Propagation Networks (CPN) (Nielsen, 1987) of supervised learning together. The proposed method consists of an extraction phase of person-specific facial expression categories using a SOM and a generation phase of an FEMap using a CPN. During the first phase, we particularly examine the unsupervised learning function and data compression function using the SOM of a narrow mapping space. The topological change of a face pattern in the expressional process of facial expression is learned hierarchically using the SOM of a narrow mapping space. The number of person-specific facial expression categories is generated along with the representative images of each category. Next, psychological significance based on a neutral expression and those of six basic emotions (anger, sadness, disgust, happiness, surprise, and fear) is assigned to each category. In the latter phase, we specifically address the supervised learning function and data extension function using the CPN of a large mapping space. The categories and the representative images described above are learned using the CPN of a large mapping space; a category map that expresses the topological characteristics of facial expression is generated. This study defines this category map as an FEMap. Experimental results for six subjects illustrate that the proposed method can generate a person-specific FEMap based on topological characteristics of facial expression appearing on face images.

2. Algorithms of SOM and CPN

2.1 Self-Organizing Maps (SOM)

The SOM is a learning algorithm that models the self-organizing and adaptive learning capabilities of a human brain (Kohonen, 1995). A SOM comprises two layers: an input layer, to which training data are supplied; and a Kohonen layer, in which self-mapping is performed by competitive learning. The learning algorithm of a SOM is described below.

1. Let $w_{i,j}(t)$ be a weight from an input layer unit i to a Kohonen layer unit j at time t . Actually, $w_{i,j}$ is initialized using random numbers.

2. Let $x_i(t)$ be input data to the input layer unit i at time t ; calculate the Euclidean distance d_j between $x_i(t)$ and $w_{i,j}(t)$ using (1).

$$d_j = \sqrt{\sum_{i=1}^I (x_i(t) - w_{i,j}(t))^2} \quad (1)$$

3. Search for a Kohonen layer unit to minimize d_j , which is designated as a winner unit.
4. Update the weight $w_{i,j}(t)$ of a Kohonen layer unit contained in the neighborhood region of the winner unit $N_c(t)$ using (2), where $a(t)$ is a learning coefficient.

$$w_{i,j}(t+1) = w_{i,j}(t) + a(t)(x_i(t) - w_{i,j}(t)) \quad (2)$$

5. Repeat processes 2)–4) up to the maximum iteration of learning.

2.2 Counter Propagation Networks (CPN)

The CPN is a learning algorithm that combines the Grossberg learning rule with the SOM (Nielsen, 1987). A CPN comprises three layers: an input layer to which training data are supplied; a Kohonen layer in which self-mapping is performed by competitive learning; and a Grossberg layer, which labels the Kohonen layer by the counter propagation of teaching signals. A CPN is useful for automatically determining the label of a Kohonen layer when a category in which training data will belong is predetermined. This labeled Kohonen layer is designated as a category map. The learning algorithm of a CPN is described below.

1. Let $w_{n,m}^i(t)$ and $w_{n,m}^j(t)$ respectively indicate weights to a Kohonen layer unit (n, m) at time t from an input layer unit i and from a Grossberg layer unit j . In fact, $w_{n,m}^i$ and $w_{n,m}^j$ are initialized using random numbers.
2. Let $x_i(t)$ be input data to the input layer unit i at time t , and calculate the Euclidean distance $d_{n,m}$ between $x_i(t)$ and $w_{n,m}^i(t)$ using (3).

$$d_{n,m} = \sqrt{\sum_{i=1}^I (x_i(t) - w_{n,m}^i(t))^2} \quad (3)$$

3. Search for a Kohonen layer unit to minimize $d_{n,m}$, which is designated as a winner unit.
4. Update weights $w_{n,m}^i(t)$ and $w_{n,m}^j(t)$ of a Kohonen layer unit contained in the neighborhood region of the winner unit $N_c(t)$ using (4) and (5), where $a(t)$, $\beta(t)$ are learning coefficients, and $t_j(t)$ is a teaching signal to the Grossberg layer unit j .

$$w_{n,m}^i(t+1) = w_{n,m}^i(t) + a(t)(x_i(t) - w_{n,m}^i(t)) \quad (4)$$

$$w_{n,m}^j(t+1) = w_{n,m}^j(t) + \beta(t)(t_j(t) - w_{n,m}^j(t)) \quad (5)$$

5. Repeat processes 2)–4) up to the maximum iteration of learning.
6. After learning is completed, compare weights $w_{n,m}^j$ observed from each unit of the Kohonen layer; and let the teaching signal of the Grossberg layer with the maximum value be the label of the unit.

3. Proposed method

Figure 1 depicts the procedure used for the proposed method. The proposed method consists of two steps: extraction of person-specific facial expression categories using a SOM and generation of FEMap using a CPN. The proposed method is explained in detail below.

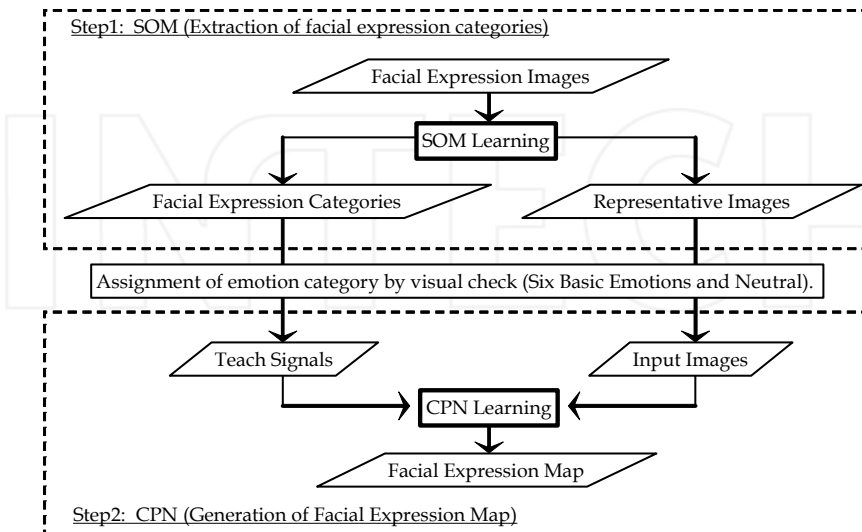


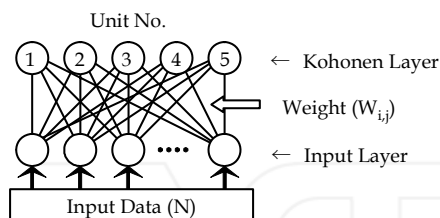
Fig. 1. Flow chart of proposal method.

3.1 Extraction of person-specific facial expression categories with SOM

The proposed method was used in an attempt to extract a person-specific facial expression category hierarchically using a SOM with a narrow mapping space. A SOM is an unsupervised learning algorithm; it classifies given facial expression images in a self-organized manner based on their topological characteristics. For that reason, it is suitable for classification problems with an unknown number of categories. Moreover, a SOM compresses the topological information of facial expression images using a narrow mapping space and performs classification based on features that roughly divide the training data. We speculate that repeating these hierarchically renders the classified amount of change of facial expression patterns comparable; thereby, a person-specific facial expression category can be extracted. Figure 2 depicts the extraction procedure of a facial expression category. Details of the process are explained below.

1. Expression images described in Section 4 were used as training data. The following processing was performed for each facial expression. The number of training data is assumed as N frames.
2. The facial expression topological characteristics of the training data were learned using the 1-D SOM of the Kohonen layer consisting of five units (Fig. 2(a)). The brightness value of images was used as input data because the brightness distribution represents the topological structure of the facial expression. The unit number of the input layer corresponds to the input image size.

3. The weight of the Kohonen layer $W_{i,j}$ ($0 \leq W_{i,j} \leq 1$) was converted to a value of 0–255 after the end of learning; visualized images were generated (Fig. 2(b)), where $n_1 - n_5$ are the numbers of training data classified into each unit.



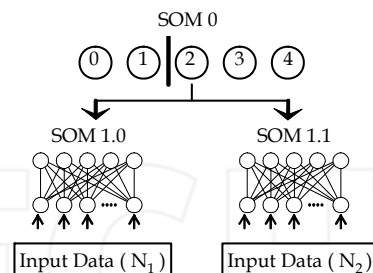
(a) Structure of SOM.

Unit No.	1	2	3	4	5
Visualized Image ($W_{i,j}$)					
Classification Result	n_1	n_2	n_3	n_4	n_5
Correlation Coefficient	0.9853	0.9786	0.9794	0.9866	
New Training Data	N_1		N_2		

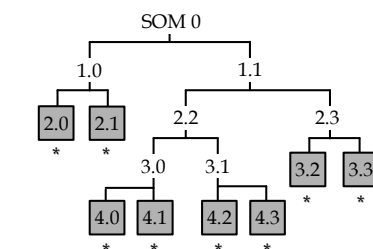
$$* N = n_1 + n_2 + n_3 + n_4 + n_5$$

$$* N_1 = n_1 + n_2, \quad N_2 = n_3 + n_4 + n_5$$

(b) Learning with SOM and setup of new training data.



(c) Hierarchical learning with SOM.



Extracted categories	8 (*)
Representative Images	40 (5 units × 8)

(d) Generation of binary-tree structure.

Fig. 2. Extraction procedure of facial expression category.

4. Five visualized images can be considered as representative vectors of the training data classified into each unit ($n_1 - n_5$). Therefore, the images of five units were verified visually. All images were regarded as belonging to one category; processing was terminated if they were considered to represent the same facial expression. Subsequent processing was continued if multiple facial expressions were found to be mixed in the visualized images.
5. The correlation coefficient of weight $W_{i,j}$ between each adjacent unit in the Kohonen layer was calculated. The Kohonen layer was then divided into two borders between the unit pair where the coefficient was minimal because the input group categorized into both sides of the border was presumed to have a large difference in topological characteristics; the weight of an adjacent unit pair would be updated by the neighborhood learning of the SOM to a similar value (Fig. 2(b)).
6. The groups of training data categorized into both sides of the divided Kohonen layers (N_1 and N_2 , where $N = N_1 + N_2$) can be considered as two independent sub-problems (Fig. 2(b)). Actually, N_1 and N_2 were used as new training data, and processes 2)–5) were repeated recursively (Fig. 2(c)).

7. By repeating the processes described above, a hierarchical structure of the SOM (binary-tree structure) was generated (Fig. 2(d)). The lowermost layer of the hierarchical structure was defined as a facial expression category and five visualized images were defined as representative images of each category. Then the photographer of the facial expression images performed visual confirmation to each facial expression category and inferred their associated emotion categories.

The proposed method set the iterations of learning as 200,000 times. The radius of the neighborhood region $N_c(t)$ was fixed as the first neighborhood of the winner unit. The learning coefficient $a(t)$ was defined to decrease linearly from the initial value of 0.5–0.02 for learning iterations of 100,000 times; then subsequently to 0 at an iteration of learning of 200,000 times. The updating ratio of weights was set to 1 for the winner unit, and to 0.5 for its neighborhood units.

3.2 Generation of facial expression map with CPN

It is considered that recognition to a natural facial expression requires generation of a facial expression pattern (mixed facial expression) that interpolates each emotion category. The proposed method used the representative image obtained in Section 3.1 as training data and carried out data expansion of facial expression patterns among emotion categories using CPN with a large mapping space. The reason for adopting CPN, a supervised learning algorithm, is that the teaching signal of training data is known by processing in Section 3.1. The mapping space of CPN has a greater number of units than the number of training data; in addition, it has a toroidal structure because it is presumed that a large mapping space allows CPN to perform data expansion based on the similarity and continuity of training data. Figure 3 depicts the FEMap generation procedure. The processing details are described below.

1. The categories and representative images obtained in Section 3.1 were used as teaching signals and input data, which were then adopted as CPN training data.
2. The facial expression topological characteristics of an input group were learned using CPN with a two-dimensional Kohonen layer of 30×30 units and a Grossberg layer having as many units as the categories obtained in Section 3.1. The brightness values of the representative images were used as input data. Teaching signals to the Grossberg layer were set to 1 for units representing categories and 0 for the rest. The unit number of the input layer corresponded to the input image size.
3. The process described above was repeated until the maximum iterations of learning.
4. The weights (W_g) of the Grossberg layer were compared for each unit of the Kohonen layer after learning completion; an emotion category of the greatest value was used as the unit label.
5. A category map generated by the process described above was defined as a person-specific FEMap.

The proposed method set the iterations of learning as 20,000 times. The radius of the neighborhood region $N_c(t)$ was defined to decrease linearly from the initial value of the 14th to the first neighborhood of the winner unit at an iteration of learning of 10,000 times, and to be fixed at the first neighborhood of the winner unit for the subsequent 10,000 iterations. The learning coefficients $a(t)$ and $\beta(t)$ were defined to decrease linearly from the initial value of 0.5–0.02 at an iteration of learning of 10,000 times; then subsequently to 0 at an iteration of learning of 20,000 times. The updating ratio of weights was set to 1 for the winner unit, and to 0.5 for its neighboring units.

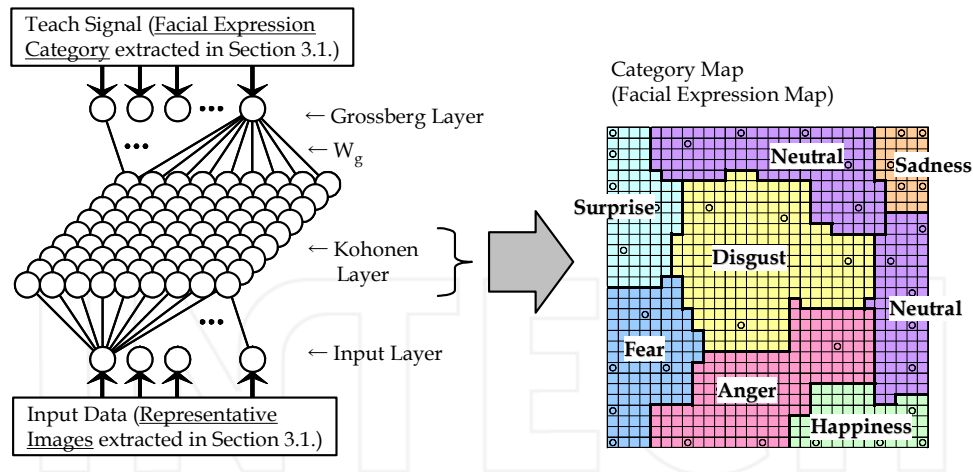


Fig. 3. Generation procedure of FEMap.

4. Facial expression images

Examples of facial expression images used in this study are presented in Fig. 4. This paper presents a discussion of six basic facial expressions and a neutral facial expression that six subjects manifested intentionally. Each subject’s front face image was photographed under normal indoor conditions (lighting by fluorescent lamps) with the head enclosed inside the frame. Basic facial expressions were obtained as motion videos including a process in which a neutral facial expression and facial expressions were manifested five times respectively by turns for each facial expression. Neutral facial expressions were obtained as a motion video for about 10 s. The motion videos were converted into static images (10 frame/s, 8 bit gray, 320×240 pixels). Regions containing facial components, i.e., eyebrows, eyes, nose, and mouth, were extracted from each frame and used as training data. Table 1 presents the number of frames of all subjects’ training data.

ID	An.	Sa.	Di.	Ha.	Su.	Fe.	Ne.	ID	An.	Sa.	Di.	Ha.	Su.	Fe.	Ne.
A								D							
B								E							
C								F							

Fig. 4. Examples of facial expression images (ID, Subject; An., Anger; Sa., Sadness; Di., Disgust; Ha., Happiness; Su., Surprise; Fe., Fear; Ne., Neutral).

Open facial expression databases are generally used in conventional studies (Pantic et al., 2005; Gross, 2005). These databases contain a few images per expression and subject. For this study, we obtained facial expression images of ourselves because the proposed method

extracts person-specific facial expression categories and the representative images of each category from large quantities of data.

ID	An.	Sa.	Di.	Ha.	Su.	Fe.	Ne.	Total
A	136	198	143	169	127	140	100	1013
B	152	136	153	162	154	190	100	1047
C	192	173	154	158	153	156	100	1086
D	152	158	178	177	158	170	100	1093
E	95	113	108	112	109	108	100	745
F	165	197	198	163	165	167	100	1155

Table 1. Numbers of frames of all subjects' training data.

5. Results and discussion

5.1 Extraction of person-specific facial expression categories

Figure 5 shows binary-tree structures generated with the proposed method applied to six subjects. Table 2 shows quantities of categories of facial expressions and representative images extracted from Fig. 5. Figure 5 shows that the binary-tree structure differs for each subject. Table 2 presents that the number of categories for each facial expression also differs for each subject.

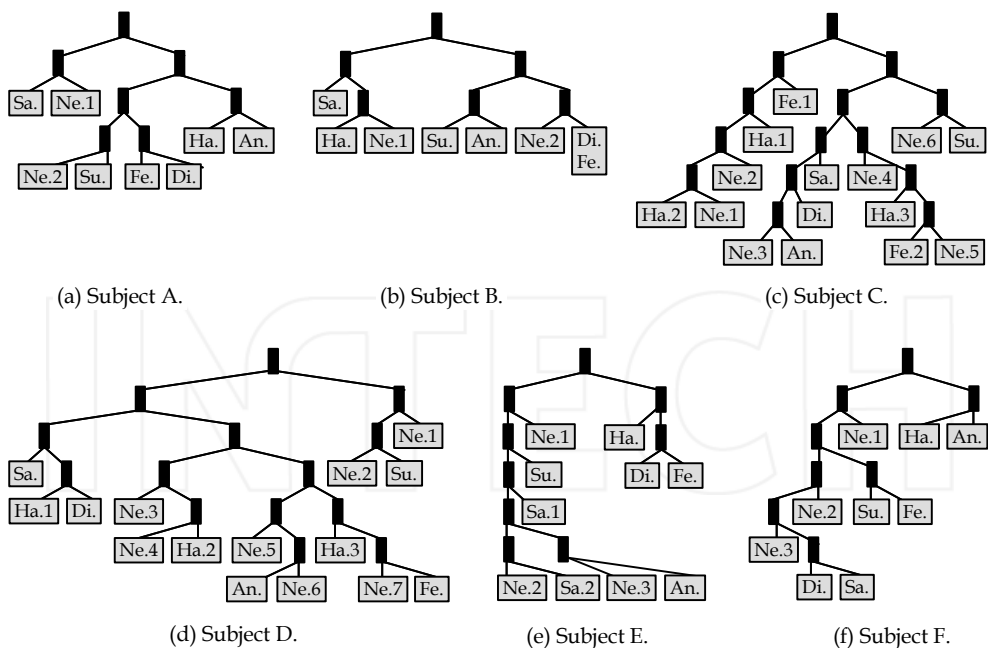


Fig. 5. Binary-tree structures generated with the proposed method.

ID	An.	Sa.	Di.	Ha.	Su.	Fe.	Ne.	Extracted Categories	Representative Images
A	1	1	1	1	1	1	2	8	40 (5 units * 8)
B	1	1	1	1	1	-	2	7	35 (5 units * 7)
C	1	1	1	3	1	2	6	15	75 (5 units * 15)
D	1	1	1	3	1	1	7	15	75 (5 units * 15)
E	1	2	1	1	1	1	3	10	50 (5 units * 10)
F	1	1	1	1	1	1	3	9	45 (5 units * 9)

Table 2. Numbers of facial expression categories and representative images.

For Subject A, 8 categories are generated and 40 representative images are extracted. In fact, Subject A presented stable facial expression patterns within training data, and his six basic emotions were generated as one category each. A neutral expression was generated as two categories.

On the other hand, 15 categories were generated and 75 representative images were extracted for Subject D. Regarding happiness, three categories were generated from her one facial expression. Figure 6 shows representative images of happiness of Subject D, which reveals that three types of categories representing happiness were generated: (a) eyes are closed and the mouth is opened (showing teeth), (b) smiling, and (c) mouth is opened widely. These images suggest that the facial expression for the happiness of Subject D had multiple facial expression patterns, which were learned as different facial expression topological characteristics, and which were categorized into different categories in the binary-tree structure of SOM.

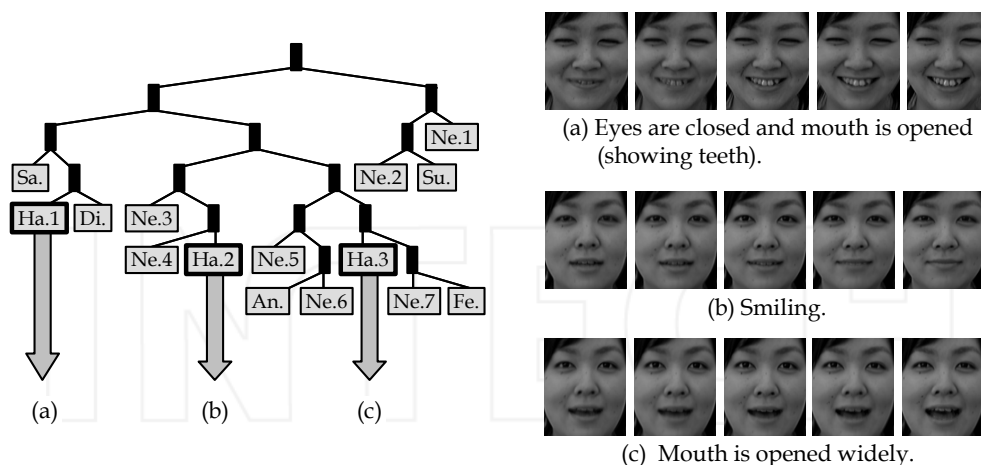


Fig. 6. Representative images of happiness of Subject D (Detail of Fig. 5(d)).

For Subject B, 7 categories were generated and 35 representative images were extracted. Regarding disgust and fear, both were classified into a single category (Fig. 7). Comparison of disgust and fear as facial expressions of Subject B shown in Fig. 4 suggests similarities in the patterns of facial expression and the consequent difficulty in visual distinction between

both, which indicates that the binary-tree structure of SOM generated the facial expression of similar topological characteristics as one category.

The following were revealed. The proposed method enables classification of multiple facial expression patterns into separate different categories even if they are of the same facial expression. On the other hand, visually similar facial expressions are classifiable into one category.



Fig. 7. Representative images of “disgust” and “fear” (Subject B, Detail of Fig. 5(b)).

Psychological significance is assigned to every category obtained with the binary-tree structure in this study. The operator might also assign importance to categories that are selected according to personal subjectivity. Moreover, intentional further hierarchization permits us to subdivide categories (subdivision of facial expression categorization). For example, Fig. 8 shows the subdivision result of the surprise category related to Subject E. The fourth layer, Fig. 8(a), was defined as a surprise category. Classification based on local and small changes of a facial expression pattern was performed by further intentional hierarchization: eyebrows are raised greatly (Fig. 8(b)), eyebrows are raised slightly (Fig. 8(c)), the mouth is opened narrowly (Figs. 8(d) and 8(f)), and the mouth is opened widely (Figs. 8(e) and 8(g)).

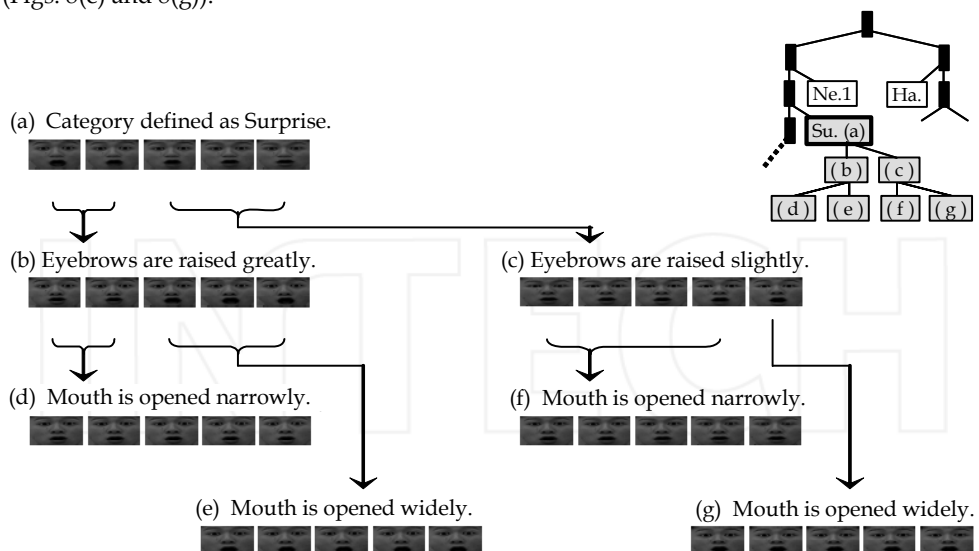


Fig. 8. Subdivision of a surprise category of Subject E (Detail of Fig. 5(e)).

5.2 Generation of facial expression map

The categories and representative images extracted in Section 5.1 were used respectively as teacher signals and input data of the CPN; the FEMaps shown in Fig. 9 were generated using the proposed method. Units with a round mark in the figures denote winner units when training data were input into the CPN after learning. These figures suggest that the area size of facial expression categories (number of labels) on FEMaps differs for each subject. Even within one subject, differences are apparent in the number of labels for each facial expression category.

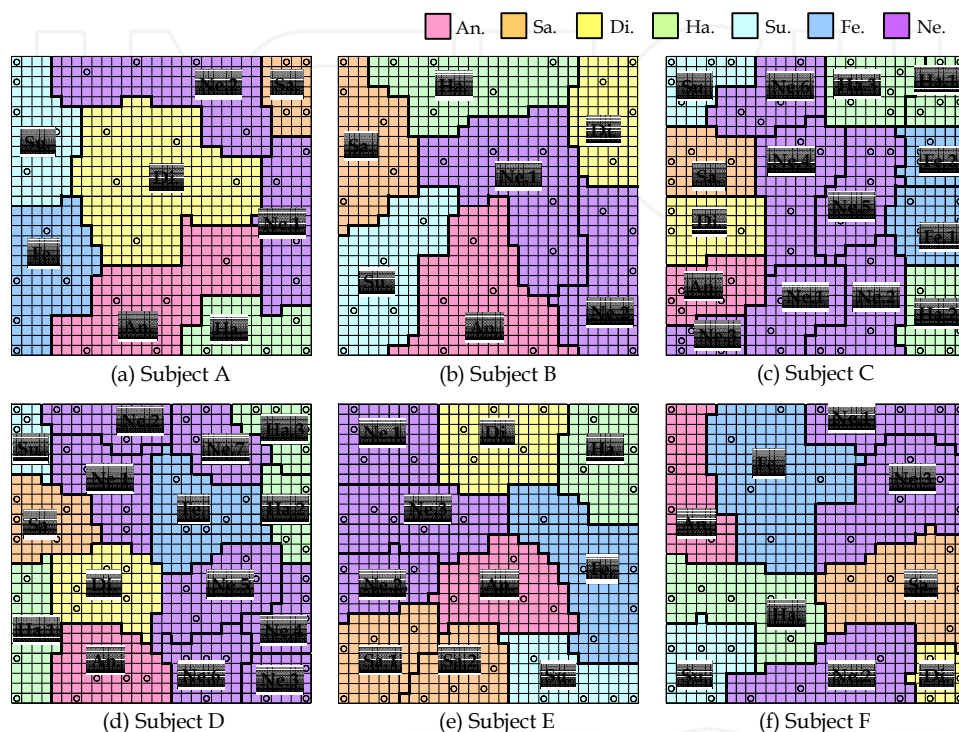


Fig. 9. FEMaps generated with the proposed method.

The percentages of the number of labels for each subject are listed in Table 3. Sadness and disgust occupy 4.1% and 25.2%, respectively, for Subject A. Even though training data of the same number for both categories (five images per category) are being used, great differences are apparent in the number of labels. Figure 9(a) portrays that winner units of training data for sadness are crowded, whereas those for disgust are dispersed widely, which are presumed to suggest the following. Regarding sadness, the topological characteristics of training data are very similar compared to other facial expressions that the facial expression pattern changes little. However, for disgust, differences in the topological characteristics of training data are so large that the facial expression pattern changes greatly. For Subject D, the facial expression of happiness, for which three categories were generated, changes greatly (15.6%), although that of surprise shows little change (3.0%). For Subject F, the facial expression of fear changes greatly (20.2%), whereas that of disgust shows little change

(3.3%). These results suggest that the number of labels on an FEMap express the extent of difference of topological characteristics within a category, i.e., expressiveness of person-specific facial expressions.

Figure 10 portrays a magnified view of a part of surprise in the FEMap of Subject E, with the weights of each unit visualized. Units with the white frame in the figure denote winner units when training data were input into the CPN after learning. This figure suggests that facial expressions whose patterns differ slightly are generated in the neighborhood of five winner units. These results suggest that data expansion is performed based on the similarity and continuity of training data, and that more facial expression patterns such as mixed facial expressions between categories can be generated in the CPN mapping space.

ID	An.(%)	Sa. (%)	Di. (%)	Ha. (%)	Su. (%)	Fe. (%)	Ne. (%)
A	17.7	4.1	25.2	7.2	9.4	11.9	24.4
B	18.0	11.7	9.2	13.3	14.8	-	33.0
C	6.3	6.6	7.1	17.1	5.0	10.7	47.2
D	9.1	6.8	9.2	15.6	3.0	11.0	45.3
E	11.6	16.2	11.6	9.4	8.0	15.7	27.6
F	9.1	13.9	3.3	12.8	7.1	20.2	33.6

Table 3. Percentages of number of labels in the FEMap.

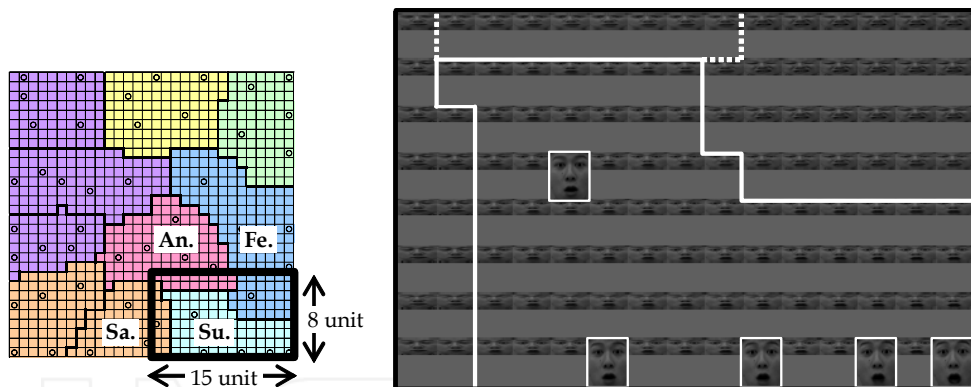


Fig. 10. Magnified view of a part of surprise in the FEMap of Subject E (Detail of Fig. 9(e)).

6. Conclusion

On the assumption that facial expression is a problem of classification into an unknown number of categories, this chapter describes an investigation of a generation method of a person-specific FEMap. The essential results obtained in this study are the following.

Hierarchical use of SOM with a narrow mapping space enables extraction of person-specific facial expression categories and representative images for each category. Psychological significance is assigned to every category obtained with the binary-tree structure in this study. The operator might also give special importance to categories selected according to personal subjectivity. Moreover, intentional further hierarchization of a binary-tree structure permits the additional subdivision of facial expression categorization.

The categories and category representative images obtained from the binary-tree structure were used as training data of a CPN with a large mapping space. Results revealed that data expansion is performed based on the similarity and continuity of training data, and that more facial expression patterns such as mixed facial expressions between categories can be generated in the CPN mapping space. It is expected that the use of an FEMap generated using the proposed method can be useful as a classifier in facial expression recognition that contributes to improvement in generalization capability.

This chapter specifically described a generation method of an FEMap and used facial expression images obtained during the same period. However, it is difficult to obtain all of a subject's facial expression patterns at one time; in addition, faces age with time. In future studies, we intend to take aging of a facial expression pattern into consideration, and study an automatic FEMap updating method using additional learning functions.

7. Acknowledgments

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