

Fuzzy Integral-based Composite Facial Expression Generation for a Robotic Head

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Abstract—Conventional methods produced composite facial expressions by interpolating the representative facial expressions under the assumption that the transitions between facial expressions are linear. Considering the nonlinear property, this paper proposes a fuzzy integral-based method for generating composite facial expressions. Fuzzy measures represent the relationship among emotions and the partial evaluation of current emotion state is obtained from a predefined error function of the ideal basic emotion states and the current emotion state. Fuzzy integral of the partial evaluation with respect to fuzzy measures is employed to globally evaluate the current emotion state for generating composite facial expressions. The effectiveness of the proposed method for generating composite facial expressions is demonstrated through the experiments with a robotic head with 19 degrees of freedom, developed in RIT Laboratory, KAIST.

Keywords: Facial expression generation, choquet integral, λ -fuzzy measure, robotic head, diamond pairwise comparison method.

I. INTRODUCTION

Nowadays, robots have been used in many areas. Robots can guide people in a museum or play with children [1], [2]. It is expected that robot can be developed as a sociable partner in the future [3]. Considering the symbiosis between robots and humans, it is unavoidable for robots to interact with humans. In this sense, there have been many researches on human robot interaction (HRI) [4]- [6].

When robots interact with humans, robots should imitate the human's interaction because human can interact naturally with robots without additional education or knowledge. Facial expressions play an important role in human's interaction. According to Mehrabian, only 7% of information is delivered by language, 38% of information is delivered by paralinguistic like voice and 55% of information is delivered by non-verbal communication like facial expressions and gestures [7], [8]. Therefore, facial expression is an important mean in communication.

There have been many researches on how to generate natural facial expressions. For example, linear dynamic affect-expression model and simple recurrent network were developed to generate facial expressions dynamically [9], [10]. Fuzzy rule based system was applied to generate facial expressions [11]. Grizard and Lisetti used three-levels architecture

by adapting psychological theory and Lin and Huang used anatomical theory for generating facial expressions [12], [13].

However, researches on composite facial expressions have not been much progressed. To generate composite facial expressions, relationship among emotions should be considered. According to the psychologist Ekman, happiness is a positive emotion, surprise is a neutral emotion and anger, disgust, fear and sadness are negative emotions [14]. Therefore, both anger and disgust are very similar and they often appear together. However, being happy and disgust at the same time is highly unlikely produced. To generate more natural facial expressions, relationship between emotions should be considered. In addition, each emotion has its own main features in facial expressions. Happiness is chiefly expressed by stretching a mouth and surprise is mainly expressed by raising a forehead and eyebrows. When composite facial expressions are generated, each emotion is expressed separately in some parts of face such that they are produced in a big picture. Conventional methods for generating the composite facial expressions used the linear interpolation of the representative facial expressions under the assumption that the transitions between facial expressions are linear. Thus, linear interpolation method cannot generate natural facial expressions.

In this paper, fuzzy integral and fuzzy measure are used to generate natural composite facial expressions. The fuzzy measure deals with the ambiguity of the crisp set. Emotion state can be represented by the fuzzy measures because the relationship among them are ambiguous such that people cannot easily tell how much a subject is in a happy state, sad state, etc. Thus, the fuzzy measures are employed to represent the relationship among emotions. The partial evaluation of current emotion state is obtained from a predefined error function of the ideal basic emotion states and the current emotion state. Fuzzy integral of the partial evaluation with respect to fuzzy measures is employed to globally evaluate the current emotion state for generating composite facial expression by separately actuating the parts of a robotic face. The effectiveness of the proposed method for generating composite facial expressions is demonstrated through the experiments with a robotic head with 19 degrees of freedom, developed in RIT Laboratory, KAIST.

The rest of this paper is organized as follows. In Section II, the generation process of composite facial expressions is proposed based on the fuzzy measure and fuzzy integral.

Simulation and experimental results are presented in Section III. Finally, concluding remarks follow in Section IV.

II. GENERATION OF FACIAL EXPRESSION

A. Composite Facial Expressions

According to the psychologist Ekman, human's basic emotions are anger, disgust, fear, happiness, sadness and surprise. Emotions are represented by facial expressions. When two emotions are mixed, facial expression is not produced with the average value. Each emotion is expressed separately in parts of face, and composite facial expressions are produced in a big picture [14]. Expressed parts in composite facial expressions are summarized in Table I. In several composite facial expressions, the expressed parts are exchangeable. For example, when fear and surprise are mixed, surprise can be expressed in a mouth and fear can be expressed in eyes, eye brows, and eye lids.

B. Fuzzy Measure and Fuzzy Integral

In this paper, Sugeno λ -fuzzy measure is used to reflect the relationship among emotions and the Choquet fuzzy integral is used to generate facial expressions. The fuzzy measure is defined in the following [15].

Definition 1: A fuzzy measure on the set X of symbols is a set function $g : P(X) \rightarrow [0, 1]$ satisfying the following axioms;

- i) $g(\emptyset) = 0, g(X) = 1$;
- ii) $A \subset B \subset X$ implies $g(A) \leq g(B)$.

The Sugeno λ -fuzzy measure satisfies the following [16]:

$$g(A \cup B) = g(A) + g(B) + \lambda g(A)g(B). \quad (1)$$

TABLE II
MEANING OF FUZZY MEASURE

Fuzzy measure property	λ	ξ	Symbol relation
$g(A \cup B) > g(A) + g(B)$	$+\infty$	0	Negative correlation
$g(A \cup B) = g(A) + g(B)$	0	0.5	Independent
$g(A \cup B) < g(A) + g(B)$	-1	1	Positive correlation

In (1), g represents the fuzzy measure, λ represents the interaction degree, and ξ is a normalized value of λ . If λ is positive, $g(A \cup B) > g(A) + g(B)$, which means that $g(A \cup B)$ is overestimated and hence A and B have a negative correlation.

The Choquet fuzzy integral is defined in the following [17].
Definition 2: Let h be a mapping from finite set X to $[0, 1]$. For $x_i \in X, i = 1, 2, \dots, n$, assume $h(x_i) \leq h(x_{i+1})$ and $E_i = \{x_i, x_{i+1}, \dots, x_n\}$. The Choquet fuzzy integral of h over X with respect to the fuzzy measure g is define as

$$\int_X h \circ g = \sum_{i=1}^n (h(x_i) - h(x_{i-1}))g(E_i), \quad h(x_0) = 0. \quad (2)$$

In (2), fuzzy measure g should be calculated for all the power sets of X and partial evaluation values h are calculated from a predefined error function of the ideal basic emotion states and the current emotion state of a robot.

C. Diamond Pairwise Comparison

Six symbols are used because the number of human's basic emotions is six. Without fuzzy measure identification method, it is hard to identify $2^6 - 2 = 62$ fuzzy measures. Diamond pairwise comparison method is used to reflect the relationship among emotions [18]. Every two pair should be compared with the diamond pairwise comparison. In Fig. 1(a), one point in the diamond is marked. The Diamond can be translated to the coordinate axis on the right-hand side in Fig. 1(b) which X-axis represents sv_i and Y-axis represents I_{ij} . sv_i means the relative importance between two symbols. I_{ij} is the parameter to represent whether two symbols are positive relations or negative relations, which can be replaced with ξ_{ij} . ξ_{ij} is the normalized value and it can sufficiently express the relationship among emotions. The meaning of ξ is summarized in Table II. In this paper, ξ_{ij} is used instead of I_{ij} .

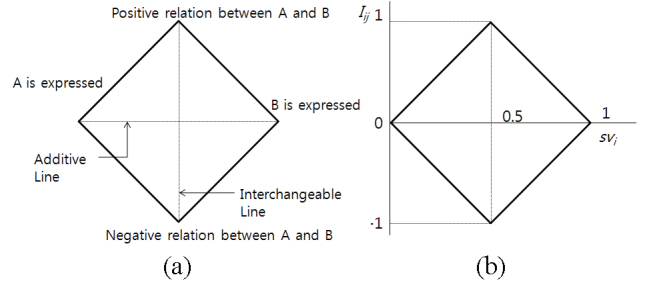


Fig. 1. Diamond pairwise comparison

$$sv_i + sv_j = 1, \quad c_{ij} = sv_i / sv_j \quad (3)$$

c_{ij} is calculated from sv_i through (3). c_{ij} means the relative importance between two elements. If sv_i is more important, c_{ij} is greater than one and if sv_j is more important, c_{ij} is smaller than one. From C matrix in (4), the normalized eigenvector of maximum eigenvalue is the weight vector on each symbol. It will be changed by combining with information about relationship among emotions. Based on Table I, face consist of four parts, i.e. eye lids and eye brows, mouth and jaw, eyes, and neck. Each part has different weight so that there are four C matrices and four weight vectors.

$$C = \begin{pmatrix} c_{11} & c_{12} & \dots & c_{16} \\ c_{21} & c_{22} & \dots & c_{26} \\ \vdots & \vdots & \ddots & \vdots \\ c_{61} & c_{62} & \dots & c_{66} \end{pmatrix} \quad (4)$$

D. Hierarchical Structure

A dissimilarity graph is obtained from the interaction degrees ξ_{ij} . Two closest clusters in the dissimilarity graph are merged through a step-by-step process until only one

TABLE I
EXPRESSED PARTS IN COMPOSITE FACIAL EXPRESSIONS

Emotion	expressed part	Emotion	expressed part
Anger	eyes, eye brows, eye lids	Disgust	mouth
Anger	eyes, eye brows, eye lids	Fear	mouth
Anger	eyes, eye brows, upper eye lids	Happiness	mouth, lower eye lids
Anger	eyes, eye brows, eye lids	Sadness	mouth
Anger	eyes, eye brows, eye lids	Surprise	mouth
Disgust	eyes, eye brows, upper eye lids	Fear	mouth, lower eye lids
Disgust	eyes, eye brows, eye lids	Happiness	mouth
Disgust	eyes, eye brows, upper eye lids	Sadness	mouth, lower eye lids
Disgust	eyes, eye brows, upper eye lids	Surprise	mouth, lower eye lids
Fear	eyes, eye brows, upper eye lids	Happiness	mouth, lower eye lids
Fear	mouth	Sadness	eyes, eye brows, eye lids
Fear	mouth	Surprise	eyes, eye brows, eye lids
Happiness	mouth	Sadness	eyes, eye brows, eye lids
Happiness	mouth	Surprise	eyes, eye brows, eye lids
Sadness	mouth	Surprise	eyes, eye brows, eye lids

cluster remains. Dissimilarity between two clusters, G_p and G_q , means the average distance in difference to the others except G_p and G_q , which is calculated as follows:

$$D_{G_p, G_q} = \frac{\sum_{G_r \in \mathfrak{G}, G_r \neq G_p, G_r \neq G_q} [\xi_{G_p, G_r} - \xi_{G_q, G_r}]^2}{|\mathfrak{G}| - 2} \quad (5)$$

where $\mathfrak{G}$ is the set of all clusters and $|\mathfrak{G}|$ is the number of clusters in that stage. If the difference of dissimilarity is smaller than a certain threshold, more than three symbols can be merged at the same time. Large threshold will generate a simplified hierarchical structure and small threshold will generate a complex but accurate hierarchical structure. Note that 0.1 is used as a threshold in this paper. The interaction degree graph from ξ_{ij} is shown in Fig. 2 and the dissimilarity graph from the interaction degree graph is shown in Fig. 3.

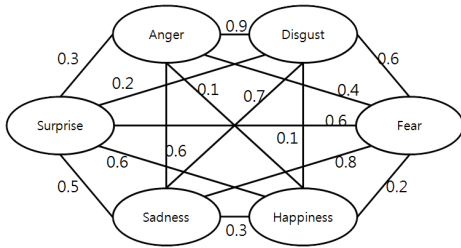


Fig. 2. Interaction degree graph

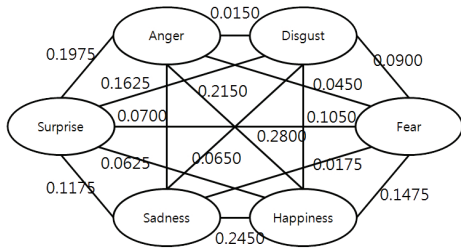


Fig. 3. Dissimilarity graph

In Fig. 4, the hierarchical structure from the dissimilarity graph and the four weight vectors from pairwise comparison matrices C are combined to produce the fuzzy measures of all sets.

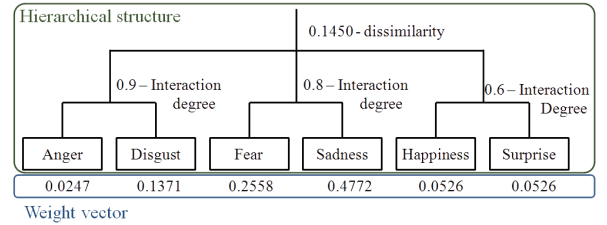


Fig. 4. A hierarchical structure

E. Fuzzy Measure Identification

ϕ_s transformation is used to get fuzzy measures $g(A)$. ϕ_s transformation is defined as follows [19]:

$$\phi_s : [0, 1] \times [0, 1] \rightarrow [0, 1] \quad (6)$$

$$\phi_s(\xi, u) = \begin{cases} 1 & \text{if } \xi = 1 \text{ and } u > 0 \\ 0 & \text{if } \xi = 1 \text{ and } u = 0 \\ 1 & \text{if } \xi = 0 \text{ and } u = 1 \\ 0 & \text{if } \xi = 0 \text{ and } u < 1 \\ \frac{s^u - 1}{s - 1} & \text{other cases} \end{cases} \quad (7)$$

where $s = \frac{(1-\xi)^2}{\xi^2}$. Fuzzy measure $g(A)$, where $A \subset X$, is calculated as follows:

$$g(A) = \phi_s(\xi_R, \sum_{B \subset R} u_B^R) \quad (8)$$

where R means root level set and ξ_R is the dissimilarity degree in root level and B is upper level set. Weights in upper level are calculated as follows:

$$u_C^B = \begin{cases} w_i & \text{if } |C| = 1 \text{ and } i \in A \\ 0 & \text{if } |C| = 1 \text{ and } i \notin A \\ \phi_s^{-1}(\xi_B, \phi_s(\xi_C, \sum_{D \subset C} u_D^C) \times T_C^B) & \text{other cases} \end{cases} \quad (9)$$

where $w_i, i \in C$, is the weight in lower level and $\phi_s^{-1}(\xi, u)$ is the inverse function of $\phi_s(\xi, r)$. Weights in lower level should be changed to weights in upper level. In this paper, the hierarchical structure has only two levels so that ξ_C is an interaction degree in a lower level and ξ_B is a dissimilarity degree in an upper level. T_C^B is a conversion ratio from lower-level to upper-level which is defined as follows:

$$T_C^B = \frac{\phi_s(\xi_B, \sum_{D \in C} w_D^C)}{\phi_s(\xi_C, \sum_{D \in C} w_D^C)} \quad (10)$$

where

$$w_C^B = \begin{cases} w_i & \text{if } |C| = 1 \\ \sum_{D \in C} w_D^C & \text{other cases} \end{cases} \quad (11)$$

where $w_i, i \in C$, is a weight from pairwise comparison matrix C .

F. Partial Evaluation

Partial evaluation values are obtained from the emotion state of robot. Let the current emotion state vector $X = [x_1; x_2; \dots; x_6]^T$, where each of $x_i, i = 1, 2, \dots, 6$ is between 0 and 1. The emotion state is represented by six parameters and each parameter represents each emotion, i.e. $x_1, x_2, \dots, x_6$ means anger, disgust, fear, happiness, sadness, and surprise, respectively.

Let $S_i = \{s_{i1}; s_{i2}; \dots; s_{i6}\}^T, i = 1, 2, \dots, 6$ be the ideal emotion state vector. The ideal emotion state means that the corresponding emotion is fully activated. Ideal emotion states parameter $s_{ij}, i = 1, 2, \dots, 6$ and $j = 1, 2, \dots, 6$ is calculated as follows:

$$s_{ij} = \begin{cases} 0 & \text{if } i \neq j \\ 1 & \text{if } i = j. \end{cases} \quad (12)$$

For example, anger is fully activated when emotion state is $S_1 = \{1; 0; 0; 0; 0; 0\}^T$. Current emotion state should be close to S_i to activate i -th emotion. $E = \{E_1; E_2; \dots; E_6\}$ is a distance matrix containing the every distance from current emotion state vector to the ideal emotion state vectors, which is calculated as follows:

$$\begin{pmatrix} E_1 \\ E_2 \\ \vdots \\ E_5 \\ E_6 \end{pmatrix} = \begin{pmatrix} I - |S_1 - X| \\ I - |S_2 - X| \\ \vdots \\ I - |S_5 - X| \\ I - |S_6 - X| \end{pmatrix} \quad (13)$$

where $E_i = \{e_{i1}; e_{i2}; \dots; e_{i6}\}^T$ is a size six matrix and $I = \{1; 1; 1; 1; 1; 1\}^T$.

Each e_{ij} has a different importance in E_i . For example, when anger expression is generated, anger parameter is more important than other parameters. Therefore, e_{ii} is multiplied to E_i to get partial evaluation vector H_i such that $H = \{H_1; H_2; \dots; H_6\}$ is a calculated as follows:

$$\begin{pmatrix} H_1 \\ H_2 \\ \vdots \\ H_5 \\ H_6 \end{pmatrix} = \begin{pmatrix} e_{11} \times E_1 \\ e_{22} \times E_2 \\ \vdots \\ e_{55} \times E_5 \\ e_{66} \times E_6 \end{pmatrix} \quad (14)$$

where $H_i = \{h_{i1}; h_{i2}; \dots; h_{i6}\}^T$ is a size six matrix. Every H_i and fuzzy measures from Fig. 4 are globally integrated by the Choquet integral. Each $H_i, i = 1, 2, \dots, 6$ is evaluated and the largest output of the Choquet integral is selected with the Choquet integral output.

III. SIMULATION AND EXPERIMENTAL RESULTS

A. Parameter Setting

People see the relationship among emotions differently. 20 subjects were asked to fill out the interaction degree graphs. 20 types of hierarchical structures were produced and 5 subjects generated the same type of hierarchical structure as shown in Fig. 4, which was used in this experiment.

Based on Table I, pairwise comparison matrix C was produced. If i -th emotion was more important than j -th emotion, six times of relative weight was assigned to sv_i . Weight vectors in each part were shown in Table III.

TABLE III
WEIGHT VECTORS ON EACH PART

	Mouth and jaw	Eye lids and eye brows	Eyes	Neck
Anger	0.0247	0.4771	0.2547	0.1666
Disgust	0.1371	0.0860	0.2069	0.1666
Fear	0.2558	0.0461	0.1059	0.1666
Happiness	0.4772	0.0247	0.2058	0.1666
Sadness	0.0526	0.1831	0.1569	0.1666
Surprise	0.0526	0.1831	0.0702	0.1666

B. Robotic Head

Robotic head's width, height, length, weight are 16cm, 26cm, 25cm, and 2.85kg, respectively. It can receive three-dimensional images through a stereo camera. Facial movements are controlled by 15 servo motors and neck's movements are controlled by 4 DC motors. Thus, it has 19 degrees of freedom. Three servo motors move jaw left and right, up and down, forward and backward. Four servo motors can push and pull the end of upper lip and lower lip. Two servo motors can move the eyes left and right, up and down. Four servo motors control the eye brows left and right, up and down, and two servo motors control the eye lids up and down. Neck is controlled by four DC motors. To sustain strong torque, harmonic drives are also used together with the DC motors. Each of the three DC motors rotates the head along the yaw, pitch and roll axes, respectively and the last one is to add one more degree of freedom to the pitch axis for nodding. Note that robotic head's movements are designed based on the facial action coding system (FACS) [20]. Normally, to maximize degrees of freedom, many robotic heads contains only mechanical structure in robotic heads and other modules

such as control module and motor module are placed near the robotic heads. Lots of wires are used to convey motors force from motor module to mechanical structure. However, the robotic head used in this experiment is designed to contain every module in its head. Thus, it does not have many degrees of freedom. However, it has good expandability.

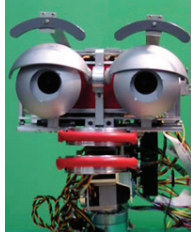


Fig. 5. Robotic head

The robotic head is controlled by digital signal processors (DSP) and electrically programmable logic devices (EPLD). Because DSP does not have enough counters, it is supported by EPLD to count the encoder's output.

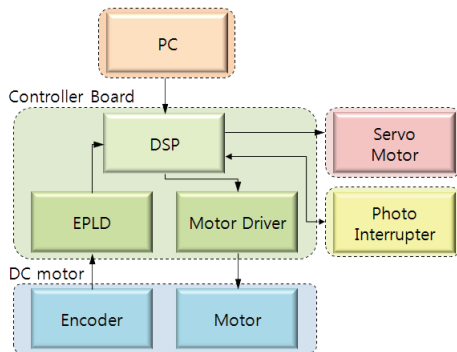


Fig. 6. Control circuit diagram

C. Simulation Results

Initial emotion state was set as $\{Anger, Disgust, Fear, Surprise, Sadness, Surprise\} = \{x_1, 0.09, 0.14, 0.10, 0.11, 0.65\}$ and the anger parameter x_1 was increased from zero to one to observe the variation of the composite facial expression. In the initial state, surprise was dominant.

In Fig. 7, X-axis is for the anger parameter and Y1-axis is for the normalized motor output value and Y2-axis shows the selected emotion. When the anger parameter was zero, surprise was selected in all the four parts because the surprise parameter value was much larger than the other parameter values. As the anger parameter value was increased, surprise was still selected in some initial time period but the normalized motor output value was decreased because the anger parameter moved far from zero to one. When the anger parameter value was continuously increased, eye brows and eye lids chose anger even though its value was smaller than that of the surprise parameter. When the anger parameter value was the same as the surprise parameter value, mouth, jaw and neck expressed

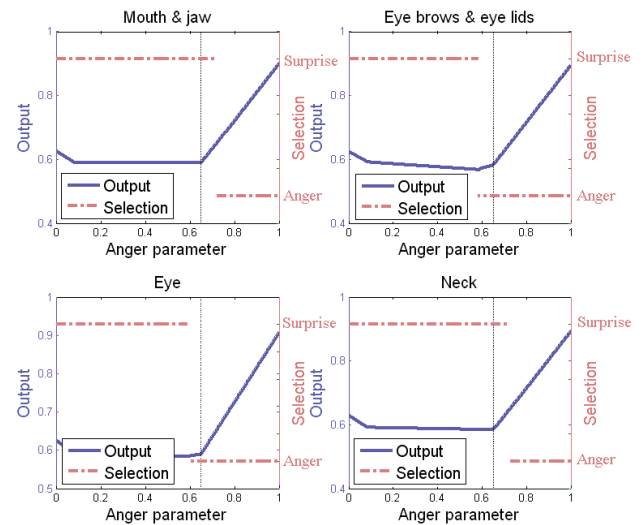


Fig. 7. Transition from surprise to anger

surprise and eyes, eye brows and eye lids expressed anger. Thus, the composite facial expression was generated. If the anger parameter value was increased more, all the four parts selected anger and the output became much larger. However, since the emotion state vector in this simulation could not be the ideal emotion state vector of anger S_1 , the output could not reach the maximum value. Note that similar result for generating various composite facial expressions could be obtained for the other case, for example, by increasing the disgust parameter value when the anger was dominant.

D. Experiments

Ekman's six basic emotions were generated and shown to 12 subjects. Facial expressions were generated by random order and subjects who had not seen the robotic head before were surveyed. The result was shown in Table IV.

TABLE IV
A SURVEY ON BASIC EXPRESSIONS

	Correct	Wrong	Percentage
Anger	9	3	75%
Disgust	9	3	75%
Fear	10	2	83%
Happiness	12	0	100%
Sadness	12	0	100%
Surprise	12	0	100%

As the Table IV shows, most of people could distinguish every basic facial expression except anger and disgust. These two emotions were quite similar that some subjects got confused in distinguishing them.

Fifteen composite facial expressions were generated by random order and shown to 10 subjects. The result was shown in Table V. People could not easily distinguish composite facial expressions. The reason was that some composite facial expressions were not familiar and hard to be identified. For example, being disgust and happiness together was unlikely generated in

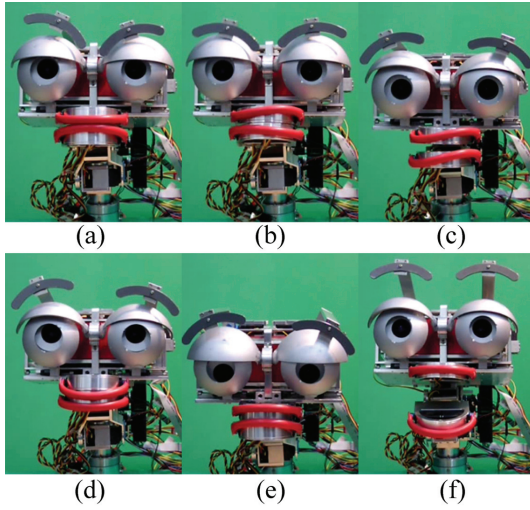


Fig. 8. Six basic emotions. (a) Angry (b) Disgust (c) Fear (d) Happiness (e) Sadness (f) Surprise

a normal life. Even if this facial expression was well generated, subjects could not easily recognize it. However, most subjects could identify familiar composite facial expressions easily, i.e. anger and disgust, happiness and surprise, etc.

TABLE V
A SURVEY ON COMPOSITE FACIAL EXPRESSIONS

	Anger	Disgust	Fear	Happiness	Sadness
Anger	x	x	x	x	x
Disgust	8	x	x	x	x
Fear	5	2	x	x	x
Happiness	5	3	2	x	x
Sadness	9	4	4	6	x
Surprise	4	7	3	9	4

Other reason was that some facial movements could not be generated by the developed robotic head. Happiness was mainly expressed by stretching a mouth and naso-labial folds. Robotic head did not have wrinkles so that it could not produce some facial movements. This point made subjects hard to identify the generated facial expressions. Easily and hardly recognizable facial expressions by the subjects are shown in Fig. 9 and Fig. 10, respectively.

Among the composite facial expressions, several familiar composite facial expressions were generated by the linear interpolation method and showed to 10 subjects. Only facial expressions with easily recognizable were generated because it is not important to generate facial expressions with unlikely produced in normal life. Table VI shows the result of comparison. The percentage of correct answers of linear interpolation method was lower than that of fuzzy integral-based method. Because characteristics of each emotion were disappeared by the linear interpolation, fewer people could recognize them.

Fig. 11 shows the composite facial expressions generated by the linear interpolation method. The linear interpolation method could generate continuous facial expressions transitions. However, it could not express the characteristics of each

TABLE VI
A COMPARISON WITH LINEAR INTERPOLATION METHOD AND FUZZY INTEGRAL-BASED METHOD

Facial expression	Anger and disgust	Anger and sadness	Happiness and surprise
Linear interpolation	6	5	5
Fuzzy integral-based	8	9	9

emotion in composite facial expressions. Thus, compared to Fig. 9(b) and Fig. 10(b), it become more difficult to identify which emotions are expressed in composite facial expressions.

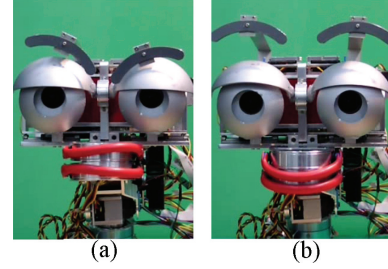


Fig. 9. Easily recognizable expressions. (a) Anger and disgust (b) Happiness and surprise

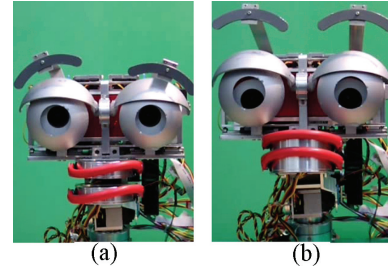


Fig. 10. Hardly recognizable expressions. (a) Happiness and fear (b) Surprise and sadness

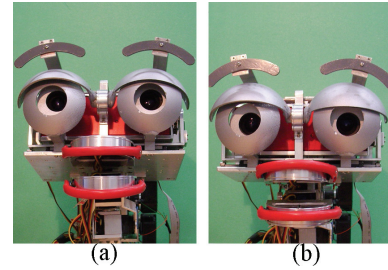


Fig. 11. Facial expressions from linear interpolation method. (a) Happiness and surprise (b) Surprise and sadness

IV. CONCLUSION

In this paper, a fuzzy integral-based generation method of composite facial expressions was proposed and demonstrated its effectiveness through the experiment with the developed robotic head. Fuzzy measures reflected the relationship among

emotions and the partial evaluation of current emotion state was obtained from a predefined error function. The Choquet fuzzy integral of the partial evaluation with respect to fuzzy measures was employed for generating composite facial expressions by separately actuating the parts of a robotic face. Experimental results showed that basic facial expressions were successfully generated and identified by the subjects. Composite facial expressions were also generated and some of them were hard to be identified, however, some familiar facial expressions were easily identified. It also showed that people could easily recognize the composite facial expressions generated by fuzzy integral-based method.

In future research, one microphone and one speaker will be added to the robotic head. Proper sound will be produced with the generation of facial expressions. Then people can recognize robot's facial expressions easily with sound.

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