# Facial Expression Generation Using Fuzzy Integral for Robotic Heads

Bum-Soo Yoo, Se-Hyoung Cho, and Jong-Hwan Kim

Department of Electrical Engineering, KAIST, 355 Gwahangno, Yuseong-gu, Daejeon, Republic of Korea
{bsyoo,shcho,johkim}@rit.kaist.ac.kr
http://rit.kaist.ac.kr

**Abstract.** This paper proposes a generation method of facial expressions using fuzzy measure and fuzzy integral for robotic heads. Human's emotion state can be represented by a fuzzy measure which can effectively deal with ambiguity. Because facial expressions are usually ambiguous such that it is difficult to discern emotions and assign a sharp boundary to each emotion. In this method, users can adjust the personality of robot by assignign fuzzy measure to every set of emotions. The partial evaluation values of the current emotion state are obtained from a difference between the ideal basic emotion states and the current emotion state. The Choquet integral of the partial evaluation values with respect to the fuzzy measure is calculated to decide which emotion should occur. The effectiveness of the proposed method is demonstrated through computer simulations and experiments with a robotic head with 19 degrees of freedom, developed in RIT Lab., KAIST.

**Keywords:** Robotic head, facial expression, fuzzy integral, fuzzy measure.

## 1 Introduction

Robots have been steadily coming into our daily life. They need interaction capability to provide humans with better service. A desired approach to make natural human-robot interaction (HRI) is learning from human-human interaction (HHI) [1]. In HHI, facial expressions play an important role. According to the psychologist Mehrabian, 55% of information is delivered by non-verbal communications [2],[3]. As facial expressions are essential components in non-verbal communication, they are also important in HRI.

The robotic head Kismet generated facial expressions using a three dimension emotional space and an interpolation [4]. It could produce natural facial expression transitions. However, it could not produce facial expressions dynamically and the interpolation was done by assuming that facial expressions were changing linearly. Besides Kismet, many researches have been progressed to generate natural facial expressions for robotic heads. J.-W. Park used linear dynamic affect-expression model to generate facial expressions for mascot type robotic

T.-H.S. Li et al. (Eds.): FIRA 2011, CCIS 212, pp. 58–65, 2011.

heads[5]. Y. Matsui used recurrent network to consider the time in generating facial expressions[6]. T. B. Bui applied fuzzy rule based system to generate facial expressions,[7]. However, these methods did not consider the personality of the robot. Considering the various facial expressions according to people,even in the same emotion state, personality of the robot should be reflected in generating facial expressions.

In this paper, a generation method of facial expressions for robotic heads using the fuzzy integral and fuzzy measure is proposed. Fuzzy measure is assigned to every sets of emotions according to the personality of the robot. The partial evaluation values of the current emotion state are obtained from a difference between the ideal basic emotion states and the current emotion state. The Choquet integral of the partial evaluation values with respect to the fuzzy measure is calculated to decide which emotion will occur with a certain degree. The effectiveness of the proposed method is demonstrated through computer simulations and experiments with a robotic head with 19 degrees of freedom, developed in RIT Lab., KAIST.

In Section 2, a robotic head is introduced. In Section 3, a method of generating facial expressions using the fuzzy integral and fuzzy measure is proposed for robotic heads. In Section 4, computer simulations and experimental results are presented. Finally, concluding remarks follow in Section 5.

## 2 Robotic Head

Robotic head's width, height, length and weight are 16 cm, 26 cm, 25 cm and 2.85 kg, respectively. It contains a stereo camera which can receive three dimension images. Totally, 15 servo motors generate facial expressions and 4 DC motors control the movements of neck. Table 1 shows the movements of each part, which is designed based on the facial action coding system [8]. Digital signal processors (DSP) and electrically programmable logic devices (EPLD) control a robotic head. Servo motors are controlled every 20 ms and DC motors are controlled every 5 ms.

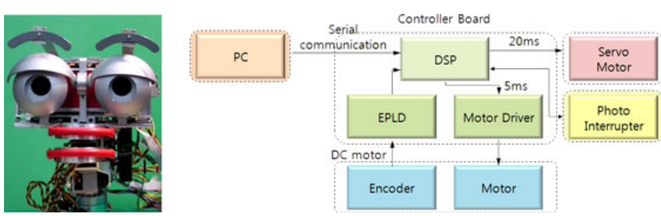


**Fig. 1.** Robotic head and control diagram

**Table 1.** Movements of each part

| Parts | Degrees of freedom | Movements |
|---|---|---|
| Jaw | 3 | Up and down, left and right, forward and backward |
| Upper lip, Lower lip | 2, 2 | Stretch of left and right ends |
| Eyes | 2 | Up and down, left and right |
| Left eye brow, Right eye brow | 2, 2 | Up and down, left and right |
| Left eyelid, Right eyelid | 1, 1 | Up and down |
| Neck | 4 | Yaw, pitch, roll axes<br>One more for pitch axis |

# 3 Facial Expression Generation

## 3.1 Fuzzy Measure and Fuzzy Integral

In this paper, fuzzy measure is used to express the personality of the robot and the Choquet fuzzy integral is used to generate facial expressions. Fuzzy measure means an importance of each set. Among various fuzzy measures, Sugeno $\lambda$-fuzzy measure is used to reflect the personality of the robot. Fuzzy measure is defined in the following [9].

*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) $g(\varnothing) = 0, g(X) = 1$;
ii) $A \subset B \subset X$ implies $g(A) \leq g(B)$.

The Sugeno $\lambda$-fuzzy measure satisfies the following [10]:

$$g(A \cup B) = g(A) + g(B) + \lambda g(A)g(B). \tag{1}$$

Note that users can set a proper $\lambda$ value, $-1 \leq \lambda \leq \infty$, to adjust the relationship among emotions. If $\lambda$ is smaller than zero, it means two symbols are in a positive correlation. If $\lambda$ is greater than zero, it means two symbols are in a negative correlation.

The choquet integral is used to generate facial expressions, which is defined in the following [11].

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

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

In (2), fuzzy measure $g$ should be calculated for all the power sets of $X$. Partial evaluation values $h$ are derived from a difference between the ideal basic emotion states and the current emotion state.

**Table 2.** Relative importance among emotions

| | Anger | Disgust | Fear | Happiness | Sadness | Surprise |
|---|---|---|---|---|---|---|
| Anger | 1.0000 | 0.8333 | 0.7000 | 0.5000 | 0.8000 | 0.5556 |
| Disgust | 1.2000 | 1.0000 | 0.8000 | 0.5556 | 0.9000 | 0.6250 |
| Fear | 1.4286 | 1.2500 | 1.0000 | 0.6667 | 0.8000 | 0.7142 |
| Happiness | 2.0000 | 1.8000 | 1.5000 | 1.0000 | 1.2000 | 2.0000 |
| Sadness | 1.2500 | 1.1111 | 1.2500 | 1.2000 | 1.0000 | 0.8333 |
| Surprise | 1.8000 | 1.6000 | 1.4000 | 0.5000 | 1.2000 | 1.0000 |

### 3.2 Weight Assignment

According to the Ekman's research, the number of human's basic emotions is six, i.e. happiness as a positive emotion, surprise as a neutral emotion and anger, disgust fear and sadness as negative emotions [12]. These six parameters are used to represent the robots emotion states and each parameter represent each emotion's degree. It is a difficult task to assign all the fuzzy measures satisfying the axioms of fuzzy measure and to design user's desired personality by hand. In this paper, $\lambda$ and $\phi_s$ transformation are used to identify fuzzy measures [13].

Every two pairs should be compared to assign the relative importance in Table 2. Each number means the relative importance of emotion in the row compared to emotion in the column. Therefore, diagonal terms should be one and users should assign the upper triangular values of Table 2. Then lower triangular part will be filled automatically with the reciprocal numbers of the upper triangular values. The normalized values of each row's summation are weights on each emotion. For example, if users want to make a positive personality robot, happiness should more important than other emotions. From Table 2, weight on each emotion is $\{anger, disgust, fear, happiness, sadness, surprise\} = \{0.113, 0.126, 0.151, 0.245, 0.171, 0.193\}$.

### 3.3 Fuzzy Measure Identification

Based on the weights on each emotion, a fuzzy measure on a set $A$ is identified as follows:

$$\mu_\lambda(A) = \phi_{\lambda+1}(\sum_{i\in A} u_i) = \frac{\lambda^{u_1+u_2+\ldots+u_n} - 1}{\lambda} \tag{3}$$

where $\phi$ is the $\phi_s$ transformation, $u_i$ is the weight of $i$-th symbol and $\lambda$ is the interaction degree.

### 3.4 Partial Evaluation

The current emotion state of the robot is used for calculating the partial evaluation values. Let us denote the current emotion state by a vector $X = [x_1; x_2; \ldots; x_6]^T$, where $x_i, i = 1, 2, \ldots, 6$ is between 0 and 1. The six parameters are used to represent each emotion, i.e. $x_1, x_2, \ldots, x_6$ represents anger, disgust, fear, happiness, sadness, and surprise, respectively.

The partial evaluation values are produced from a difference of the current emotion state vector and the ideal emotion state vectors. Let $S_i = \{s_{i1}; s_{i2}; \ldots; s_{i6}\}^T$, $i = 1, 2, \ldots, 6$ denote the ideal emotion state vector. The ideal emotion state vector is defined as a state vector when a certain emotion is fully occurred. The ideal emotion state vectors parameter $s_{ij}, i, j = 1; 2; \ldots; 6$ is calculated as follows:

$$s_{ij} = \begin{cases} 0 \text{ if } i \neq j \\ 1 \text{ if } i = j. \end{cases} \tag{4}$$

For example, anger is fully occurred when a robot's emotion state vector is $S_1 = \{1; 0; 0; 0; 0; 0\}^T$. $E = \{E_1; E_2; \ldots; E_6\}$ is a distance matrix from the current emotion state vector to the ideal emotion state vectors, which is calculated as follows:

$$\begin{pmatrix} E_1 \\ E_2 \\ \vdots \\ E_5 \\ E_6 \end{pmatrix} = \begin{pmatrix} I - |S_1 - X| \\ I - |S_2 - X| \\ \vdots \\ I - |S_5 - X| \\ I - |S_6 - X| \end{pmatrix} \tag{5}$$

where $E_i = \{e_{i1}; e_{i2}; \ldots; e_{i6}\}^T$ is a size six vector and $I = \{1; 1; 1; 1; 1; 1\}^T$. Each $e_{ij}$ has a different importance in the evaluation of the $i$-th emotion. For example, when anger expression is generated, anger parameter is more important than other parameters. Therefore, $e_{ii}$ should be considered more than other parameters in $E_i$. $e_{ii}^2$ is multiplied to $E_i$ to get partial evaluation vector $H_i$ such that the partial evaluation matrix $H = \{H_1; H_2; \ldots; H_6\}$ is calculated as follows:

$$\begin{pmatrix} H_1 \\ H_2 \\ \vdots \\ H_5 \\ H_6 \end{pmatrix} = \begin{pmatrix} e_{11}^2 \times E_1 \\ e_{22}^2 \times E_2 \\ \vdots \\ e_{55}^2 \times E_5 \\ e_{66}^2 \times E_6 \end{pmatrix} \tag{6}$$

where $H_i = \{h_{i1}; h_{i2}; \ldots; h_{i6}\}^T$ is a size six vector. Each $H_i$, the partial evaluation value $h$ in (2), is integrated along with the fuzzy measure $g$ from (3) through the Choquet integral. Each $H_i$ are globally evaluated and the biggest emotion is selected to generate facial expressions.

## 4 Computer Simulation and Experiment

### 4.1 Simulation

The transition between two similar emotions was simulated. Initial emotion state vector was set as $X = \{Anger, Disgust, Fear, Surprise, Sadness, Surprise\}$ $= \{0.45, x_2, 0.15, 0.08, 0.16, 0.05\}$ and the disgust parameter $x_2$ was increased from zero to one.

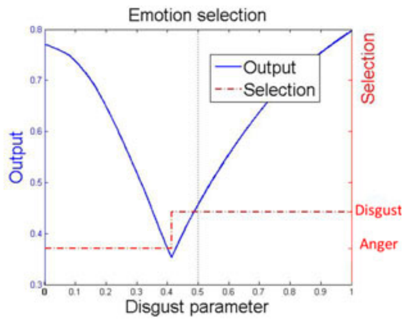


**Fig. 2.** Transition from anger to disgust

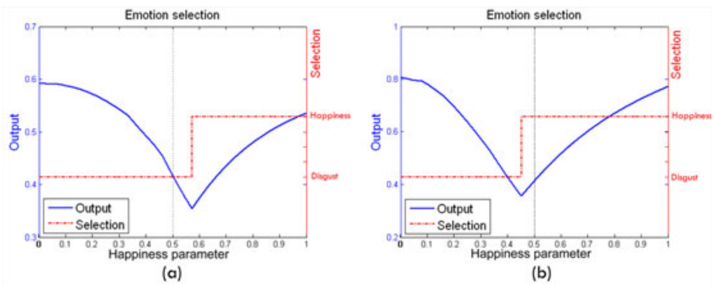


**Fig. 3.** Comparison between positive personality and negative personality. (a) Positive robot (b) Negative robot

.

In Fig. 2, X, Y1 and Y2-axes represent the disgust parameter, the normalized motor output value and the selected emotion, respectively. When the disgust parameter was zero, anger was selected. As the disgust parameter value was increased, anger was still selected however the magnitude of output decreased because the disgust parameter moved far from zero to one. In addition, the partial evaluation value in (6) is a function of $e_{ii}^2$ so that the output decreased like second-order equations. The transition occurred when the disgust parameter was around 0.35. After the transition, disgust was selected and its magnitude became larger when the disgust parameter increased.

Comparison between two personalities was simulated. A robot with positive propensity was tuned to have the highest weight on the happiness and robot with negative propensity was tuned to have the highest weight on the disgust. Initial emotion state vector was set as $X = \{Anger, Disgust, Fear, Surprise, Sadness, Surprise\} = \{0.1, 0.5, 0.15, x_4, 0.16, 0.05\}$ and the happiness parameter $x_4$ was increased from zero to one.

In Fig. 3, X, Y1 and Y2-axes represent the happiness parameter, the output value by a blue line and the selected emotion by a red line, respectively. Black vertical line represents 0.5 which was the same with the disgust parameter's initial value. Fig. 3(a) shows the output of a robot with negative propensity and Fig. 3(b) shows the output of a robot with positive propensity. A positive robot changed to happiness facial expressions in a lower degree of happiness parameter than a negative robot. The difference of emotion selection was caused by the fuzzy measure.

### 4.2 Experiment

The transition between two opposite emotions was tested. When the disgust parameter was dominant, the happiness parameter increased to make happiness a dominant emotion. Fig. 4 shows the transition from disgust emotion to happiness emotion.

Facial expressions were changed from Fig. 4(a) to Fig. 4(d). The transition had a little discontinuity because at the transition point, facial movements were generated suddenly due to change of selected emotion. However, facial expression transitions between opposite emotions including a transition from disgust to happiness do not usually happen in daily life.

The transition from anger to disgust was tested. Two emotions are so similar that they often appear together and some people are confused in distinguishing them. Facial expressions were changed from Fig. 5(a) to Fig. 5(d). It showed a continuous facial expression transition and did not have any discontinuity as in Fig. 4. Both facial expressions are similar and these facial expression transitions are happened frequently in daily life.

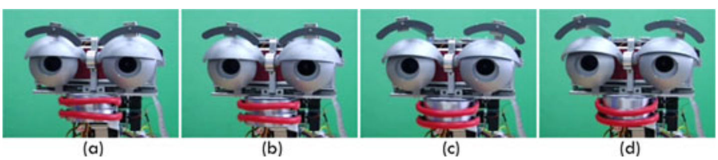


**Fig. 4.** Transition from disgust to happiness

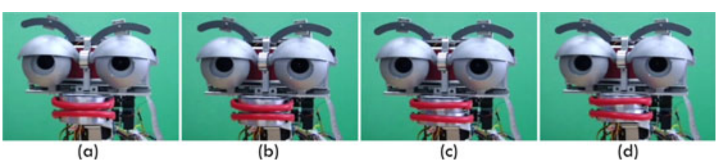


**Fig. 5.** Transition from anger to disgust

## 5 Conclusion

In this paper, facial expression generation using the fuzzy measure and fuzzy integral was proposed and applied to a robotic head. The proposed method used the Sugeno $\lambda$-fuzzy measure to reflect a robot's personality. The partial evaluation values of the current emotion state were obtained from a difference between the ideal basic emotion states and the current emotion state. The partial evaluation values were integrated along with the fuzzy measure through the Choquet integral to generate facial expressions. The proposed method was demonstrated by the experiments with a robotic head and it could generate natural facial expressions.

## References

1. Muhl, C., Nagai, Y.: Does Disturbance Discourage People from Communication with a Robot? In: 16th IEEE International Conference on Robot & Human Interactive Communication, Jeju, Korea, pp. 1137–1142 (2007)
2. Mehrabian, A.: Nonverbal Communication. Aldine-Atherton (1972)
3. Mehrabian, A.: Communication without words. Psychology Today 2(4) (1968)
4. Breazeal, C.L.: Designing Sociable Robots. MIT Press, Cambridge (2002)
5. Park, J.-W., Kim, W.-H., Lee, W.-H., Kim, W.-H., Chung, M.-J.: Lifelike Facial Expression of Mascot-Type Robot based on Emotional Boundaries. In: IEEE Int. Conf. Robotics and Biomimetics, Guilin, China, pp. 830–835 (2009)
6. Matsui, Y., Kanoh, M., Kato, S., Nakamura, T., Itoh, H.: Evaluating A Model for Generating Interactive Facial Expressions using Simple Recurrent Network. In: IEEE Int. Conf. Syst. Man Cybern., Texas, USA, pp. 1639–1644 (2009)
7. Bui, T., Heylen, D., Poel, M., Nijholt, A.: Generation of Facial Expressions from Emotion Using a Fuzzy Rule Based System. In: 14th Australian Joint Conf. Artificial Intelligence, Adelaide, Australia (2001)
8. Ekman, P., Friesen, W.: Facial Action Coding System: A Technique for the Measurement of Facial Movement. Consulting Psychologists Press, Palo Alto (1978)
9. Sugeno, M.: Theory of fuzzy integrals and its applications. Ph.D. dissertation, Tokyo Institute of Technology (1974)
10. Kim, J.-H., Han, J.-H., Kim, Y.-H., Choi, S.-H., Kim, E.-S.: Preference-based Solution Selection Algorithm for Evolutionary Multiobjective Optimization. IEEE Transactions on Evolutionary Computations (December 2010) (accepted)
11. Grabisch, M., Nguyen, H.-T., Walker, E.-A.: Fundamentals of uncertainty Calculi, with Applications to Fuzzy Inference. Kluwer, Dordrecht (1995)
12. Ekman, P., Friesen, W.: Unmasking the face: A Guide to Recognizing Emotions From Facial Expressions. Prentice Hall, Englewood Cliffs (1975)
13. Takahagi, E.: On identification methods of $\lambda$-fuzzy measures using weights and $\lambda$. Journal of Japan Society for Fuzzy Theory and Systems 12(5), 665–676 (2000)