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An Emotion Transition Model using Fuzzy Inference

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Abstract: This paper proposes an emotion transition model considering internal emotions and external inputs. The proposed model has internal emotion values representing each intensity of multiple emotions as internal states. Each intensity of emotions estimated from the input texts is given as the external inputs. These values of intensity are used in the antecedent part, and emotion transition is estimated by fuzzy inference. The proposed model can treat the same external inputs differently considering the internal states and it employs the idea of a psychological phenomenon, the mood congruency effect: The proposed model can express emotion transition more naturally. According to subjective evaluation experiments, high correlation between the proposed model and humans is obtained.

Keywords: *Affective computing, Emotion transition, Fuzzy inference*

1. INTRODUCTION

Spiritual enrichment plays an important role in our lives. In engineering fields, research to give mental satisfaction is required [1]. In the development of robots, not only industrial robots but also service ones are required. As a result, communication between humans and robots is becoming more and more important [2].

Emotion is one of the fundamental elements to communicate. It influences a lot on human actions [3]. Therefore, understanding of emotion is requisite in communication with human.

There are various researches and technological developments focused on emotion. In the case of service robots, a personal robot “Pepper” [4] of Aldebaran estimates and cognizes user’s emotion. In the field of engineering, there are some approaches; a system which estimates emotion from news articles [5], an emotion appraisal network based on machine learning [6], an emotion estimation approach considering preference which users have peculiarly [7]. Also, there are some researches concerning emotion for daily conversation. For example, estimating emotion of speakers [8-10] and listeners [11] in dialogue, a method of emotion judgement from colloquial expression based on knowledge base and association mechanism [12], and so on. Other than that, a system in [13] estimates emotion from sitting postures. Furthermore, emotion estimation has various applications; a method to support searching TV programs by analyzing the tweets and identifying and visualizing emotion of the audiences [14], a facemark recommendation system by estimating emotion category [15], a formulation of

emotion coloration model and an image emotion model to get coloration with considering emotion of human [16]. In addition, not only estimating user’s emotion but also expressing or generation of emotions for a robot is studied. In [17], robot changes its facial expression using emotion space. In [18], an emotion generation model for dialogue considering the partner is studied. In [19], the authors propose a method to generate mixed emotional behavior in interactive emotion communication using self-organizing maps.

Above-mentioned studies are conducted to mainly estimate or show superficial emotion. On the other hand, there are some studies dealing with emotion transition. In [20], the authors developed a psychological state transition network that transits among states of emotion with various probabilities. Also in [21], an emotion model which shifts the emotion state dynamically based on the external environment is implemented in a robot. In the existing studies on emotion, there are few studies treating multiple emotions. Also, there are few studies considering the internal state for transition of emotions.

In this paper, we focus on emotion transition depending on an internal state, and propose an emotion transition model which considers internal emotion by fuzzy inference. One of the main purposes of this model is to estimate natural transition of emotion. The proposed model estimates the emotion transition using fuzzy inference whose antecedent parts are composed of the internal emotion of the system and the emotion estimated by the external input.

The contents of the paper were presented at ISIS2015 [28].

Following this introduction, the proposed emotion transition model is explained in 2. The emotion transition by fuzzy inference is explained in 3, and the evaluation experiments are shown in 4. The paper is concluded in 5.

2. EMOTION TRANSITION MODEL

Figure 1 shows the flow of emotion transition in the proposed model. The model estimates transition to the next internal emotion using fuzzy inference whose antecedent parts are composed of internal emotion values and emotion values obtained from the external input. Here, the internal emotion values represent the internal state of the system. We should note here that the internal state represents the internal emotional state of the system and is expressed in a set of four emotion values in this paper (joy, sadness, fun, anger). Similarly, the external inputs mean the external inputs to the model and are also expressed in a set of four emotion values.

2.1 Emotion

There are several emotion models. Among them, Russell's emotion circular ring model [22] is widely used. Figure 2 shows the model.

Figure 1: Flow of the proposed emotion transition model.

Figure 2: Russell's emotion circular ring model [22].

Figure 3: Larsen and Diener's eight-way split model [23].

In the Russell's model, each emotion is represented as the magnitude and direction of a vector on two-dimensional coordinate axes: pleasure-discomfort and arousal-drowsiness. Synonyms are located in the closer places in the circular ring, and antonyms are located in the opposite places. Larsen and Diener divided this model into eight regions considering activity and inactivity [23]. Figure 3 shows their model.

This model is easy to treat because the placement of emotions is simple. Therefore, we employ it in the definition of fuzzy rules in the proposed model as a reference to consider the relationship among emotions. We selected four major emotions: joy, sadness, fun and anger. Each emotion value is expressed in a set of (joy, sadness, fun, anger). The larger emotion value means that the emotion is more intensive. Each emotion value changes within a range of 0.0-1.0 using fuzzy inference.

3. EMOTION TRANSITION BY FUZZY INFERENCE

Here, we explain the behavior of the proposed model. It estimates transition of internal emotion values using fuzzy inference.

3.1 Antecedent part and consequent part

The antecedent parts in the fuzzy inference in the proposed model are the internal emotion values and the external input values. They are classified into 3 classes, large, middle, and small according to the degree, and a membership function is prepared for each class. Figure 4 shows the examples of the membership functions of internal emotion values and external input values for the antecedent part.

Figure 5 shows the examples of the membership functions of emotion transition values. Each membership

Figure 4: Membership function of the antecedent part.

Figure 5: Membership function of the consequent part.

function has 13 classes; D_1, D_2, D_3, D_4, D_5 , and D_6 , they mean decrease, U_1, U_2, U_3, U_4, U_5 , and U_6 , they mean increase, and E means stable. In the functions D_i and U_j , the larger the indexes i and j are, the larger the amount of change is. The domain of the membership function is adjusted manually by reference to the data collected from preliminary experiments as explained later.

3.2 Fuzzy rules

The fuzzy rules used in the proposed model basically change the internal emotion values according to the external inputs and the present internal emotion values. At first, the proposed model calculates each membership value of “large”, “middle” and “small” for the inputted emotion values. Then, it calculates the emotion transition value to the next step for each emotion using fuzzy rules.

In order to consider more delicate emotion transition, a psychologically well-known phenomenon, the mood congruency effect [24], is employed in the proposed model. The mood congruency effect means that the mood at a time affects the way of perceiving things by human. When the content of a thing is consistent with the mood at a time, human tends to memorize it. For example, when we feel good, we tend to see things as good ones, and vice versa [25].

In order to implement this effect, we made the fuzzy rules as follows: when the values of an emotion both in the external inputs and in the internal state are large, the value of emotion transition is also positive large as shown in Fig. 6.

Furthermore, relations among emotions are considered in the fuzzy rules. As for similar emotions, these emotion

Figure 6: Implementation of mood congruency effect (1).

Figure 7: Implementation of mood congruency effect (2).

values change similarly. Figure 7 illustrates the example. Since the emotion, fun, is similar to joy, the internal emotion value of fun contributes to enhance joy value. On the other hand, since the emotions of sadness and anger are opposite to joy, these emotion values tend to weaken the internal emotion value of joy.

3.3 Updating of internal emotion value

The emotion transition value obtained by fuzzy inference can be used to estimate the emotion at the time step. In the proposed model, the internal emotion is expressed by cumulative generated emotion. Also, events acting on emotion tend to be faded from memory as time proceeds. The proposed model updates the internal emotion values considering this effect.

The internal emotion value $In(n)$ is updated by the following equation.

$$In(n) = \alpha \times In(n-1) + Tr(n) \quad (1)$$

where Tr is the outputted emotion transition value, n is the time step and $\alpha (< 1.0)$ is the forgetting coefficient.

If there is no restriction for the range of each emotion value, sometimes it might take too large value or negative value. Such a situation might correspond to an abnormal or diseased situation and is very difficult to treat. In addition, in order to use fuzzy inference effectively, emotion value is limited within the range between 0.0 and 1.0 using the following equation.

$$In = \begin{cases} 0.0 & (In < 0.0) \\ 1.0 & (In > 1.0) \\ In & (\text{otherwise}) \end{cases} \quad (2)$$

4. EXPERIMENTS

Evaluation experiments were conducted to test the effectiveness of the proposed model.

4.1 Preparation for experiments

To evaluate the performance of the proposed model, we carried out the preliminary experiments to obtain the appropriate emotion value for each of the input sentence. We employed one of the famous Japanese fairy stories, “Urashima Taro” in the experiments. This is because 4 kinds of emotions tend to appear relatively clear in the story. We selected some appropriate parts for the experiments in the story using the website [26]. Finally, 25 sentences were selected.

We asked subjects (5 persons in their twenties, including 4 males and 1 female) to imagine the emotions and their degrees of the main character to each sentence. Table 1 shows some examples of the sentences and the corresponding averaged emotion values by subjects.

4.2 Evaluation experiment

We conducted the evaluation experiment using sentences with emotion values obtained in the preliminary experiment.

First, we showed the sentences one by one to 13 subjects in their twenties including 10 males and 3 females. Then, they imagine the internal emotion values of the 4 emotions for each input sentence. We told them that range of the internal emotion is between 0.0 and 1.0, and the initial state is 0.0 in all of 4 emotions. We also asked them to consider the continuity of emotion. In this way, we compared transitions of the internal emotion value which were answered by the subjects and the one outputted by the proposed model.

Data of 4 subjects out of 13 subjects were used to adjust parameters in the proposed model. The 4 subjects were determined by selecting top 4 subjects in alphabetical order in their family name. We compared the averaged data of the selected 4 subjects with the output of the proposed model, and some parameters were adjusted manually. Table 2 summarizes the adjusted parameters. After adjusting, we compared average of the data of remaining 9 subjects and the outputs of the proposed model. Figures 8, 9, 10, and 11 show the results, and Table 3 shows the correlation coefficient between the subjects’ data and the model’s output.

In Figs. 8, 9, 10, 11, the curves of the emotion transition outputted by the proposed model tend to be resemble to the ones answered by subjects. Also, it is said that if

Table 1: Result of preliminary experiment.

Sentence representing an event	Joy	Sadness	Fun	Anger
Children caught a turtle and bullied it.	0.0	0.52	0.0	0.6
A pretty music started, and fish performed dances and entertained Urashima Taro.	0.34	0.0	0.5	0.0
When arrived at the beach, he could not find his own house.	0.0	0.7	0.0	0.06

Table 2: Adjusted parameters.

	before adjustment	after adjustment
Forgetting coefficient	0.9	0.85
Labels of membership functions to control similar emotion values	U_6 (quite large increase) U_5 (large increase) D_6 (quite large decrease) D_5 (large decrease)	U_6 (quite large increase) U_5 (large increase) U_4 (moderate increase) U_3 (a bit increase) D_6 (quite large decrease) D_5 (large decrease) D_4 (moderate decrease) D_3 (a bit decrease)
Interval between the membership functions in the consequent part		Shift of each membership func in the x axial direction: $D_6 - D_1 : +0.03$ $U_1 - U_4 : +0.03$ $U_5, U_6 : -0.03$

Table 3: Correlation coefficient between 9 subjects’ data for evaluation and the model’s output.

Emotion	Correlation coefficient
Joy	0.884
Sadness	0.781
Fun	0.777
Anger	0.808

the correlation coefficient between two things is more than 0.7, these things are correlated strongly with each other [27]. From Table 3, it can be observed that the correlations between the outputs of the proposed model and the subjects’ evaluations are relatively high for all emotions.

4.3 Consideration of the forgetting coefficient

It might be natural to think that duration degrees of emotions differ emotion by emotion. For example, the emotion of sadness tends to last relatively long, whereas that of fun lasts relatively short, although it depends on personality. To examine this idea, we made an assumption that forgetting degree for each emotion differs and we carried out experiments. Using the same 4 subjects’ data for adjustment in 4.2, we changed the forgetting coefficient of the model and calculated the corresponding correlation coefficient.

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Figure 8: Result of evaluation experiment (joy).

Figure 9: Result of evaluation experiment (sadness).

Figure 10: Result of evaluation experiment (fun).

Figure 11: Result of evaluation experiment (anger).

Figure 12 shows the results. This figure indicates the relevance of the assumption: each emotion has its own appropriate forgetting coefficient. Table 4 summarizes the optimum forgetting coefficients obtained from Fig. 12 for each emotion.

Figures 13, 14, 15, and 16 show the results, and Table 5 shows the correlation coefficient between the subjects' data and the model's output. From these figures, it is

Figure 12: Correlation coefficient and forgetting coefficient.

Table 4: Optimum forgetting coefficients obtained from Fig. 12.

Emotion	Forgetting coefficient
Joy	0.75
Sadness	0.75
Fun	0.60
Anger	0.70

Figure 13: Result of evaluation experiment using different forgetting coefficient for every emotion (joy).

Figure 14: Result of evaluation experiment using different forgetting coefficient for every emotion (sadness).

Figure 15: Result of evaluation experiment using different forgetting coefficient for every emotion (fun).

Figure 16: Result of evaluation experiment using different forgetting coefficient for every emotion (anger).

Table 5: Correlation coefficient between 9 subjects' data for evaluation and the output of the model using different forgetting coefficient for every emotions.

Emotion	Correlation coefficient
Joy	0.947
Sadness	0.851
Fun	0.952
Anger	0.816

confirmed that the accuracy of the model which uses appropriate forgetting coefficient for every emotions is better than the one using the same forgetting coefficient for all emotions.

5. CONCLUSIONS

In this paper, a novel emotion transition model that makes the internal emotion transition based on fuzzy inference has been proposed. The features of the proposed model are the followings.

- Natural emotion transition can be estimated by fuzzy inference. Here, the emotion transition depends on the current state of internal emotion and the emotion estimated from the external input.
- Multiple emotions can be expressed by dealing with multiple emotions simultaneously.

- Forgetting of emotion by time can be expressed by means of decrease of the cumulative emotion transition value using forgetting coefficient.

It has shown that the proposed model expresses human-close natural emotion transition through evaluation experiments.

Comparisons with the conventional methods such as probabilistic models and statistical models are future research.

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