

Classification of EGC output and Mental State Transition Network using Self Organizing Map

Kazuya Mera

Faculty of Information Sciences
Hiroshima City University
Hiroshima, Japan
mera@hiroshima-cu.ac.jp

Takumi Ichimura

Department of Management and Information Systems
Prefectural University of Hiroshima
Hiroshima, Japan
ichimura@pu-hiroshima.ac.jp

Abstract—Mental State Transition Network which consists of mental states connected one another is a basic concept of approximating to human psychological and mental responses. It can represent transition from an emotional state to other one with stimulus by calculating Emotion Generating Calculations method. However, this method ignores most of emotions except for an emotion which has the strongest effect although EGC can calculate the degree of 20 emotions in parallel. In this paper, we investigate the discrepancy between the group of emotions by EGC and the clustering results of the relation of sentences and their emotions by Self Organizing Map. Mental state transits based on the group of emotions on the map. For example, a set of emotions in a group transits the mental state “happy,” and negative mental state is enfeebled.

Index Terms—Emotion Oriented Interface, Emotion Generating Calculations, Mental State Transition Network, Self Organizing Map

I. INTRODUCTION

At a beginning of the 21th century, some people said that although the 20th century was the “time of matter,” the 21st century will be the “time of the heart.” The expression “time of the heart” indicates mental health care, change of the sense of values considering emotion, and so on. Researchers in various fields such as information science, psychology[1], [2], [3], human engineering[4], [5], brain physiology[6],[7] and so on are approaching to ‘mind.’ It was difficult to deal with mind and emotion in science field because they are ambiguous and vague to formulate a way to measure the degree of them. However, recent researches can approach the process of the mind scientifically by development of measurement machines, measurement method using computer which simulates the mind[8]. Emotions such as love, hate, courage, fear, joy, sadness, pleasure, and disgust are represented in both psychological and physiological terms. An essential role of emotions in working of the mind was analyzed in philosophy[9], [10], [11], psychology[12], and from the learning and cognition perspective [13], [14], [15].

Our research group proposed methods to calculate the agent’s emotion from the contents of utterances and to express emotions which are aroused in computer agent by using synthesized facial expression [16], [17], [18], [19]. Emotion Generating Calculations (EGC) method [17] can decide whether an event is pleasure or not for the agent and quantify the degree under the event. The calculated pleasure/displeasure are

classified into 20 types of emotions based on Emotion Eliciting Condition Theory [20].

Calculated emotions cause effect to the mental state of the agent. Ren [21] describes Mental State Transition Network (MSTN) which has the basic concept of approximating to human psychological and mental responses. The assumption of discrete emotion state is that human emotion are classified into some kinds of stable discrete states, called “mental state,” and the variance of emotions occurs in the transition from a state to other state with an arbitrary probability. Mera [22] developed a computer agent to be able to transit a mental state in MSTN based on analysis of emotion by EGC method. EGC calculates emotion and the type of the aroused emotion is used to transit mental state [22].

However, when the system calculates the mental state of the agent, some emotions are gathered and dealt with an emotion group. Furthermore, the mental state transition considers only the most effective emotion group. In spite that EGC can output multiple emotions in parallel, most of the emotions are ignored in the system. On the other hand, the transition of the mental state of human is caused not only from the strongest emotion but also from some weak emotions. The effects are too ambiguous to express them using strict rules.

In this paper, we propose a method to classify input emotions automatically to develop our Mental State Transition method. In order to deal with effect from all of aroused emotions at the same time, Self Organizing Map (SOM) is applied. SOM learns multi-dimensional vectors without teacher signals and classified them into some groups on two-dimensional layer. The features of the SOM are the EGC output (20 emotions), the results of word matching (8 emotions), and the type of present mental state (7 states).

The remainder of this paper is organized as follows. Section 2 and Section 3 explain the emotion calculating process by EGC and the mental state calculating method using MSTN, respectively. Section 4 explains input emotion classifying method using SOM. The experimentation of our proposed method using a scenario is shown in Section 5. Conclusions and future works are presented in Section 6.

II. EMOTION GENERATING CALCULATIONS METHOD

Initially, the Emotion Generating Calculations method (EGC) mechanism is explained briefly. The EGC extracts

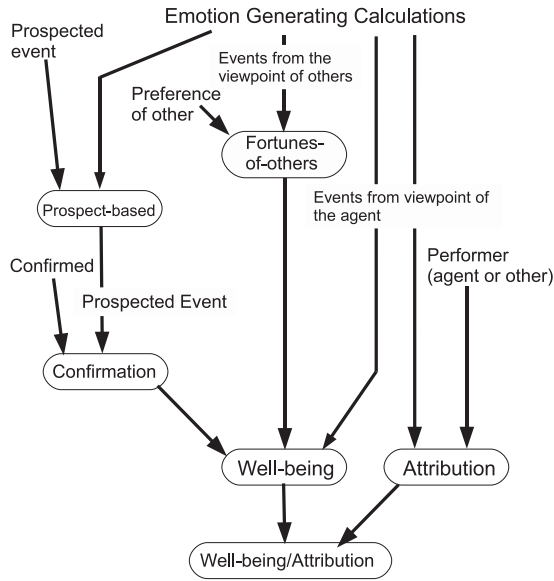


Fig. 1. Dependency among Emotion Groups

pleasure/displeasure from an input event expressed by the case frame representation. Favorite Values (FVs) which show the degree of like/dislike for objects are defined. The FVs are given a real number on a ratio of [-1.0, 1.0]. Each equation consists of two or three terms like subject, object, and predicate and it calculates the pleasure/displeasure for the input event based on the relation among the terms. An emotional space is assumed as three-dimensional space. Pleasure/displeasure for input event is calculated by judging in which area the synthetic vector exists[17][23].

Based on emotion degree calculated by the EGC and the situation, the pleasure/displeasure is classified into 20 types of emotions. The classifying method requires judging such conditions as follows; “feeling for another,” “prospect and confirmation,” “approval/disapproval”[17][18]. The 20 emotions are classified into six emotional groups as follows; “joy” and “distress” as a group of “Well-Being”; “happy-for,” “gloating,” “resentment,” and “sorry-for” as a group of “Fortunes-of-Others”; “hope” and “fear” as a group of “Prospect-based”; “satisfaction,” “relief,” “fears-confirmed,” and “disappointment” as a group of “Confirmation”; “pride,” “admiration,” “shame,” and “reproach” as a group of “Attribution”; and “gratitude,” “anger,” “gratification,” and “remorse” as a group of “Well-Being/Attribution.” Figure 1 shows the dependency among the groups of emotion types.

III. MENTAL STATE TRANSITION NETWORK(MSTN)

A. Mental State Transition Network[21]

The Mental State Transition Network, proposed by Ren[21], has the basic concept of approximating to human physiological and mental responses. He focuses not only information included in the elements of phonation, facial expressions, and speech usage, but also human psychological characteristics based on the latest achievements of brain science and

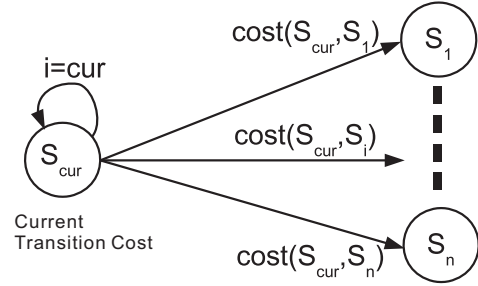


Fig. 2. Transition Cost

psychology in order to derive transition networks for human psychological states. The assumption of discrete emotion state is that human emotion are classified into some kinds of stable discrete states, called “mental state,” and the variance of emotions causes in the transition from a state to other state with a probability. The probability of transition is called “transition cost” and it is not the same. Moreover, with no stimulus from the external world, the probability may converge to fall into a certain value as if the confusion of the mind leaves and is relieved. On the contrary, with a stimulus from external world and/or attractive thought in internal world, the continuous accumulated emotional energy cannot jump to the next mental state and remains in its mental state still. The simulated model of MSTN[21] describes the simple relations among some kinds of stable emotions and the corresponding transition probability. The probability was calculated from analysis of many statistical questionnaire data.

The MSTN denotes a mental state as a node, a set of some kinds of emotion state S , the current emotional state S_{cur} , and the transition cost $cost(S_{cur}, S_i)$, which is the transition cost as shown in Figure 2.

In [21], six kinds of emotion state and quiet state are considered for questionnaire. That is, the transition table of $cost(S_i, S_j)$, $i = 1, 2, \dots, 7$, $j = 1, 2, \dots, 7$ is prepared. The experiment for participants was examined without stimulus from external world. Each participant fills in the numerical value from 1 to 10 that means the strength of relation among emotional states. Moreover, same questionnaire was examined under the condition with the stimulus from external world. 200 participants answered the questionnaire. The numerical values in Table I show the statistical analysis results. The transition cost from each current state to the next state is summarized to 1.

B. EGC with Mental State Transition Network[24]

Even if there are no signals from external world, the mental state will change a little. In this case, the transition costs represented in Table I are adopted to calculated emotion by EGC. In this paper, we assume that the stimulus from an external world is the communication by language and the emotion is calculated as follows.

$\#(S_i \rightarrow S_j)$ is the number of transition from an emotional state S_i ($1 \leq i \leq 7$) to S_j ($1 \leq j \leq 7$). The transition cost is calculated by using the total of $\#(S_i \rightarrow S_j)$ for all emotional

TABLE I
TRANSITION COST IN MSTN

current\next	happy	quiet	sad	surprise	angry	fear	disgust
happy	0.421	0.362	0.061	0.060	0.027	0.034	0.032
quiet	0.213	0.509	0.090	0.055	0.039	0.051	0.042
sad	0.084	0.296	0.320	0.058	0.108	0.064	0.068
surprise	0.190	0.264	0.091	0.243	0.086	0.076	0.048
angry	0.056	0.262	0.123	0.075	0.293	0.069	0.121
fear	0.050	0.244	0.137	0.101	0.096	0.279	0.092
disgust	0.047	0.252	0.092	0.056	0.164	0.075	0.313

state. Eq.(1) means that the higher transition cost is, the less transition occurs.

$$cost(S_i, S_j) = 1 - \frac{\#(S_i \rightarrow S_j)}{\sum_{k=1}^7 \#(S_i \rightarrow S_k)}, 1 \leq i, j \leq 7 \quad (1)$$

Eq.(2) calculates the next emotional state from the original emotional state by using the emotion vector.

$$next = argmax_i \left(\frac{e_i}{cost(S_{cur}, S_i)} \right), 1 \leq i, j \leq 7 \quad (2)$$

The emotion vector consists of nine kinds of emotion groups which are classified 28 kinds of emotions as shown in Table II. Figure 3 shows the mental state transition network by using EGC. The circled numbers in Figure 3 are the number in the left side of Table II. The e_i is the strength of mode group i and $e_i (1 \leq i \leq 9)$ is the maximum value of elements belonged in the each set e_i as follows.

$$\begin{aligned} e_1 &= \max(e_{gloating}, e_{hope}, \dots, e_{shy}) \\ e_2 &= \max(e_{joy}, e_{happy-for}) \\ &\vdots \\ e_9 &= \max(e_{surprise}) \end{aligned}$$

The emo in Eq.(3) calculates the maximum emotion group k according to the transition cost between current state and next state.

$$emo = argmax_k \left(\frac{e_k}{cost(S_{cur}, next(S_{cur}, k))} \right), 1 \leq k \leq 9 \quad (3)$$

, where $next(S_{cur}, k)$ is transition from the current state to next state by selecting mode group k .

C. Mental State Transition Learning Network[25]

Mental State Transition Network may meet the distortion by inputted the signals from external world. For such a case, it might be natural to adjust the transition cost. Eq.(3) is useful for the change of transition cost, because it can select only a mode among nine kinds of emotion group. Then if human feels strong emotion, they can forget the event which aroused the emotion, but the emotion remains in their mind. Therefore, if e_i is larger than the threshold value, the modification of e_i ,

TABLE II
CLASSIFICATION OF GENERATED EMOTION

Emotion Group	Emotion
1	gloating, hope, satisfaction, relief, pride, admiration, liking, gratitude, gratification, love, shy
2	joy, happy-for
3	sorry-for, shame, remorse
4	fear-confirmed, disappointment, sadness
5	distress, perplexity
6	disliking, hate
7	resentment, reproach, anger
8	fear
9	surprise

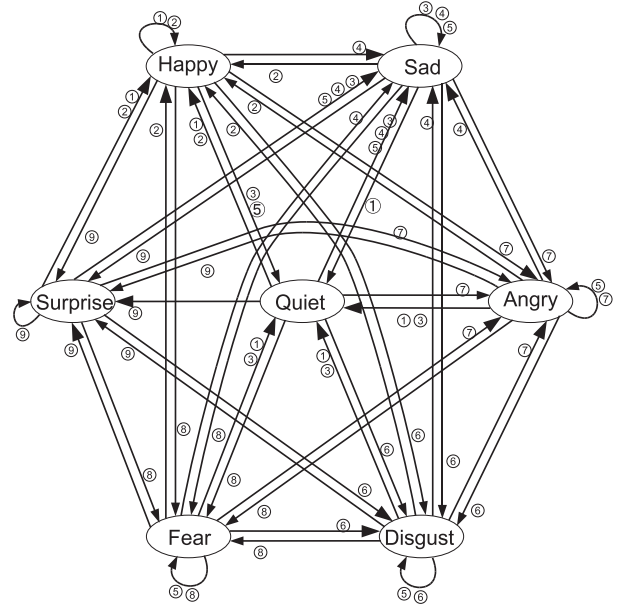


Fig. 3. Mental State Transition Network with EGC

which takes the maximum value of emotion, is required as follows.

$$\begin{aligned} Modify_{e_i} &= \alpha_i[t] \times e_i \\ Modify_{otherwise} &= \frac{1}{5} \alpha_i[t] \times e_i \end{aligned} \quad (4)$$

, where $\alpha_i[t]$ is a decay or amplifier parameter depending on emotion group i and time t . ‘5’ means current state to i and itself were excluded from seven kinds of mental states. When we feel a kind of strong emotion, we cannot get out of the situation. Therefore, Eq.(4) means that only a value to the specified emotion still be large.

Figure 4 shows an example of when the current state is ‘Quiet’ and the next state is ‘Sad.’ If the $Modify_{e_i}$ is a positive number, the mental state transition learning network decreases $Modify_{otherwise}$ from the current transition cost connected with the dot lines and adds $Modify_{e_i}$ to the current transition cost with the normal line. There is no modification for the self-loop.

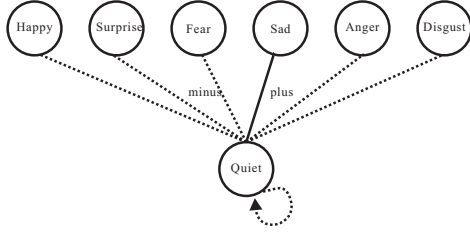


Fig. 4. Concept of Learning in MSTN

Although the value of $\alpha_i[t]$ depends on emotion group i , we can see the continuousness of emotion in Table I. That is, the emotion is not easy to change and remains in its situation, because human emotion may be stored in the memory. As shown in Table I, the values of transition cost from i to i , $cost(S_i, S_i)$, and that from i to “Quiet”, $cost(S_i, S_{quiet})$ are higher than other transition costs. Therefore, for such cases, $\alpha_i[t]$ is set to high as if the emotion remains still. However, the $cost(S_{cur}, S_i)$ cannot exceed 1. Therefore, we set the threshold θ to the maximum value of $cost(S_{cur}, S_i)$. On the contrary, even if there is no stimulus from external world, the strength of emotion will decrease gradually depending time t . The phenomenon resembles to forgetting curve which Hermann Ebbinghaus[26] discovered the exponential nature of forgetting: $R = e^{-\frac{t}{S}}$, where R is memory relation, S is the relative strength of memory, and t is time.

D. Simulation of Mental State Transition Model

The following example is a process of mental state transition method from point of view of Juliet when an event “Romeo dates with Juliet” is inputted.

Apply Causal Relationship to Physical Event

“Romeo dates with Juliet.”
 → “Romeo will marry with Juliet.”
 → “Juliet’s parents will oppose the marriage.”

Arouse pleasure/displeasure

input event: “Romeo dates with Juliet.”
 predicate = “date with” FV=+0.6
 subject = “Romeo” FV=+0.9
 object = “Juliet” FV=+1.0
 → Pleasure

Calculate complicated emotions

- (1) arouse “pleasure” → “Happy”
- (2) action taker is “Romeo” and “Juliet” feels “Happy”
 → “Admiration”
- (3) “Happy” and “Admiration” are aroused → “Gratitude”

“Romeo will marry with Juliet.”
 → “Joy” and “Hope”

“Juliet’s parents will oppose the marriage.”
 → “displeasure” of Juliet’s parents → “Distress” and “Fear”

Transit Mental State

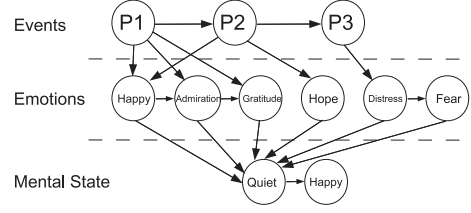


Fig. 5. Simulation Result

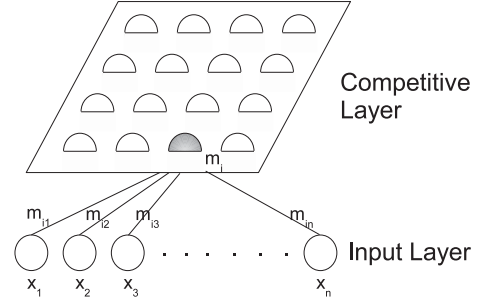


Fig. 6. An Overview of SOM

present mental state → “Quiet”
 $e_1 = 1.47, e_2 = 1.47, e_5 = 1.10, e_8 = 1.10$
 next mental state → “Happy”

Figure 5 shows the simulation result. Node P1, P2, and P3 indicate “Romeo dates with Juliet,” “Romeo will marry with Juliet,” and “Juliet’s parents will oppose the marriage,” respectively.

IV. CLASSIFYING EMOTION VECTOR USING SOM

A. Self Organizing Map

The basic SOM [27] can be visualized as a sheet-like neural network array as shown in Figure 6, the cells (or nodes) of which become specifically tuned to various input signal patterns or classes of patterns in an orderly fashion. The learning process is competitive and unsupervised, which means that no teacher is required to define the correct output for an input. Only one map node called “winner node” at a time is activated corresponding to each input. The map consists of a regular grid of processing units. A model of some multidimensional observations, eventually a vector consisting of features, is associated with each unit. The map attempts to represent all the available observations with optimal accuracy using a restricted set of models. At the same time the models become ordered on the grid so that similar models are close to each other and dissimilar models are far from each other.

A sequential regression process usually carries out fitting to the model vectors. The n is the number of input signals. An input vector x is compared with all the model vectors $m_i(t)$. The best-match unit on the map is identified. The unit is called the winner. For each sample $x = \{x_1, x_2, \dots, x_n\}$, first the winner index c (best match) is identified by the condition.

$$\forall i, \|x - m_c\| \leq \|x - m_i\| \quad (5)$$

TABLE III
INPUT FEATURES FOR SOM

Group	Feature
EGC	gloating, hope, satisfaction, relief, pride, admiration, gratitude, gratification, joy, happy-for, sorry-for, shame, remorse, fear-confirmed, disappointment, distress, resentment, reproach, anger, fear
word matching	liking, love, shy, sadness, perplexity, disliking, hate, surprise
mental state	quiet, happy, surprise, fear, sad, anger, disgust

After that, all model vectors or a subset of them that belong to nodes centered around node c are updated at time t as

$$\begin{cases} \mathbf{m}_i(t+1) = \mathbf{m}_i(t) + h_{ci}(\mathbf{x}(t) - \mathbf{m}_i(t)) & \text{for } \forall i \in N_c(t) \\ \mathbf{m}_i(t+1) = \mathbf{m}_i(t) & \text{otherwise} \end{cases} \quad (6)$$

Here h_{ci} is the neighborhood function, a decreasing function of the distance between the i th and c th nodes on map grid. The $N_c(t)$ specifies the neighborhood around the winner in the map array. This regression is usually reiterated over the available samples.

At the beginning of the learning process, the radius of the neighborhood is large and the range of radius becomes small according to the convergence state of learning. That is, as the radius gets smaller, the local correction of the model vectors in the map will be more specific. The h_{ci} also decreases during learning.

B. Features

Input data for SOM is multi-dimensional vector. In this proposed method, value of each dimension corresponds to the degree of each emotion. The mental state transition method using MSTN [21] calculates next mental state based on aroused emotions from input event and present mental state. Although the method considers 28 types of emotions, some of them cannot calculate by EGC. Such emotions are calculated by word matching method which checks whether typical emotion expressing words such as “surprise,” “suddenly,” “disgust,” and so on are contained in the input event.

Table III shows the features which this proposed method deals. 20 features are calculated from EGC, and 8 features are calculated by word matching.

Furthermore, present mental state should be inputted because same input emotion vector may cause the different mental state. For example, slight happy leads the mental state “Happy” from “Quiet” but it will not be able to cause the mental state “Happy” from deep sadness.

We prepared seven features for mental states because MSTN deals with seven types of mental states. The value of the features are 1 or 0.

V. EXPERIMENTATION

In order to confirm the classification of emotion vectors by SOM, we simulated the emotion vectors appeared in a story “Romeo and Juliet [28].” There were 31 events which arouse emotion in ten scenes. Results of mental state transition were

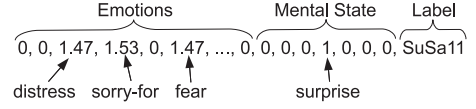


Fig. 7. Example of Input Data

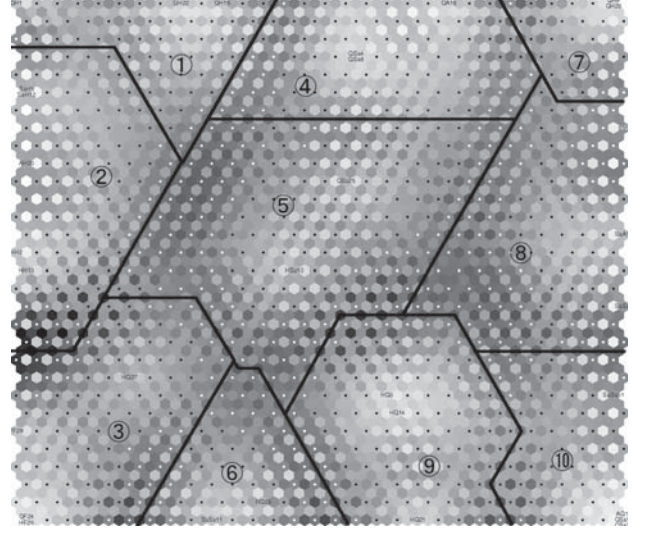


Fig. 8. Generated map by SOM

calculated by using the method as shown in section 3. At the beginning of scenes, the mental state was “Quiet.” Then, input emotion vector causes transition of the mental state to next state.

We experimented with our method using a 15*15 sized map and it was trained by 10,000 epochs. Figure 7 is an example of input vector for an event “if any of her kinsmen should find him there, it would be death to him.” This event arouses three emotions (fear, distress, and sorry-for) by using EGC. Because an event just before the input event caused the mental state “Surprise,” the present mental state is also “Surprise.” The value of the mental state feature for “Surprise,” is 1 and the values of the other features are 0. All the input data are attached the label. The labels consist of present mental state + next mental state + serial number. Q, H, Su, F, Sa, A, D are indicates quiet, happy, surprise, fear, sadness, anger, and disgust, respectively. Because there are not any disgust events in this simulation scenario, we could not simulate about the mental state disgust.

Figure 8 is the learning result of 31 input vectors by using SOM. There are ten groups in the map. The vectors for each group have the tendencies of the mental state transitions as shown in Table IV.

Input vectors in group (1) and (7) make transition the mental state from Quiet to Happy. However, vectors in group (1) arouses happy-for emotion, and vectors in group (7) arouses hope emotion. Group (3) has two areas at upper-right and lower-left. The difference between these areas is the present mental state. Although vectors in the group arouse surprise,

TABLE IV
TENDENCIES OF MENTAL STATE TRANSITION

number	mental state transition
(1)	from Quiet to Happy
(2)	to Happy
(3)	to Fear / from Happy to Quiet
(4)	from Quiet to Sadness or Anger
(5)	to Surprise
(6)	(negative emotion)
(7)	from Quiet to Happy
(8)	from Sadness to Anger, Sadness, Quiet
(9)	from Happy to Quiet
(10)	to Sad or Quiet

mental state transits to fear when the present mental state is quiet. On the other hand, when the present mental state is happy, it is enfeebled and mental state transits to quiet. It corresponds to mental state transition using MSTN.

Happy-for, fear, hope, and surprise calculated by EGC have strong relation to the classification of group on the map. However, some vectors in group (6) and (8) cannot be classified by EGC data. We should improve EGC method or find some other features to be able to classify such vectors. Furthermore, some clusters in SOM may slide by a little change of EGC output. We are going to propose a method which learns such change and makes effect to mental state transition adaptively.

VI. CONCLUSION

In this paper, we proposed a mental state transition method which can consider all of aroused emotions. In order to deal with such emotions at the same time, SOM was applied. The degrees of 20 emotions and 8 features of word matching and seven mental states were used as features. The degrees of emotions were calculated by using EGC. The map generated by SOM indicated several groups of input vectors. From the learning result of SOM, some rules were obtained which classify emotion vector and suggest the tendencies of mental state transition.

For the future work, the threshold for mental transition should be implemented because weak emotions rarely have enough energy to transit mental state. The conflict among aroused emotions and ambiguous state of emotion also should be considered.

REFERENCES

- [1] K.Fujiwara and I.Daibo, *The Function of Positive Affect in a communication content: Satisfaction with Conversation and hand movement*, The Japanese Journal of Research on Emotions, Vol.17, No.3, pp.180-188, 2010 (Japanese)
- [2] K.T.Strongman, *The Psychology of Emotion, Theories of Emotion in Perspective*, John Wiley & Sons, 1996.
- [3] M.Power, and T.Dalgleish, *Cognition and Emotion -From Order to Disorder*, Psychology Press, 2007.
- [4] M.Kimura, I.Daibo, and M.Yogo, *The Study of Emotional Contagion from the Perspective of Interpersonal Relationships*, Social Behavior and Personality, Vol.36, No.1, pp.27-42, 2008.
- [5] M.Nagamachi, and A.M.Lokman, *Innovations of Kansei Engineering (Industrial Innovation)*, CRC Press, 2010.

- [6] M.Matsunaga, T.Isowa, K.Kimura, M.Miyakoshi, N.Kanayama, H.Murakami, S.Fukuyama, J.Shinoda, J.Yamada, T.Konagaya, H.Kaneko, and H.Ohira, *Associations among positive mood, brain, and cardiovascular activities in an affectively positive situation*, Brain Research, Vol.1263, pp.93-103, 2009.
- [7] P.S.Foster, V.Drago, D.G.Webster, D.W.Harrison, G.P.Crucian, and K.M.Heilman, *Emotion Influences on Spatial Attention*, Neuropsychology, Vol.22, No.1, pp.127-135, 2008.
- [8] J.Y.Park, B.M.Gu, D.H.Kang, Y.W.Shin, C.H.Choi, J.M.Lee, and J.S.Kwon, *Integration of Cross-Modal Emotional Information in the Human Brain: an fMRI study*, Cortex; a journal devoted to the study of the nervous system and behavior, Vol.46, No.2, pp.161-169, 2010.
- [9] R.Descartes, *the passions of the Soul: Les Passions De Lame*, Hackett Publishing Company, Indianapolis IN, 1646, 1989.
- [10] I.Kant, *Critique of Judgment*, Tr.J.H. Bernard, Macmillan & Co., London, 1790, 1914.
- [11] J.P.Sarte, *Existentialism and Human Emotions*, Citadel Press; Reissue edition 1984
- [12] C.G.Jung, *Psychological Types*, In the collected Works, Vol.6, Bollingen Series XX, 1971, Princeton University Press, Princeton, NJ, 1921
- [13] L.I.Perlovsky, *Emotions, Learning, and Control*, Proc. of Intl. Symp. Intelligent Control, Intelligent Systems & Semiotics, Cambridge MA, pp.131-137, 1999.
- [14] L.I.Perlovsky, *The Knowledge Instinct*, Basic Books. New York, NY, 2006.
- [15] L.I.Perlovsky, *Integrated Emotions, Cognition, and Language*, Proc. of IJCNN2006, pp.2879-2884, 2006.
- [16] T.Ichimura, T.Yamashita, K.Mera, A.Sato, N.Shirahama, *Emotion oriented intelligent systems*, In *Internet-based Intelligent Information Processing Systems*, R.J.Howlett, N.S.Ichalkaranje, L.C.Jain, G Tonfoni Eds., pp.183-226, World Scientific Publishing Company, 2003).
- [17] K.Mera, *Emotion Orientated Intelligent Interface*, Doctoral Dissertation, Tokyo Metropolitan Institute of Technology, Graduate School of Engineering, 2003.
- [18] K.Mera, T.Ichimura, and T.Yamashita, *Complicated Emotion Allocating Method based on Emotion Eliciting Condition Theory*, Journal of the Biomedical Fuzzy Systems and Human Sciences, Vol.19, No.1, pp.1-10, 2003.
- [19] K.Mera and T.Ichimura, *Emotion Generating Method on Human - Computer Interfaces In Computationally Intelligent Hybrid Systems: The Fusion of Soft Computing and Hard Computing*, Seppo J. Ovaska Eds., pp.277-312 Wiley-IEEE Press, 2005.
- [20] C.Elliott, *The Affective Reasoner: A process model of emotions in a multi-agent system*, Ph.D thesis, Northwestern University, The Institute for the Learning Sciences, Technical Report No. 32, 1992.
- [21] F.Ren, *Recognizing Human Emotion based on appearance information and Mental State Transition Network*, IPSJ SIG Technical Report, pp. 43-48, 2006 (Japanese).
- [22] K.Mera, T.Ichimura, Y.Kurosawa and T.Takezawa, *Mood Calculating Method for Speech Interface Agent by using Emotion Generating Calculation Method and Mental State Transition Network*, Journal of Japan Society for Fuzzy Theory and Intelligent Informatics, Vol.22, No.1, pp.10-24, 2010 (Japanese).
- [23] K.Mera, T.Ichimura, T.Aizawa, and T.Yamashita, *Invoking Emotions in a Dialog System based on Word- Impressions*, Journal of Japan Society of Artificial Intelligence, Vol.17, No.3, pp.186-195, 2002 (Japanese).
- [24] A. Hakamata, S. Tsuchiya, and F. Ren, *Expression Generation Method of Conversation Agent based on Mental Model*, JSAI-SIG-SLUD, Vol.52, pp.3-8, 2008 (Japanese).
- [25] T.Ichimura, K. Mera, *Estimation of Hierarchical Emotion in Mental State Transition Learning Network*, Proc. of 5th International Workshop on Computational Intelligence and Applications 2009 (IWCIA2009), IEEE SMC Hiroshima Chapter, pp.35-40, 2009.
- [26] Hermann Ebbinghaus, *Memory: A Contribution to Experimental Psychology*, in New York by Teachers College, Columbia University, 1885; <http://psy.ed.asu.edu/classics/Ebbinghaus/index.htm>, (Internet resource)
- [27] T. Kohonen, "Self-Organizing Maps (3rd Ed.)", Springer-Verlag, 1997.
- [28] C.Lamb, M.Lamb, *Romeo and Juliet*, In "Tales from Shakespeare": Puffin Classics, 1807.