A Model of Mental State Transition Network

Hua Xiang Member (The University of Tokushima)

Peilin Jiang Non-member (The University of Tokushima)

Shuang Xiao Non-member (The University of Tokushima)

Fuji Ren Non-member (The University of Tokushima)

Shingo Kuroiwa Member (The University of Tokushima)

Keywords : artificial psychology, a mental state transition network, predict, psychological questionnaires

Emotion is one of the most essential and basic attributes of human intelligence. Current Artificial Intelligent research is concentrating on physical components of emotion, rarely is it carried out from the view of psychology directly. Study on the model of artificial psychology is the first step in the development of human-computer interaction. A pragmatic mental model is the fundament of some key topics such as recognition and synthesis of emotions. In this paper a Mental State Transition Network Model is proposed to detect human emotions. By a series of psychological experiments, we present a new way to predict coming human's emotions depending on the various current emotional states under various stimuli. Besides, people in different

Network for describing the transitions in distribution among the emotions and relationships between internal mental situations and external are concluded. Further more the coefficients of the mental transition network model were achieved. Comparing seven relative evaluating experiments, an average precision rate of 0.843 is achieved using a set of samples for the proposed model.

In the theory of the Mental State Transition Network, it hypothesizes that the human emotion is simplified to be seven basic categories and to transit among these discrete states. These states are defined as mental states. The transitions among them can be happened under certain conditions (stimuli). By means of statistic gathering from a large set of psychological questionnaires,

transition from state a_i to state a_j is $P(a_j | a_i, E) = P(a_j | a_i) \cdot P(E)$ We use the Conditional Probability Table as the foundation of the model of Mental State Transition Network. The questionnaires were administered in a classroom setting. Each of the participants was required to fill out the questionnaire giving serious thought about emotional state transitions. The experiment firstly requires the participants to imagine a certain emotional situation under certain clues, and select the possibility of what the next emotional state will be with some effect. Then we compare each item to calculate the probabilities. The clues include seven different standard types which category into seven prototype emotions.

Under Neutral Condition							
	Happy	Calm	Sad	Surprise	Angry	Fear	disgust
H	0.443	0.210	0.079	0.175	0.052	0.047	0.042
C	0.368	0.546	0.314	0.287	0.285	0.262	0.288
Sa	0.054	0.081	0.338	0.081	0.118	0.120	0.085
Su	0.050	0.048	0.051	0.257	0.068	0.093	0.051
A	0.024	0.035	0.093	0.085	0.305	0.086	0.146
F	0.028	0.039	0.058	0.068	0.059	0.301	0.068
D	0.028	0.037	0.063	0.044	0.109	0.087	0.317

Under Happy Condition							
	Happy	Calm	Sad	Surprise	Angry	Fear	disgust
H	0.596	0.575	0.462	0.522	0.432	0.400	0.462
C	0.202	0.203	0.231	0.177	0.219	0.229	0.223
Sa	0.027	0.029	0.097	0.043	0.046	0.044	0.035
Su	0.133	0.151	0.134	0.200	0.155	0.153	0.131
An	0.012	0.013	0.029	0.019	0.093	0.026	0.034
F	0.015	0.017	0.021	0.017	0.023	0.114	0.031
D	0.011	0.010	0.022	0.018	0.029	0.031	0.081

genders and characters are taken into consideration in our investigation. According to the psychological experiments data derived from 200 questionnaires, a Mental State Transition

By the statistic of psychological questionnaire, we have obtained the transition probabilities and the transitional constraints among various conditions.

A Model of Mental State Transition Network

Hua Xiang [*]	Member
Peilin Jiang [*]	Non-member
Shuang Xiao [*]	Non-member
Fuji Ren ^{*,**}	Non-member
Shingo Kuroiwa [*]	Member

Emotion is one of the most essential and basic attributes of human intelligence. Current AI (Artificial Intelligence) research is concentrating on physical components of emotion, rarely is it carried out from the view of psychology directly⁽¹⁾. Study on the model of artificial psychology is the first step in the development of human-computer interaction. As affective computing remains unpredictable, creating a reasonable mental model becomes the primary task for building a hybrid system. A pragmatic mental model is also the fundament of some key topics such as recognition and synthesis of emotions. In this paper a Mental State Transition Network Model⁽²⁾ is proposed to detect human emotions. By a series of psychological experiments, we present a new way to predict coming human's emotions depending on the various current emotional states under various stimuli. Besides, people in different genders and characters are taken into consideration in our investigation. According to the psychological experiments data derived from 200 questionnaires, a Mental State Transition Network Model for describing the transitions in distribution among the emotions and relationships between internal mental situations and external are concluded. Further more the coefficients of the mental transition network model were achieved. Comparing seven relative evaluating experiments, an average precision rate of 0.843 is achieved using a set of samples for the proposed model.

Keywords: artificial psychology, a mental state transition network, predict, psychological questionnaires

1. Introduction

Not only many people believe that emotions distinguish man from the machines, but also AI (Artificial Intelligence) scientists have merely focused on logical inference and rational thinking for a quite long time. Nevertheless more and more scientific findings indicate that emotions play an essential role in decision making, perception, learning, and moreover they influence the very mechanisms of rational thinking⁽³⁾. Nowadays a machine that lacks of emotion computing ability cannot realize artificial intelligent sufficiently and cannot meet the increasing requirement of human-computer interaction either. Along with the technological development and new era of "individuality", emotion has become a fashionable topic within AI (Artificial Intelligence) and cognitive science in these couple of years.

As a matter of fact, people have a really long history in studying the natures of emotions even from the Aristotle's time. Nearly hundred definitions of emotion and related concepts have been recorded and categorized⁽⁴⁾. Psychological tradition which has probed the nature of emotion systematically are shaped by major figures in several discipline—philosophy, biology, and

Psychology⁽⁵⁾. The physical indicators include respiration, heart rate, temperature, electro-dermal response, perspiration, muscle action potentials etc. And the behavior indicators include facial expression, voice intonation, gestures, movements, posture, pupil dilation etc. For instance, some defined emotions in terms of observable physical behaviors (such as weeping, jump for joy, etc.), measurable physiological changes (such as sentic modulation⁽³⁾) or conscious experience (such as mood, sentiment) etc.⁽⁶⁾. Even many preliminary studies have done in physical and behavior measures, none of them can describe emotions accurately and thoroughly. For example H.Yamasaki, K.S Labar, and G. McCarthy used functional MRI (Magnetic Resonance Imaging) to determine whether attentional and emotional functions are segregated into dissociable prefrontal networks in the human brain⁽⁷⁾. M. Bradley, Maurizio Codispoti explored the natures of emotions by measuring several physical indicators in their study in 2002. They studied different responses to various picture stimuli between men and women in multiple response systems, including kin conductance, heart rate, reflex modulation, facial EMG (electromyography) activity, and evaluative judgments of the participants.⁽⁸⁾ In another methodologically sophisticated study Hager and Ekman examined whether facial expressions of emotions are biased or asymmetrical in ways predicted by theories of hemispheric specialization for emotion-relevant processing. They stud-

^{*} Faculty of Engineering, The University of Tokushima, Japan, 770-8506

^{**} School of Information Engineering, Beijing University of Posts and Telecommunication, China, 100876

ied both spontaneous and simulated facial expressions of emotion and quantitatively measure all facial movement exhibited under these conditions, including the symmetry of facial actions (differences in intensity of muscular contraction for each distinct type of facial action that occurred)⁽⁹⁾. Everyday usage divides emotional states into categories that are related to time, reflecting the fact that emotional life has a definite temporal structure. Emotion in its narrow sense—full-blown emotion is generally short lived and intense⁽⁷⁾. Emotions may be defined as states elicited by reinforcements (rewards and punishments)⁽⁶⁾. An example of an emotion might thus be happiness produced by being given a reward, such as a pleasant touch, praise, or winning a large sum of money. Another example of an emotion might be fear produced by the sound of a rapidly approaching bus, or the sight of an angry expression on someone's face.

As a complex and advanced human intelligence, emotions are multidimensional psychological phenomena. They are both cognitive and physical⁽³⁾. Generally 4 aspects of emotions are taken into consideration in contemporary psychology: cognitive assessment, emotional states, emotional experience, and emotional expression⁽¹¹⁾. Therefore the emotion information processing can be studied by various approaches: physiological, psychological and information theoretic and computer engineering. The approach of building an emotion information processing model is Analysis-by-Synthesis⁽¹²⁾. Consequently, human emotion recognition is obviously becoming the first obligatory subject for building a more humanoid machine. As R. Cowie and E. Douglas-Cowie pointed out: human emotion recognition has gained more attention because of the desire to develop natural and effective interfaces for human-computer interaction application⁽¹³⁾.

Though discussion of primary emotion theory and dimension emotional theory has been debated decades, both of them reflect one aspect of emotion. There is definitely some cross-culture emotions widely exist in each nationality⁽¹⁴⁾, and at the same time evidences also show that separation between positive and negative affective emotions exist certainly⁽¹⁵⁾. Numerous physical experiments have been done (Ekman⁽¹⁶⁾, Winton⁽¹⁷⁾, Frijda⁽¹⁸⁾ etc.), but external information such as language, voice and facial expressions are not enough to model human emotion⁽²⁾. Because sometimes two different emotions may have very similar physiological indicators. For example: blood vessels expansion, red face, high level of pitch will occur when people in either happy or angry mood.

Though, various emotional models have been proposed in previous studies (the Plutchik's Multidimensional Model⁽¹⁹⁾, the Circumplex Model of Affect etc.⁽²⁰⁾), there are few studies in which describe the mental situation appropriately in a numerical way, that can be simulated in a machine directly. For this reason, an emotion model, which can be realized by engineering, should necessarily be created. Picard pointed out that a model such as the HMM (Hidden Markov Model) can be used not only to recognize certain affective patterns, but

also to predict what state a person is most likely to be in next, given the state they are in now⁽³⁾. Associating with classical information process model⁽²¹⁾ ⁽²²⁾ ⁽²³⁾ and cognitive information model⁽²⁴⁾. We can deduce process of emotion-information processing based on emotional states.

In this paper, we present a novel model of Mental State Transition Network to simulate human emotion. The model explores human emotions from the viewpoints of both engineering and psychology; simultaneously it provides a new method to predict the future emotion state in natural equilibrium. This model is derived from the common sense emotional events compilations and the simplified mental network by considering the whole priori conditional probability under the various affective environments. The detail network structure is acquired from the psychological experiment designed on the basis of the Mental Transition State Network and be testified by random data from 50 people survey.

In the theory of the Mental State Transition Network, it hypothesizes that the human emotion is simplified to be seven basic categories and to transit among these discrete states. These states are defined as mental states. The transitions among them can be happened under certain conditions (stimuli). Nevertheless, there existed some certain expectation value with some external causes. We consider the whole emotional states movements of human's heart as a similar Markov random process. By means of statistic gathering from a large set of psychological questionnaires, the conditional transition probabilities among mental states can be calculated. Accordingly, we believed that the model is quite useful in reflecting some common aspects of human emotion. And even if the model is still rudimentary and not absolutely precise yet, the high precision rate which was obtained from further test experiments prove that the model is reliable and pragmatic to a certain extent.

2. Model Introduction and Analysis

2.1 The Emotional Information Processing Based on the Mental States Transition Network

As we mentioned above, emotion can usefully be defined as states elicited by reinforcements⁽²⁰⁾. These reinforcements, or we can call them stimuli, can be considered as a kind of emotional information. For emotion that has four aspects⁽¹¹⁾, we can learn that emotional information processing is supposed to comprise these four aspects.

Emotional information processing has some attributions of common information processing, but at the same time in the psychological phenomena, it has some unique attributions of cognitive psychology as well. Classical information processing model includes several elements: information resource, information transmission, information cognition, information regeneration, information effect, and information destination. Similarly, emotional information processing also has similar procedure. Emotional information occurs when environmental conditions change. At this point, the environmental changes can be considered as emotional information

Fig. 1. An emotional information processing based on a Mental State Transition Network

changes.

As Figure 1 shows: emotions are elicited when environments are changing. When stimuli are given, the emotional information (visual, auditory, taste, smell, tactile information etc) is required by the sensors (eyes, ears, tongue, nose, skin etc.)^{(24) (3)}. Then the emotional information is transmitted from external environments to the human mental world by the neural system. At this time, the cognitive system exchange information with memory and assess for the stimuli. Associating with the cognitive assessment and match up to memory, the emotional state changes. Changing of emotional states arouse different emotional experiences in human mental world, simultaneously different emotional expressions occur by effectors in physiology, behavior or “Subjective Language Report” (a psychological measure—people report their emotional experience by language description)⁽¹¹⁾.

2.2 The Emotion Recognition Method Based on a Mental State Transition Network and the Common Sense Emotion Events Though contemporary cognitive research has made obvious progression with intellectual processing simulating (for instance: think, judgment, decision, learning, language, attention etc.), rare emotional processing can be simulated in appropriate approach. Current technology cannot provide an effective approach to detect human mental states directly, most of researches have to only focus on apparent of mind, same as research of emotions.

As we know almost every person can recognize and understand others emotion without any special training. And cognitive assessment to emotional information is too complex to be described by current technology.

Fig. 2. The Mental State Transition Network

So it is reasonable to believe that there are some common sense emotional events existed. In our study, for simplifying the problem, temporarily, we presume that the cognitive assessments to basic emotional stimuli are same. That is: a common emotional stimulus arouses a common cognitive assessment among common people. (For instance: a wedding arouses happiness, a funeral arouses sadness etc.) In that case, we can create a Common Sense Emotion Events Corpus to categorize the emotional information in some degree. And the changes of emotional states become the main object which needs study. As aforementioned viewpoint, emotion states express themselves internally as emotional experience, externally as various physical or psychological indicators. So we can study apparently the mind of the emotional states by using “Subjective Language Reporter”, such as psychological questionnaires.

2.3 The Model of the Mental State Transition Network After studying a vast amount of literature on the signs that indicate emotion, both within the psychological tradition and beyond it⁽³⁾, we have found six archetypal emotions (happy, sad, angry, surprise, fear, and disgust) as presented by Ekman⁽¹⁴⁾. These six archetypal emotions are all short lived and intense. They are all full-blown emotions. (To simplify the study, our experiment only takes account of the full-blown emotion.) And they are all widely accepted among different areas and are easier to be captured and described than other complex emotions⁽¹⁴⁾. In our research, we presume that human emotional state is made up by these six archetypal emotional states. Besides these, we add another emotional state—neutral state (or calmness). Then, these seven discrete emotional states can construct an emotional space and the movements of emotional state can be taken as a Markov process. In that case, we can create a mental (emotional) state transition network model of a human devoid emotional information (external stimulus), as Figure 2 shows: the circles indicate the seven emotional states. The central circle represents the neutral emotional state. The other six circles indicate the six basic emotional states (happy, sad, surprise, angry, fear, and disgust). The neutral state represents calmness (nearly or completely motionless; undisturbed). In other word, the neutral state means that people in peaceful or quiet mental sit-

Fig. 3. The Mental State Transition Network Under Stimuli

uation.

From the previous Mental State Transition Network, we can access the transition probability of the next emotion state from the current one under no effect agent. But in nature, the stimuli (emotional information) from environments are existed. Contrarily, there are little place without affective stimulation in practical. A more practical model should adapt these kinds of environments. The original mental state transition network without considering external affecting factors is setup to describe the basic foundation of the emotion transition. Theoretically, the network can predict the situations of emotion transition. But in fact, it can not support the complicated situations containing certain affective stimulating which happened in common. However, it is necessary to sophisticate the model for both in theory and in practical. Hence, we propose the network with the conditional probability tables (CPT) which describe the external stimulations.

In Figure 3, we can see the model is just like the original one. The difference is that arcs represent the transitional probability from one emotional state to another one while each circle replaced by a circle with an inward arrow standing for environment affective factors (emotional information) $P(E_k)$. Since what we are dealing with is in an emotion space composed by only seven emotion state, it hypothesizes that state in model is independent from each other. The probability of each emotion situation E_k is $P(E_k)$ and we have $\sum_k P(E_k) = 1, i = 1 \dots 7$. So we obtained the probability of transition from state a_i to state a_j is $P(a_j|a_i, E_k) = P(a_j|a_i) \cdot P(E_k)$. (“P” indicates the probability. “k” indicates types of environments. “i” and “j” indicate types of emotion states.)

3. Psychological Experiments and Analysis

3.1 Purpose and Participants of the Psychological Experiments The aim of the psychological experiments is to detect and describe human emotional states changes by “Subjective Language Report”. We use the Conditional Probability Table as the foundation of the model of Mental State Transition Network. In our experiments, CPT is obtained through psycholog-

Table 1. An Example of Psychological Questionnaires

Under happy, neutral...disgust emotional condition							
	happy	calm	sad	surprise	angry	fear	disgust
h	10	5	2	4	0	1	0
c	8	9	4	6	4	5	6
sa	5	3	6	4	5	3	4
su	3	4	4	5	4	5	4
a	0	1	2	2	6	2	5
f	2	2	4	2	2	7	4
d	1	2	3	1	5	3	8

ical questionnaires. In the experiment, we had about 200 participants recruited primarily from different high schools and universities in China and Japan respectively. The ages of the participants ranged from 16 to 30 years old. 112 of them were males and 88 were females. The questionnaires were administered in a classroom setting. Each of the participants was required to fill out the questionnaire giving serious thought about emotional state transitions.

3.2 Approach and Details of the Procedures for the Psychological Questionnaires The psychological experiment required participants to fill out a table which was designed for creating transitions among seven basic emotional states (calm (neutral), happy, sad, angry, surprise, fear, and disgust). The contents of the questionnaire are described below:

Firstly, individual information of the participant, including gender, age, educational level, nationality, occupation, and self-character assessment were asked for. Second, the tables were designed based on seven mental states. Thirdly, some hint sentences depicting the situations of different stimulations are given to the participants. For instance under happy condition, the hint sentences are: please imagine you are in a certain emotional state (for example, imagine that you are angry at current time), at this moment if happy thing is taken place (for example, you have passed an important exam or have obtained promotion...), what emotional state you would be at next period of time? Fourthly, an example was set up to teach the participants how to fill out the table.

Bio-informational Theory assumes that a mental imagine is an organized set of propositions that are stored in the brain’s long-term memory (Lang, 1979). Operation on propositions may elicit corresponding physiological responses⁽²⁵⁾. Based on this theory, many experiments using proposition have been carried out. For instance: in Keiichiro Tsuji’s experiments, participants were asked to give free description of the experiences they imagined with the sentences depicting the situations of a distinct stimulation of sensory modalities. Discomfort (affect) were divided into “sensation based affect” and “cognition-based affect”: the former is the affect induced directly by sensory event, as example by “fear darkness itself” to a stimulus sentence “make a night journey alone” (visual), whilst the latter is the affect aroused through cognitive processing, as exemplified

by “I get a fright by thinking I may be assaulted”⁽²⁶⁾.

Table 1 is an example of original investigating data we have collected. In the Table 1, the header row presents current emotional state, and the first column represents the emotional state at next period of time. The digital number in each lattice means the possibility of that situation. Here we use the $A_{(i,j)}$ to denote the transitional probability from the state a_j to the state a_i , $i, j \subseteq (1 \dots 7)$.

The experiment firstly requires the participants to imagine a certain emotional situation under certain clues, and select the possibility of what the next emotional state will be with some effect. Then we compare each item to calculate the probabilities. The clues include seven different standard types which contain seven prototype emotions.

In the questionnaire, the degree of possibility takes an integer value from 0 to 10. The maximum 10 means that there is 100% probability to transfer from the current state to this state and the minimum 0 means the possibility of transition is 0%. For example, the participant is required to imagine that they are in a happy emotional state at the current time. If there is nothing exciting happened to them (with neutral stimuli, for instance Chinese characters is a neutral stimuli for Western), they are required to imagine what emotional state they will be in next period and to fill in the column with value of 0 to 10. In original data Table 1, transitional probabilities from the current happy state into happy/ calm/ sad/ surprise /angry/ fear/ fear/disgust states are 10/8/5/3/0/2/1 respectively. From the questionnaires we found that the transitional probabilities are different among each emotional state. Additionally, to allow the participants to fill out the table more easily, the sum of all the lattices in each column is not equal, so we must normalize the original data before advanced computing.

4. Experimental Results Analysis

4.1 Normalization The original items in the table are designed to be easily filled out and cannot be directly calculated as the probability distribution. The following normalization is necessary⁽²⁷⁾ :

$$P(a_i|a_j) = A_{(i,j)} / \sum_j A_{(i,j)} \dots\dots\dots (1)$$

$$\sum_{j=1}^N P(a_i|a_j) = 1_{(N=7)} \dots\dots\dots (2)$$

4.2 The Conditional Transitional Probability Tables After data normalization, the unbiased estimated means are calculated to evaluate the CTPT (Conditional Transitional Probability Tables) of the model. From these tables, the unbiased mean value of each emotional state of the network under various conditions has been calculated. And we can predict the transition procedure of mental emotional states in various situations.

As studying CTPT, we can find some general constraints of these mental states transition situations under various conditions. By comparing the graphs of

Fig. 4. The Transition Probabilities Under Neutral Stimuli

Fig. 5. The Transition Probabilities Under Happy Stimuli

CTPT we found that transition probabilities under neutral stimuli is absolutely different from the others archetypal emotion stimuli. From Figure 4 we can see that the broken from different emotional states almost have the different tendency, but the broken lines in Figure 5 under the other six archetypal emotional stimuli almost have same tendency (the broken lines in each appendix figures have almost the same tendency). In Table 2, four general constraints of these mental states transition situations under neutral stimuli can be clearly concluded.

4.3 The Four Constraints under Neutral Condition Firstly, under neutral condition, if a participant is in a particular emotional state currently, he/she will most likely remain in that state. From Table 2 (Under Neutral Conditions) it is clearly that the highest probabilities of each column are all distributed on the diagonal, except for the surprise column (the data on diagonal is the second most likely for the surprise column). These facts indicate that full-blown emotions under neutral stimuli usually do not change in the short time. They will retain the current emotional state if there is not any typical affective effect.

Secondly, Surprise is a unique emotional state in which the transition probability is absolutely different from the others six emotions under neutral condition. In our experiment, the highest transition probability from the surprise state under neutral condition is to the calm state but not to the surprise state itself. According to the Cricumplex Model of Affect⁽¹⁷⁾, surprise is a high arousal and positive emotion. A person will not remain

Table 2. The Conditional Transitional Probability Tables

Under Neutral Conditions							
	happy	calm	sad	surprise	angry	fear	disgust
h	0.444	0.210	0.080	0.176	0.053	0.047	0.043
c	0.369	0.547	0.314	0.287	0.286	0.263	0.289
sa	0.054	0.082	0.338	0.082	0.118	0.121	0.085
su	0.051	0.048	0.052	0.257	0.069	0.094	0.051
a	0.025	0.036	0.093	0.086	0.306	0.086	0.147
f	0.028	0.040	0.059	0.068	0.060	0.301	0.068
d	0.029	0.038	0.064	0.044	0.109	0.088	0.318
Under Happy Conditions							
h	0.597	0.575	0.463	0.523	0.433	0.401	0.463
c	0.202	0.203	0.231	0.178	0.220	0.230	0.223
sa	0.028	0.029	0.098	0.043	0.046	0.044	0.035
su	0.134	0.151	0.135	0.201	0.155	0.153	0.131
a	0.013	0.014	0.030	0.020	0.093	0.026	0.034
f	0.016	0.017	0.022	0.017	0.023	0.115	0.031
d	0.011	0.011	0.023	0.019	0.030	0.031	0.082
Under Surprise Conditions							
h	0.322	0.261	0.177	0.237	0.160	0.169	0.166
c	0.224	0.285	0.206	0.219	0.229	0.201	0.223
sa	0.020	0.020	0.185	0.029	0.036	0.035	0.032
su	0.307	0.296	0.246	0.381	0.273	0.274	0.254
a	0.028	0.038	0.072	0.037	0.173	0.050	0.065
f	0.060	0.062	0.044	0.049	0.052	0.207	0.063
d	0.040	0.039	0.070	0.048	0.077	0.063	0.198

in a positive or highly intense state for a very long time if the stimulating effect is swift. After a strong accidental stimulation, the emotion of a person will usually tend to transfer into the calm state and will not remain highly tense for a long time.

Thirdly, under neutral condition, the highest transition probability and the lowest one from one emotion state to another always corresponds to two states that are contradictory. According to the Circumplex Model, for instance, happy which is a low arousal and positive value is absolutely opposite to angry, which has high arousal and negative value. From the data in Table 2, it is easy to find several contradictory emotional state pairs. In our experiment, the contradictory emotion state pairs include: happy versus angry, calm versus angry, sad versus surprise, fear versus happy and happy versus disgust.

Lastly, besides remaining in the same state, the probabilities for transferring into the calm (neutral) state are obviously higher than into the other six emotional states. In Table 2, we can find that the probabilities for transferring into the calm state are always the first or second highest. This shows that a full-blown emotion is a short time psychological phenomena and a person emotional state has a tendency to be calm if there are no external stimuli.

4.4 The Three Constraints under Other Six Archetypal Conditions Firstly, under six archetypal emotional conditions, the probabilities of all transitions among states are all lower than 0.6.

Then, under archetypal emotional conditions, the largest probabilities in all situations are to the state of

the emotion that is similar to the external condition. These results indicate that the external stimulus is the largest effective elements to the transition situation of human emotional states.

Thirdly, we can find that current emotion state plays a small role in emotional state transition, under six archetypal emotional conditions.

At last, under six archetypal emotional conditions, we also found that transition probabilities between same values are higher than those have different values. For instance, under happy (positive and high aroused) stimuli, the transition probabilities from various former states to surprise (positive and high aroused too) are obviously higher than the transition probabilities to sad (negative and low aroused), disgust (negative and low aroused) etc.

4.5 Gender and Characteristic Factors on the Transitional Probabilities According to the individual information of the questionnaires we have classified the 200 participants into several groups by gender and characters. In our experiment, every participant was required to appraise his or her own characters by self-assessment. Four character options were provided to assess. They are extraverted character, introverted character, sensitive character, and rational character. After comparing the different gender (male and female) and character of the participants we have found that:

General tendency of transition between different genders and characters are approximately the same, except some special situation.

The same points are: under neutral stimuli, transitional probabilities mainly depend on the former emotional state which participants were in. And under other six archetypal emotional stimuli, the transition probabilities mainly depend on the stimuli. These indicate that the genders and characters are very small effective elements to the transition situation of human basic emotion states. But by comparing the original questionnaires we still found there are some special situation occurs between some participants. The obviously special situations are:

Under various stimuli, male participants have higher tendency to be calm than female. And also the rational participants have higher tendency to be calm than the sensitive participants. Introverted participants have higher tendency to be calm than extroverted participants.

Besides, by comparing with original questionnaires in some special situation the participants will give absolutely different reaction as following:

Under fear stimuli, most of participants have a tendency to be fear, but some participants will become to happy. The detail number is 23, which account for 9.2% of total participants (5 female/ 18 male, 9 introverted/14 extroverted, 10 sensitive/ 13 rational).

Under angry or disgust stimuli, most of participants have a tendency to be angry, but emotional state of some participants will become calm. The detailed number is 37, which account for 14.6% of total participants. (15 female/22 male, 28 introverted/9 extroverted, 2 sensitive/

35 rational).

4.6 The Bayesian Network of Emotion State Transition In our psychological experiments on the Mental State Transition Network model, the emotion of the current state, the emotion of the previous state and the stimulus from the environment are the variables that have dependence relationships among each other and the degrees of dependence are uncertain. However, we can use a simple Bayesian network here to describe the emotion transition network and the probability dependence relationship among the variables in it.

The Bayesian network modeling is composed of two components: the network architecture and condition probability distribution respectively. The first indicates the conditional independence relationship of variables with the directed acyclic graph, the arc connected between variables indicates that there is dependence relationship and vice versa. The second shows the uncertainty of this relationship and can be represented as a conditional probability distribution table. These features can be found in our emotion state transition network.

It is hypothesized that there are six variables in our transition network from our experiments: current emotion state, previous emotion state, stimulus from the outside and personal characters which includes gender, character and sense. The current emotion state depends on previous emotion state, stimulus and personal characters respectively. In our Bayesian network the node C represents the emotion of current state and the node P represents the emotion of former state, simultaneously, the node E represents the stimulus factor from external environment, the node G represents the gender, the node CH represents character and the node S represents the sense. The current state C of emotion is affected by not only the previous state P , but also other outer and inner factors together. Their dependence relationship can be showed in the Figure 6:

In order to carry out numerical calculations, it is necessary to further specify for each node C the probability distribution for C conditional on its parents. The distribution of C given its parents may have any form. In our experiments, we can obtain the condition probability distributions table over all variables represented by the nodes.

Fig. 6. The Bayesian Network of Emotion State Transition

5. Model Test Experiments

From the previous section a practical transition network model has been built up that depends on about 200 questionnaires. To test the practicality of this advanced Mental State Network Model, we used another set of 50 random survey results as the test data. They are different from the former data and can be employed to test the model.

Because the aim of the Mental State Transition Network is used to predict the future emotion state from a previous state with its stationary transitional probability distribution and external condition. And also because the probability is derived from the previous questionnaire survey experiment, a person's emotional action according to prediction of our transition network model will certify the validity of the model.

Firstly, in an intuitive viewpoint, we can verify the validity qualitatively. Comparison of the top two states transitioned from each state between the test data and corresponding model states probability distribution. The model can be proved to be useful when the states are matching and to be invalid when the states are not. Then, we test the model by comparing the transitional probability distribution of all the states. This will finally present a determinate probability that describes the level of the validity of the model.

In the first case, from the network model, the first two states with that largest probabilities are selected to compare with the two from the test data directly, which are filled out by the participants. Table 3 has shown one example result of transitioned in happy situation. The results for this part of the comparison have indicated that the model is valid qualitatively.

In the probability comparison case, the two kinds of transition probabilities, $P_i(a_i|a_j)$ and $Q_i(a_i|a_j)$ are considered. $P_i(a_i|a_j)$ indicates the probability from state a to state b in the model and $Q_i(a_i|a_j)$ is the probability calculated from the test data. The probabilities are the foundation of our comparison.

Simultaneously, four previous constraints can be verified.

$$\sum_i P_i(a_i|a_j) = 1 \dots\dots\dots (3)$$

$$\sum_i Q_i(a_i|a_j) = 1 \dots\dots\dots (4)$$

Table 3. Qualitatively Test Result of Mental State Transition Network

Under neutral/h/sa/su/a/f/d emotional condition							
	happy	calm	sad	surprise	angry	fear	disgust
happy	1	2	-	-	-	-	-
calm	2	1	2	1	2	2	2
sad	-	-	1	-	-	-	-
surprise	-	-	-	2	-	-	-
angry	-	-	-	-	1	-	-
fear	-	-	-	-	-	1	-
disgust	-	-	-	-	-	-	1

Table 4. The Conditional Transitional Probability Tables

The Model Validity Distributes on Various Situations							
	neutral	happy	sad	surprise	angry	fear	disgust
P	0.87	0.87	0.85	0.82	0.84	0.85	0.83

In our model and test data, there are seven possible states to transition into from the start state. In an ideal case, the distribution of the transitional probability of the test data must match the model. We use the difference between the model and the test data to evaluate the difference between them. The following equation is used to calculate the related difference of the states:

The equation describes the difference of one start state between the probability distributions, $P_i(a_i|a_j)$ and $Q_i(a_i|a_j)$. As the difference increases, the result decreases. If the distributions of the probability are analogous, the result becomes one. For the whole model, we use the mean value of all states to evaluate the model validity. The equation is as follows:

$$P = \frac{1}{N} \sum_j \sum_i P(a_i|a_j)(1 - |P(a_i|a_j) - Q(a_i|a_j)|) \dots \dots \dots (5)$$

N is the total number of all states. P ranges from 0 to 1. The closer to 1 the more valid the model is.

Compared with the 50 random test data, the probability of the model (Mental State Transition Network) validity distributes on seven various external situations are indicated in Table 4. It means the model is close to the actual human emotional state transition.

6. Conclusions

The Mental State Transition Network model presented in this paper proposed a new way to process emotional information. The model can be applied to predict the transition situation of emotion states in the next period under several affective stimulation environments. We implemented these functions by the psychological experiments to obtain the conditional transitional probability tables in different emotional situations and the validity of the model (Mental State Transition Network) was tested and the model (Mental State Transition Network) provided a relatively high precision average rate of 0.843 for the set of 50 random surveys.

By the statistic of psychological questionnaire, we have found some transitional constraints were drawn from the results under various conditions.

In future research, we will enlarge the scale of the psychological experiments to make the model much more accurate and practical as well as considering more complex emotional states. Also we will make further study on cognitive appraisal by building a common sense events corpus.

Acknowledgment

Our project was partly supported by The Education Ministry of Japan under Grant-in-Aid for Scientific Research B (No.14380166) and the Outstanding Overseas

Chinese Scholars Fund of the Chinese Academy of Sciences (No.2003-1-1). We would like to thank all our colleagues participating in this project.

(Manuscript received Feb. 23, 2006,
revised Sep. 15, 2006)

References

- (1) Z. Wang: "The Modeling of Artificial Psychology", Proceedings of the International Conference on Artificial Intelligence, Las Vegas, USA, pp.1253-1261 (2002)
- (2) F. Ren: "Recognize Human Emotion and Creating Machine Emotion. Information", Vol.8, No.1, ISSN 1343-4500 (2005)
- (3) R.W. Picard: "Affective Computing", The MIT Press Cambridge, Massachusetts London, England, Preface, pp.2-22, pp.188-190 (1997)
- (4) P.R. Kleinginna, Jr. and A.M. Kleinginna: "A Categorized List of Emotion Definitions with Suggestions for a Consensual Definition", Motivation and Emotion, pp.345-379 (1981)
- (5) R. Cowie, E. Douglas-Cowie, N. TSApatoulis, G. Votsis, S. Kollias, W. Fellenz, and J. Taylor: "Emotion Recognition in Human-Computer Interaction", IEEE Sig. Proc. Mag., Vol.18 (1), pp.32-80 (2001)
- (6) R. Trappl, P. Petta, and S. Payr: "Emotions in Humans and Artifacts", The MIT Press Cambridge, Massachusetts London, England, ISBN 0-262-20142-9, pp.12-36 (2002)
- (7) K. Oatley and J.M. Jenkins: "Understanding Emotions", Blackwell, pp.39-58 (1996)
- (8) H. Yamasaki, K.S. LaBar, and G. McCarthy: "Dissociable Prefrontal Brain Systems for Attention and Emotion", Proceedings of the National Academy of Sciences USA, 11447-11451, pp.99-112 (2002)
- (9) M.M. Bradley, M. Codispoti, D. Sabatinelli, and P.J. Lang: "Emotion and Motivation", The American Psychological Association, Inc. Vol.1, No.3, pp.300-319 (2001)
- (10) J.C. Hager and P. Ekman: "What the Face Reveals", Oxford University Press, ISBN 0-19-517964-1, pp.40-50 (2005)
- (11) H. Hama, N. Suzuki, and Y. Hama: "Introduction of Emotional Psychology" ISBN 4-7819-1003-3, Press Saiensu Japan, pp.4-67 (2001)
- (12) T. Saburou: "Approach of Emotional Information Processing", ISBN-7819-0828-4, Press Saiensu in Japan, pp.22-48 (1996)
- (13) R. Cowie, E. Douglas-Cowie, N. Tsapatsoulis, G. Votsis, S. Kollias, W. Fellenz, and J. Taylor: "Emotion Recognition in Human-Computer Interaction" IEEE Sig. Proc. Mag., Vol.18 (1), pp.32-80 (2001)
- (14) P. Ekman: "Universals and Cultural differences in Facial Expressions of Emotion", In J.Cole (Ed.), Nebraska Symposium on Motivation. Vol.19, Lincoln: University of Nebraska Press. pp.207-283 (1972)
- (15) M.D. Goldstein and M.J. Strube: "The Relation between Positive and Negative Affect in a Naturalistic Setting", Pers. Soc. Psychol. Bull. 20, pp.57-64 (1994)
- (16) P. Ekman, R.W. Levenson, and W.V. Friesen: "Automatic Nervous System Activity Distinguishes Among Emotion", Science, 1208-1210, pp.221-230 (1983)
- (17) W.M. Winton, L. Putnam, and R. Krauss: "Facial and Autonomic Manifestations of the Dimensional Structure of Emotion", Journal of Experimental Social Psychology, 20, pp.195-216 (2000)
- (18) N.H. Frijda: "The studies in Emotion and Social Interaction", The Emotion. Cambridge University Press, Cambridge, pp.37-59 (1986)
- (19) R. Plutchik: "Emotions: A Psychoevolutionary Synthesis", New York, Harper, Row. pp.125-118 (1980)
- (20) J.A. Russell: "A Circumplex Model of Affect", Journal of Personality and Social Psychology, 1161-1178, p.39 (1980)
- (21) J.R. Pierce: "The Early Days of Information Theory", IEEE Trans. On Information Theory, Vol.19, No.1, pp.3-11 (1973)
- (22) C.E. Shannon: "The mathematical Theory of Communication", BSTJ. Vol.27, pp.379-632 (1948)
- (23) D. Slepian: "Information Theory", IEEE Transaction on In-

- formation Theory, Vol.19, No.2, pp.3-23 (1973)
- (24) A. Murata: "Cognitive Science", Press ISBN 4-254-12121-0 C3041 Japan, pp.69-78 (1997)
 - (25) P.J. Lang: "A Bio-informational Theory of Emotional Imagery", Psychophysiology, 16, pp.495-512 (1979)
 - (26) K. Tsuji and T. Okuda: "Analyses of the Discomforts Aroused by Stimulus Sentences with Reference to Effects of Modality and Gender", The Japanese Journal of Research on Emotion, Vol.3, No.2, pp.64-70 (1996)
 - (27) T. Yamata and J. Murai: "Understanding Psychological Statistic", ISBN 4-623-03999-4 Printed in Japan. pp.32-80 (2002)

app. Fig. 1. The transition probabilities under sad stimuli

app. Fig. 2. The transition probabilities under surprise stimuli

app. Fig. 3. The transition probabilities under angry stimuli

Hua Xiang

(Member) received the M.S. degrees in Kazan State Technology University, Russia, in 2003. Currently, she is completing her Ph.D. degree, and devoting the applied research of emotional information processing in Tokushima University of Japan. She is a student member of IEEJ of Japan. Her research interests include Nature Language Processing, Affective Engineering and Emotional Psychology.

Peilin Jiang

(Non-member) received the M.S. degrees in Institute of Artificial Intelligence & Robotics, Xian Jiaotong University in 2004. He is currently a doctoral student in both Tokushima University and Xian Jiaotong University. His research interests include Pattern Recognition, Image Processing, Nature Language Processing and Affective Engineering.

Shuang Xiao

(Non-member) received the B.S. and M.S. degrees in Hunan Normal University and Kazan State Technology University in 1994 and 2002 respectively. Now, he is completing his Ph.D. degree in Tokushima University of Japan. He is a student member of JSAI of Japan. His current research interests are in Nature Language Processing, E-learning and Affective Computing.

Fuji Ren

(Non-member) received the Ph.D. degree in 1991 from Faculty of Engineering, Hokkaido University, Japan. He worked at CSK, Japan, where he was a chief researcher of NLP. From 1994 to 2000, he was an associate professor in the Faculty of Information Sciences. From 2001 he joined the faculty of engineering, the University of Tokushima as a professor. His research interests include Natural Language Processing, Machine Translation, Artificial Intelligence, Language Understanding and Communication.

Shingo Kuroiwa

(Member) received Ph.D. degree in electro-communications from the University of Electro Communications Tokyo, Japan, in 1986, 1988, and 2000 respectively. From 1988 to 2001 he had been a researcher at KDD R & D Laboratories. Since 2001, he has been with the faculty of Engineering, Tokushima University, Japan. His current research interests include Speech Recognition, NLP and Information Retrieval.