A Mind Model for an Affective Computer

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Summary
A pragmatic emotional model is one of obligatory subjects for building a humanoid computer. This paper presents a conception of a Mental State Transition Network Model using psychological research for reference [1]. The ongoing work proposes a novel approach to detect human emotions. According to Pluchik's basic emotional classification, we defined nine basic emotional states and carried out a series of psychological investigations [2]. By the results of experiments we provide a new way to predict coming human's emotions depending on the various currents emotional states under various reinforcements. By means of statistic data derived from 227 questionnaires, the transitions in distribution among the emotions and relationships between internal mental situations and external stimuli are concluded. The high precision achieved in our evaluating experiments shows the model is helping in recognition and synthesis of human emotion.

Key words:
Artificial intelligent, a mental state transition network, psychological experiments, predict

1. Background and Motivation

Classical artificial intelligence has made a great many successes at its early stage and fascinates people very much. Over the years, the limitations of the traditional AI became apparent—most of current AI applications are less efficient in affective interact. Along with coming of the 'individuality era', contemporary people began to pay more attention to individualized products. For example: the humanoid e-learning, web shopping, game, handicapped equipments etc. Nowadays a machine that lacks of emotion computing ability cannot realize artificial intelligent sufficiently and cannot meet the increasing demanding of human-computer interaction as well. Consequently, in these couple of years emotions have become fashionable topic both in AI and cognitive science. We all know that emotion as one of most essential and attributes of human intelligent is a very important part of our social life. Even quite a number of people believe that emotions distinguish man from the machines. Definitely, more and more scientific finding indicates that emotions play an essential role in decision making, perception, learning, and moreover they influence the very mechanisms of rational thinking [3]. R Cowie once pointed out: human emotion recognition has gained more attention because of the desire to develop natural and effective interfaces for human-computer communication application [4]. Even many preliminary studies have done in physical and behavior measures. (Ekaman [5], Winton [6], Frijda [7] etc.), but external information such as language, voice and facial expressions are not enough to model human emotion [8]. 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. As a complex and advanced human intelligence, emotions are multidimensional psychological Phenomena. It is not directly and accurately available to an observer [9]. Generally, four aspects of emotions are taken into consideration in contemporary psychology—cognitive assessment, emotional states, emotional experience, and emotional expression [10]. From different point of views, nearly a hundred definitions of emotion and related concepts and have been recorded and categorized [11]. General speaking, emotions may be defined as states elicited by reinforcements [8]. Though, various emotional models have been proposed in previous studies (the Plutchik's Multidimensional Model [2], the Circumplex Model of Affect etc [12].), there are few studies where they describe the mental situation appropriately in a numerical way, that can be simulate in a machine directly. The approach of building an emotion information processing model is Analysis-by-Synthesis [3]. For these reasons, an emotion model, which can be realized by engineering, should necessarily be created. Famous affective computing pioneer Picard pointed out that a model such as the HMM 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].

In this paper, we will present a novel model of a Mental State Transition Network based on Plutchik's emotion to simulate human emotion. The model explores human emotions from 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 compilation and the simplified mental network by considering the whole priori conditional probability under

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the various affective environments. In the theory of the Mental State Transition Network, it is hypothesize that the human emotion is simplified to be nine 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. By means of statistic gathered from a large set of psychological questionnaires, the conditional transition probabilities among mental states can be calculated.

2. A hypotheses of the Mind Model

2.1 Emotional Information and Emotional Experience

As we mentioned above, emotion can usefully be defined as states elicited by reinforcements [8]. These reinforcements, or we can call it stimuli, can be considered as a kind of emotional information. Associating with classical information process model [13] [14] and cognitive information model [15]. We can deduce process of emotion-information processing based on emotional states. In the role of a information, emotional information processing have some attributions of common information processing, but at the same time in the role of 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 changes. When stimuli are given, the emotional information (visual, auditory, taste, smell, tactile, image information etc) is required by the sensors (eyes, ears, tongue, nose, skin, and proposition etc.) [3][15]. 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) [8][10].

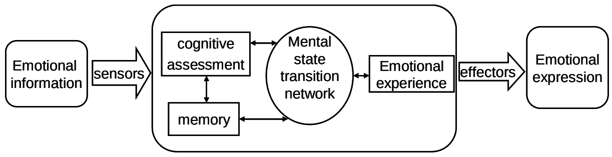

Fig. 1 Emotional information processing based on the model

2.2 The Affective Model of the Mental State Transition Network

Current technology can't provide an effective approach to detect human mental states directly, mostly research 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 describe by current technology. So it is reasonable to believe there are some 'common sense emotional events' exist. In our study, for simplified the problem, temporarily, we presume that the cognitive assessment 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 happy, a funeral arouse sad etc.) In that case, we can create a Common Sense Emotion Events Corpus to categorize the emotional information. And the changes of emotional state become the main object which needs study. As aforementioned viewpoint, emotion states express itself internally as emotional experience, externally as various physical or psychological indicators. So we can study the mind apparent of the emotional states by using Subjective Language Reporter, such as psychological questionnaires. After studying a vast amount of literature on the signs that indicate emotion, both within the psychological tradition and beyond it [16] [17], we have created a emotional space based on nine emotions (happy, sad, angry, surprise, fear, and disgust, calm, anticipant, acceptation) as presented by Plutchik. Everyday usage divides emotional states into categories that are related to time, reflecting the fact that emotional life has a definite temporal structure [10] [17]. Among these nine emotions, six of them are short lived and intense (happy, sad, angry, surprise, fear, and disgust). Three of them are more long lived and moderate. They are long lived and moderate (calm or neutral, anticipant, acceptation). In our research, we presume that human emotional state is made up by these nine archetypal emotional states. Then, these nine discrete emotional states we proposed can construct an emotional space. In that case, we can create a mental state transition network model of a human, as the following figure 2 shows:

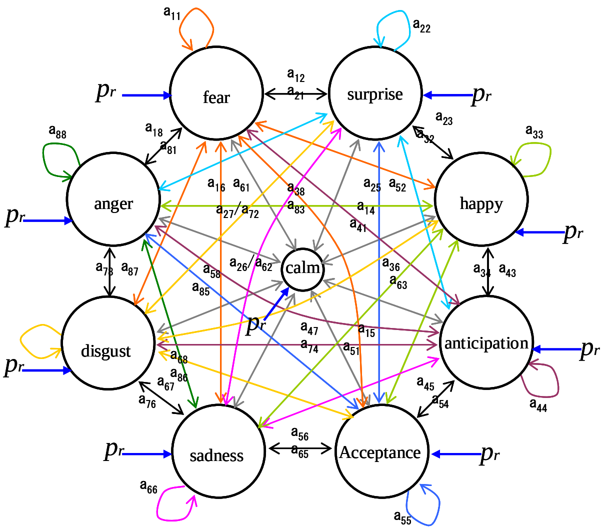

Fig. 2 The mind model for an affective computer

From the previous Mental State Transition Network, we can access the probability of the next emotion state from the current one under various conditions. Hence, we propose the network with the conditional Transition probability tables (CTPT) which describe the external stimulations. In the Fig 2, we can see that arcs represent the transitional probability from one emotion state to another one while each circle replaced by a circle with an inward arrow standing for environment affective factors (emotional information) $P_r(E_k)$ Since what we are dealing with is in an emotion space composed by only nine emotion state, it hypothesizes that state in model is independent from each other. The probability of each emotion situation E_k is $P_r(E_k)$ and we have $\sum_k P_r(E_k)=1, i=1...9$. So we obtained the probability of transition from state a_i to state a_j is $P_r(a_j \mid a_i, E_r) = P_r(a_j \mid a_i)\cdot P_r(E_k)$.

3. Experimental design and implement

3.1 Aim and Participants

The aim of the psychological experiments is detecting and describing human emotional states changes by 'Subjective Language Report'. We use the CTPT (Conditional Transition Probability Table) as the foundation of the model of Mental State Transition Network. In our experiments, CPT is obtained through psychological questionnaires. In the experiment, we had about 227 participants recruited primarily from different high schools and universities in China and Japan. The ages of the participants ranged from 16 to 30 years old. 115 of them were males and 112 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 Detail Procedure of the experiment

The psychological experiment required participants to fill out a table which was designed for creating transitions among nine basic emotional states (calm/neutral, happy, sad, angry, surprise, fear, disgust, anticipation, and acceptance). The contents of the questionnaire are described below:

Table 1: An example of Psychological Questionnaire

Under happy, neutral…disgust emotional condition									
	Ha	Ca	Sa	Sur	Ang	Fe	Dis	Ant	Ac
Ha	10								
Ca	8								
Sa	5								
sur	3								
Ang	0								
Fe	2								
Dis	1								
Ant	4								
act	1								

Firstly, individual information of the participant, including gender, age, educational level, nationality, occupation, and self-character assessment was asked for. Second, the tables that design were based on nine mental states. Third, an example was set up to show the participants how to fill out the table. Table 1 is an example of original investigating data we collected. In the table, 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 state a_j to state a_i, $\sum_k P_r(E_k)=1, i=1...9$ A clue in indicated for the certain affective situation for the transition. The experiment firstly appeals to the participants to image 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 nine different standard types which category into nine 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 transition 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 image that they are in a happy emotional state at the current time. If there is nothing excited happening 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/anticipation/acceptant states are 10/8/5/3/0/2/1/4/1 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 collecting statistics.

4. Experimental Results and Analysis

4.1 Normalization and CTPT

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 [17]:

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

$$\sum_{j=1}^{N} p(a_i \mid a_j) = 1 \; (N = 9) \tag{2}$$

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. Studying CTPT, we can find some general constraints of these mental states transition situations under various conditions. By comparing the graphs of CTPT we found that transition probabilities under moderate stimuli (under neutral, anticipated, accepted stimuli) is absolutely different from the others full-blown emotion stimuli (happy, sad, angry, surprise, fear, disgust stimuli). For instance, comparing with the figure 5/6/7 to the figure 3/4, we can see that the broken lines under moderate stimuli almost have the different tendency, but the broken lines under the other six full-blown emotional stimuli almost have same tendency. In table 2, four general constraints of these mental states transition situations under neutral stimuli can be clearly concluded.

4.2 The detail analysis and constrains

Under moderate condition, (take the neutral as an example) if a participant is in a particular emotional state, they will most likely remain in that state. From Table 2 we can clearly see that the highest probabilities of each column are all displayed on the diagonal, except for the "surprise column" (but 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 term. They will retain the current emotional state if there is not any typical affective effecting.

Under neutral condition, "Surprise" is a unique emotional state which the transition probability is absolutely different from the others six full-blown emotions. In our experiment, the highest transition probability from the surprise state under neutral condition is to the calm state and not the surprise state itself. According to the Cricumplex Model of Affect [12], surprise is a high arousal and positive emotion. A person will not remain in a positive or highly intense state for very long if the stimulating effect is swift. After a strong accidental stimulation, the emotion of a person will usually tend to transition into the calm state and will not remain highly tense for long.

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 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, happy versus disgust.

Under neutral condition, besides remaining in the same state, the probabilities for transitioning into the calm (neutral) state are obviously higher than into the other five emotional states. In table 2, we can find that the probabilities for transitioning 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's emotional state has a tendency to be calm if there are no outside stimuli.

Table 2: The Conditional Transitional Probability

Under Happy Condition									
	ha	ca	sa	sur	ang	fe	di	ant	ac
ha	0.312	0.337	0.302	0.313	0.304	0.301	0.323	0.317	0.315
ca	0.185	0.176	0.191	0.178	0.181	0.152	0.172	0.165	0.190
sa	0.026	0.021	0.041	0.043	0.046	0.024	0.035	0.011	0.021
sur	0.121	0.141	0.135	0.201	0.145	0.135	0.131	0.056	0.150
ang	0.012	0.011	0.029	0.012	0.064	0.026	0.034	0.024	0.033
fe	0.013	0.016	0.022	0.017	0.023	0.115	0.031	0.011	0.012
dis	0.011	0.011	0.023	0.019	0.030	0.031	0.082	0.121	0.009
ant	0.178	0.167	0.102	0.105	0.110	0.114	0.090	0.143	0.122
ac	0.142	0.120	0.156	0.113	0.097	0.102	0.101	0.152	0.148
Under Neutral Condition									

	ha	ca	sa	sur	ang	fe	di	ant	ac
ha	0.343	0.201	0.057	0.157	0.053	0.054	0.032	0.141	0.075
ca	0.267	0.434	0.247	0.267	0.259	0.236	0.262	0.313	0.235
sa	0.054	0.059	0.307	0.072	0.114	0.121	0.081	0.101	0.066
sur	0.051	0.028	0.041	0.245	0.048	0.074	0.051	0.011	0.079
ang	0.017	0.026	0.063	0.065	0.283	0.083	0.147	0.004	0.001
fe	0.028	0.017	0.061	0.037	0.059	0.292	0.058	0.005	0.003
dis	0.026	0.027	0.064	0.033	0.094	0.085	0.307	0.000	0.015
ant	0.111	0.101	0.088	0.079	0.037	0.024	0.037	0.321	0.175
ac	0.102	0.107	0.072	0.045	0.053	0.031	0.025	0.104	0.351
Under Anticipation Condition									
	ha	ca	sa	sur	ang	fe	di	ant	ac
ha	0.321	0.168	0.103	0.154	0.096	0.077	0.098	0.208	0.251
ca	0.121	0.303	0.092	0.081	0.123	0.109	0.102	0.164	0.118
sa	0.016	0.039	0.171	0.057	0.095	0.121	0.085	0.027	0.025
sur	0.058	0.068	0.052	0.280	0.068	0.074	0.065	0.054	0.067
ang	0.021	0.036	0.054	0.023	0.225	0.086	0.083	0.029	0.004
fe	0.023	0.040	0.059	0.042	0.063	0.234	0.068	0.021	0.019
dis	0.021	0.028	0.064	0.058	0.047	0.066	0.271	0.023	0.072
ant	0.317	0.241	0.315	0.216	0.184	0.198	0.127	0.352	0.103
ac	0.102	0.078	0.091	0.089	0.099	0.035	0.101	0.122	0.341
Under Acceptant Condition									
	ha	ca	sa	sur	ang	fe	di	ant	ac
ha	0.277	0.131	0.080	0.155	0.053	0.047	0.043	0.106	0.133
ca	0.227	0.321	0.153	0.228	0.159	0.128	0.189	0.213	0.181
sa	0.049	0.082	0.276	0.073	0.051	0.076	0.085	0.044	0.068
sur	0.042	0.048	0.052	0.205	0.069	0.076	0.051	0.042	0.076
ang	0.012	0.036	0.048	0.038	0.207	0.087	0.137	0.024	0.028
fe	0.024	0.040	0.054	0.056	0.060	0.290	0.068	0.035	0.078
dis	0.017	0.038	0.093	0.044	0.094	0.061	0.135	0.088	0.029
ant	0.105	0.092	0.072	0.088	0.076	0.088	0.064	0.346	0.031
ac	0.247	0.213	0.173	0.113	0.232	0.147	0.228	0.102	0.376

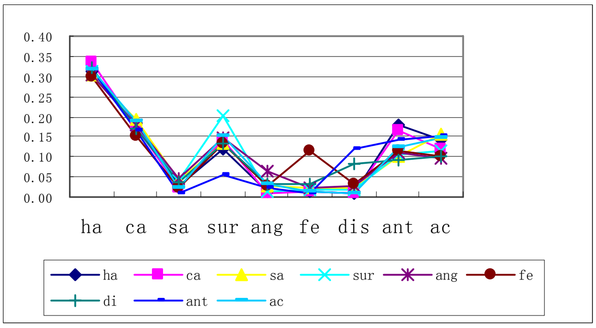

Fig. 3 Under happy conditions

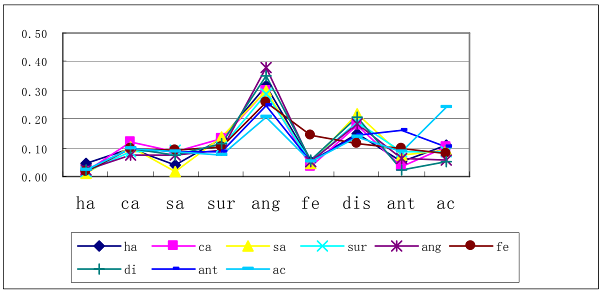

Fig. 4 Under angry conditions

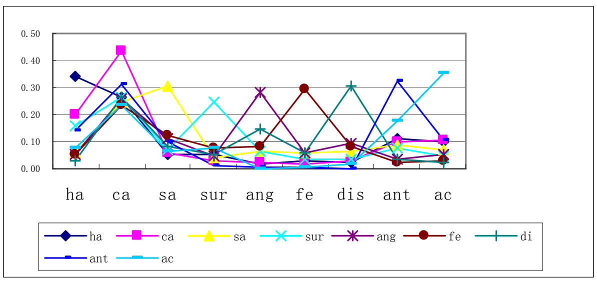

Fig. 5 Under neutral conditions

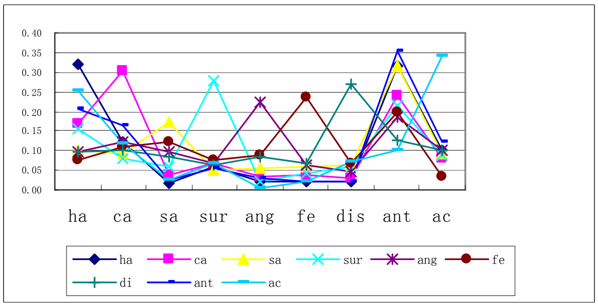

Fig. 6 Under anticipant conditions

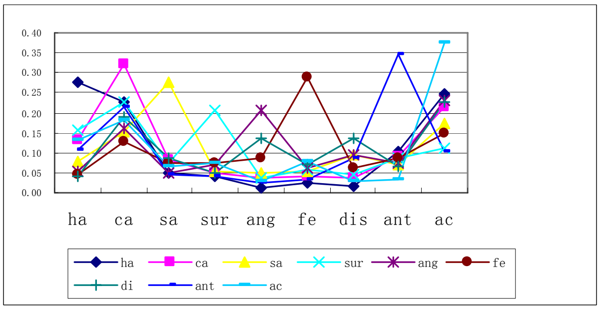

Fig. 7 Under acceptant conditions

Under full-blown emotional conditions (happy, sad, surprise, angry, fear, disgust), 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.

Under six full-blown emotional conditions, we can found that current emotion state plays a small role in emotional state transition.

Under six full-blown 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.

According to the individual information of the questionnaires we have classified the all these 227 participants into several groups by gender and characters. Comparing the different gender (male and female) and character (extraverted and introverted, sensitive and rational) of the participants we have found that:

General tendency of transition between different genders and characters are roughly same, except some special situation. Under neutral stimuli, transitional proximities mainly depend on the former emotional state which participants were in. under full-blown emotional stimuli. The transitional mainly depend on the stimuli. But comparing the original questionnaires we have found there some special situation occurs between some participants. The obviously special situations are: under various stimuli, male participants have bigger tendency to becalm than female. And also rational participants have bigger tendency to be calm than sensitive participants. Introverted participants have bigger tendency than extroverted participants. Besides, by comparing original questionnaires in some special situation the participants will give absolutely different react. Fore example; under fear stimuli, most of participants have a tendency to be fear, but emotional state of some participants will become happy.

4.3 A Bayesian Model of Emotion State Transition

In our psychological experiments on mental emotion transition network experiments, 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 between each other and the degrees of dependence are uncertain and just probability parameters. However, we can use a Bayesian network modeling here to describe the mental 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 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 three variables in our transition network from our experiments: current emotion state, previous emotion state and stimulus from the outside and the current emotion state dependents on previous emotion state and stimulus respectively. In the Bayesian model 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 out environment. The node G represents the gender, the node CH represents character and the node S represents the sense. The structure of model can be showed in the figure:

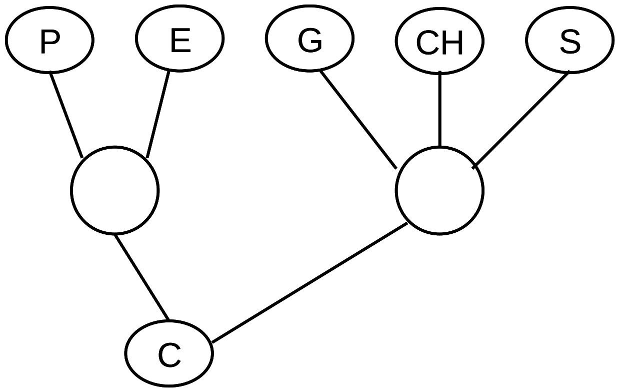

Fig. 8 The Bayesian model of emotion state transition

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. However, it is common to work with discrete distribution, since that simplifies calculations. In our experiments, we can obtain the condition probability distributions table over all variables represented by the nodes.

5. Evaluation

From the previous section a practical transition network model has been built up that depends on about 227 questionnaires. To test the practicality of this Advanced Mental State Network Model, we used another set of 70 random survey results as the test data. They are different from the former data and can be employed to test the model. As the aims 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 transited from each state between the test data and corresponding model states probability distribution. On the one hand we can compare the position of the top two probabilities in the tables; on the other hand we can magnitude of each probability of the tables. 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 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 transition 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, $P_i(a_i \mid a_j)$ and $Q_i(a_i \mid a_j)$ are considered. $P_i(a_i \mid a_j)$ indicates the probability from state a to state b in the model and $Q_i(a_i \mid a_j)$ is the probability calculated from the test data. The probabilities are the foundation of our comparison. Simultaneously, four previous constraints can be verified.

$$\sum_i P_i(a_i \mid a_j) = 1 \quad (3)$$

$$\sum_i Q_i(a_i \mid a_j) = 1 \quad (4)$$

Table 3: Qualitatively test result of the model

Under happy, neutral…disgust emotional condition									
	Ha	Ca	Sa	Sur	Ang	Fe	Dis	Ant	Ac
Ha	1	2							
Ca	2	1	2	1	2	2	2	2	2
Sa			1						
sur				1					
Ang					1				
Fe						1			
Dis							1		
Ant								1	
act									1

In our model and test data, there are seven possible states to be transitioned 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, $P_i(a_i \mid a_j)$ and $Q_i(a_i \mid a_j)$. 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:

$$P_r = \frac{1}{N}\sum_j \sum_i P(a_i \mid a_j)(1-\mid P(a_i \mid a_j - Q(a_i \mid a_j)\mid) \quad (5)$$

N is the total number of the states. It ranges from 0 to 1. The closer to 1 it is the more valid the model is. Compared with the 70 random test data, the probability of the model validity distributes on nine various external situations are indicated in the table 4.These means the model is close to the actual human emotional state transition.

Table 4: The evaluate results

	ha	ca	sa	sur	ang	fe	dis	ant	acc
P	0.83	0.78	0.76	0.81	0.79	0.77	0.75	0.70	0.71

6. Conclusion and future direction

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 was tested and the model provided a precision average rate of 0.766 for the set of 70 random surveys. By the statistic of psychological questionnaire, we have found some transitional constraints were drawn from the results under various conditions. 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 that is not absolutely precise yet, but the relatively high precision rate which was obtained from further test experiments proves that the model is reliable and pragmatic to a certain extent. In future research, we will enlarge the scale of the psychological experiments and 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.

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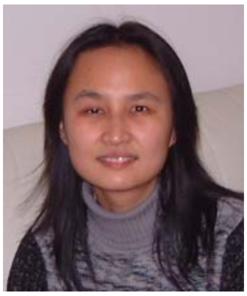

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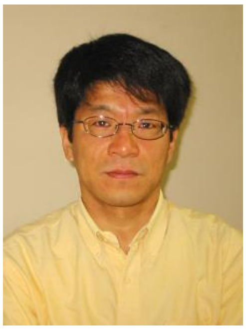

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