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Toward analysis of emotional development using physiological and behavioral data

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ABSTRACT
Emotion is one of the important elements for communication with others. It is expressed by various modalities such as body gestures, changes in the heart rate, and so on. It has been suggested by psychological studies that primitive emotions like pleasure/unpleasure differentiate into six basic emotions. For instance, unpleasure branches into anger, sadness, and fear in the sequence of the developmental process. However, previous studies have focused only on the behavioral data which could be influenced not only by emotion but also the context. This paper proposes an experimental method and a computational model to verify the theory of emotional differentiation. We employ a hierarchical Dirichlet process hidden Markov model which can determine the number of emotional state and deal with multimodal information on emotion. A new contribution of our approach is to analyze not only behavioral information but also physiological information to estimate emotional states more accurately.

Categories and Subject Descriptors
H.1.2 [**User/Machine System**]: Human information processing

General Terms
Measurement

Keywords
Emotion, Physiological data, Multimodal, Hierarchical Dirichlet process hidden Markov model

1. INTRODUCTION
To recognize human emotion is an important issue in human robot interaction. A number of emotional recognition models have been proposed in the HRI community. Some models analyze behavioral data such as facial expressions, vocalizations, and gesture[1]. Other models use physiological parameters like heart rate[2]. However, these models have focused

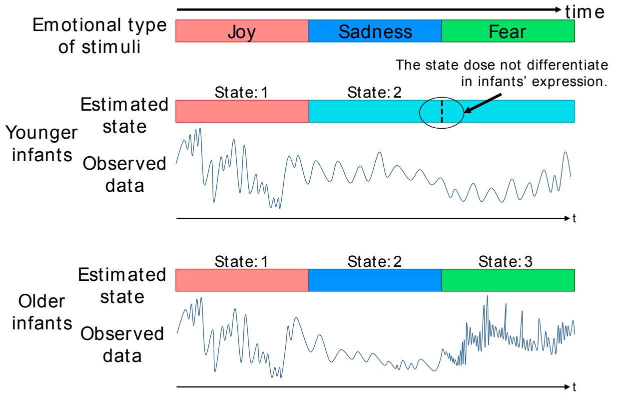


Figure 1: A prediction result of our proposed experimental method.

on the emotional state of adults but not the developmental process in infants. It has been suggested by psychological studies that human emotion differentiate as they develop[3]. Recently we proposed a computational model to reproduce the differentiation of emotion from primitive emotions (i.e., pleasure/unpleasure) to six basic emotions(e.g., happy, sad, angry, etc.)[4]. An open challenge is to develop a recognition model which can deal with such developmental process.

This study proposes a model based on a Hierarchical Dirichlet Process Hidden Markov Model (HDP-HMM) to address the above issue. HDP-HMM[5] can infer the number of hidden states from observed data, that is, it is able to estimate the number of emotional states. Our model is extended to analyze both physiological and behavioral data to improve the accuracy. We compare the number of estimated emotional states for younger infants with that for older infants to examine the developmental differentiation of emotion.

2. OUR HYPOTHESIS
We propose an experimental method to verify the theory of emotional differentiation. In the experiment, we present infants with visual and audio stimuli which evoke emotional responses of the infants(see Figure 1). The stimuli are associated with one of the six basic emotions and are continuously presented in a certain order. There are two types of transition of emotional stimuli. One produces a large change in the emotional category like positive to negative and the other way around. The other produces a little change in the emotional category like positive to a different type of posi-

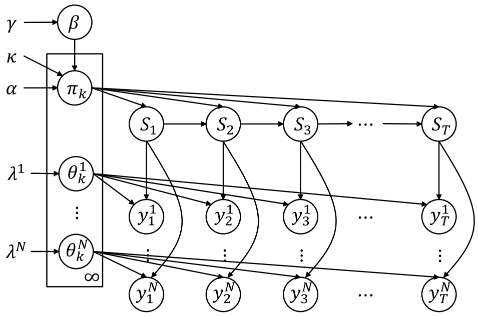


Figure 2: A Graphical model of the sticky HDP-HMM for multimodal information.

tive and negative to a different type of negative. According to the theory of emotional differentiation, emotional states of infants have not differentiated enough in an earlier developmental stage. For example, Figure 1 describes that the emotional category of stimuli changes from joy, sadness to fear. We hypothesize that younger infants show a differentiated response to joy but non-differentiated response to sadness and fear. In contrast, older infants would show three different emotional responses to the three different stimuli. To sum up, we assume that the number of emotional responses of infants is different depending on the age. We compare the number of infants' emotional states in various developmental stages to examine the evidence of the theory of emotional differentiation.

There are three issues in analyzing the emotional development in infants:

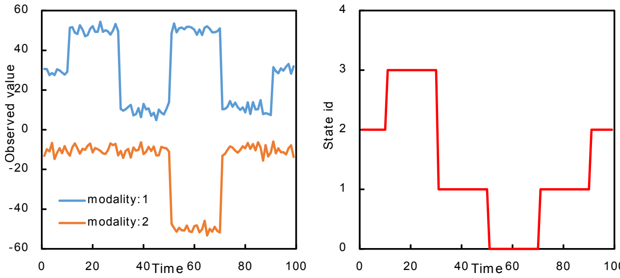
- to determine the number of emotional state,
- to consider the history of emotion, and
- to deal with multimodal information on emotion.

First, the number of estimated emotional states of infants must be optimized because the number of emotional states may have differ depending on their age. Second, the emotional change is supposed to be influenced by the history of emotion. Finally, the emotional state is expressed by multimodal expressions such as behaviors and physiological responses. However, it is not guaranteed that the estimated states express emotion. For example, the estimated states include some states which are segmented by physical movements. Since we analyze both physiological and behavioral data to extract states which relate to emotional change from all estimated states.

3. OUR PROPOSED MODEL

We apply a sticky HDP-HMM[6] to resolve the issues discussed in Sec. 2. Figure 2 illustrates our proposed model which is extended to analyze multimodal data. $y_1^1 \cdots y_T^1$ and $y_1^N \cdots y_T^N$ are observed data, where N indicates the number of modalities at time T. $S_1 \cdots S_T$ denote the hidden state of observed data. In our experiment, S_t indicates the emotional state of a subject, and y_t^n corresponds to the physiological or behavioral data.

It is known that an HMM can represent the time series information by considering the Markov chain of hidden states.



(a) Observed data (b) Estimated states

Figure 3: A result of preliminary experiment.

Moreover, the number of hidden state is modified by HDP to reproduce observed data convincingly. We estimate the emotional change as the hidden state of observed emotional expressions by employing the HDP-HMM model for multimodal information. The state at time t is optimized by

$$P(S_t|\boldsymbol{S}_{-t}, \beta, \alpha, \kappa, y^1_{1:T}, \cdots, y^N_{1:T}, \lambda^1, \cdots, \lambda^N) \qquad (1)$$

Here, $\boldsymbol{S}_{-t}$ are the state assignments for all time series observed data except time t. See [6] for the details about the sampling method.

4. PRELIMINARY EXPERIMENT

We analyze artificial data to test our proposed model. Figures 3(a) and (b) show observed data (i.e., y_t^1 and y_t^2) and the result of segmentation, respectively. There are two time series of data with noise. Despite the noise, the number of the estimated states decreases from the number of raw states of observed data. This model generates segments based on the likelihood of observed data and the relationship between each modal data. The number of estimated states has a variance due to using the Gibbs sampler.

5. CONCLUSION

We proposed the model which estimates humans' emotional states by segmenting physiological and behavioral data. For future issues, we need to decide measurement data which express change in emotional states well. Then, we will validate the theory of emotional differentiation by estimating emotional states of infants.

6. ACKNOWLEDGMENTS

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