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Emotion Recognition and Generation through Multimodal Restricted Boltzmann Machines

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***Abstract*— It is assumed that emotion recognition and generation share the same internal model. People interpret emotional expressions of a partner based on their internal emotion model, whereas the model enables people to express their emotional states. Despite the close link between generation and recognition of emotions, there has been little computational models to take the link into account. This paper presents a multimodal Restricted Boltzmann machines (RBMs), which is able to both generate and recognize emotional states. An RBM has a capability to abstract and then reconstruct input signals. By hierarchically integrating RBMs for multiple sensory modalities (e.g., vision, audio, and tactile), our model represents emotional states as the activations of the units at the higher layer. Our preliminary experiments demonstrate that the model can generate emotional expressions similar to those presented by an interaction partner like mirroring. Additionally, the model can infer the pater's emotion from deficient modality inputs through the recognition and regeneration process. We discuss the advantage of our emotion recognition-generation model in relation to the mirror neuron system.**

I. Introduction

Emotion has important rolls for many cognitive functions (e.g., decision making and communication etc.). In social contexts, people perceive others' emotional states from facial expressions and vocalizations and share their emotional states by multimodal expressions. Humans' internal states which are base of emotion are very complex. They are influenced by external and internal changes of one's body. However, we are able to share generalized emotional categories as typified by happiness, anger, and so on with each other.

A circumflex model [1] is one of the low dimensional model which can represent emotional states. This model shows that our emotional categories are abstracted in two dimensional space defined by pleasure/unpleasure and arousal/sleep axes. If communication robots learn the categorical model like the circumplex model, they can interpret emotional state of a partner and express emotional states in social situations

This paper presents emotion recognition-generation model in interactions. We assume that emotion recognition and generation processes share the same internal model. Our proposed model, is constructed of restricted Boltzmann machines (RBMs) acquires representations of multimodal emotional signals. Experimental results show that the proposed model is able to both recognize and to generate emotional expressions from multimodal interaction data. Finally, we discuss the relationship between our model and the mirror neuron system.

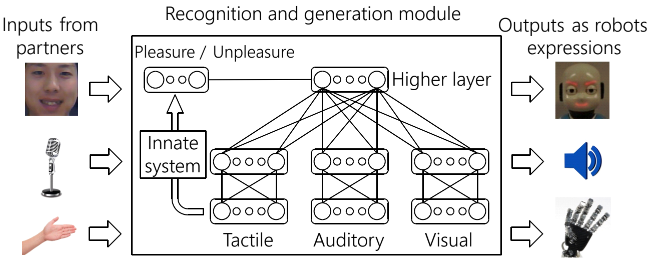
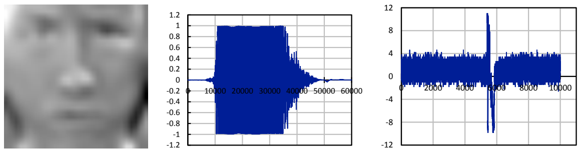


Fig. 1. Overview of interaction and proposed model



(a) Visual input (b) Auditory input (c) Tactile input

Fig. 2. Example of multimodal emotional sensory inputs

II. Problem Setting and Proposed model

We focused on a face-to-face interaction between a human and a pater robot as shown in Fig. 1. The robot receives multiple sensory inputs as tactile, auditory, and visual information like Fig. 2.

We proposed an emotion recognition-generation model based on an emotional differentiation model which is proposed in [2]. This model is composed of restricted Boltzmann machines (RBMs) [3], is a type of stochastic neural networks. Horii et al. [2] used Gaussian-Bernoulli RBMs whose variance of Gaussian distribution of input node fixed 1.0 for each sensory module. We apply a method of Cho et al. [4] to update variances of each input node. See [2] for the details about network structures.

The advantage of our model from other emotional recognition models is that our model is a generative model. The generative model estimates a data distribution of inputs. The proposed model is able to abstract emotional states in a higher layer from multiple sensory inputs of interaction and recognize emotional states of each data as well as other recognition models. Additionally, this model can replenish a deficient input data through the network and generate sensory information from abstracted data.

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TABLE I

RMSE BETWEEN INPUT AND RECONSTRUCTED DATA

Experimental condition	RMSE
Using complete multimodal inputs	1.37
Using deficient inputs (w/o visual)	2.36

(a) From complete inputs

(b) From deficient inputs

Fig. 3. Reconstructed data

III. Experiment and Results

We evaluated the proposed model using the multimodal interaction dataset as shown in Fig. 2. The dataset includes 6 basic emotions (i.e., joy, surprise, anger, fear, sadness, and disgust) and neutral states stimuli. It is assumed that multimodal inputs does not conflict with each modality in these experiments. After training by the dataset, we use the same model for each experiment.

A. Reconstruction from complete multimodal inputs

The first experiment has been performed to validate a basic ability of the proposed model. We inputted a set of multimodal stimuli for the proposed model to reconstruct sensory data through higher layer. The proposed model sampled activations from lower layers to higher layers sequentially by using input data. After a forward sampling, the model resampled data in the opposite direction. Fig. 3(a) shows the reconstructed data of the visual modality from the angry stimuli (Fig. 2). The root mean squared error (RMSE) between the visual input and the reconstructed data is summarized in Table I. According to Fig. 3(a), the proposed model is able to reconstruct a same emotional expression as well as inputs.

B. Emotion recognition and generation from deficient inputs

The second experiment has been carried out to investigate the advantage of this model that the model can replenish a deficient input through the forward-backward sampling. We inputted multimodal stimuli except a visual input from Fig. 2 and sampled a reconstructed visual data by using a Gibbs sampling method in 10000 steps. Fig. 3(b) depicts the reconstructed data of the visual modality at $step = 10000$. According to Fig. 3(b), the proposed model can imagine the deficient modality data from other modality inputs. The estimation accuracy is lower than the previous experiment. The dataset includes same auditory and tactile signal combination with different visual stimuli. It has an influence on the dispersion of reconstructions.

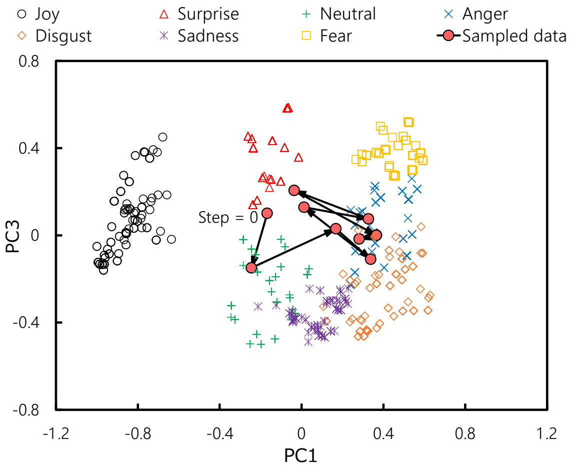

Fig. 4. Transition of recognitions at each 10 step in PC space.

We illustrates the transition of sampled activations in higher layer at each 10 step from 0 to 100 steps in the principal component (PC) space of outputs in Fig. 4. The each emotional state of the learning dataset distribute like the circumplex model. This figure shows that the model recognized the deficient input as the surprise signal at first recognition process. However, through the sampling method with reconstructed data, the estimated emotional state changed into the anger which is the correct state.

From the above results, we could confirm that the proposed model has advantages which is discussed in section 2. Robots can recognize partners' emotional states and generate emotional expressions by using our model with action modules which converts outputs into robot action.

IV. Conclusion

We discuss the relation between our emotion recognition-generation model and the mirror neuron systems (MNSs) and the mentalizing systems [5]. The result of first experiment shows that our model can mirror the expressions through the abstracted activations like the MNSs. This model automatically mimics others' expressions and emotional states, similar to the emotional contagion. It is clear from the second result that the model can infer the deficient data and update the belief of others' emotional state sequentially through the sampling. This behavior suggests that the reconstruction process relates the MNSs and the estimation process through the sampling relates the mentalizing systems.

For future improvements, we extend the model with action modules by using reconstructed data for real-time human robot interactions. In addition, we verify the detail of relation to the MNSs and the mentalizing systems.

Acknowledgment

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