Analyzing the Rules of Social Dialogue and Building a Social Dialogue Model in Human-Robot Interaction*

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***Abstract*— With the rapid development of artificial intelligence, social robots are also using advanced technologies in the fields of vision, hearing, touch, and motion. However, even if the social robot uses cutting-edge technology, it is not human, so it lacks empathy, emotion, and reasoning. Therefore, this paper attempts to solve the empathy and emotional deficiency of robots by forming intimacy through social dialogue. The method is to build a simple social dialogue model by statistically showing the behavior of dialogue and setting rules. We analyzed the previously obtained chatting scripts between counselor and visitor to understand social cues. We found that most visitor uses self-disclosure 4.8 times more than other social cues and counselor often adopt a strategy for agreement and suggestions. We also show sequence of social behaviors of counselors and social dialogue model based on Hidden Markov Models. In the future, we are going to evaluate how closeness is felt in the conversation in which the model is applied through human user study.**

I. INTRODUCTION

These days, if you are curious about the weather, you can easily ask the conversation of agent, "How is the weather today?". As many people ask questions to conversational agents, the number of interactions between humans and robots has also increased. In addition, a human-friendly social dialogue is needed rather than a task-oriented dialogue in order to develop a social agent [1]. However, because most research on social robot has been primarily concerned with non-verbal(visual, vocal etc.), there is little social-interaction research focused on "conversation" between artificial agent and human. In this paper, we analyze dialogue from the social aspect and tried to build a social dialogue model when humans interact with robots. We built a social dialogue model based on a text-based chatting data that was conducted under the assumption of a visitor-counselor role, which includes many social factors (speaker - visitor, interlocutor - counselor).

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As a method, a social dialogue strategy was identified in a collected conversation dataset to construct a social dialogue model. The social dialogue model is based on 9 different social cues defined in previous studies [10]. All the dialogue data were collected in text using the 'automatic conversation data acquisition system' [14], and the intention of each speech was classified as social cues. As a result, we show the frequency of using different social cues between speaker and interlocutor in collected dialogues. Finally, we used the HMM (Hidden Markov Model) to create the social dialogue model that can create sequences of social cues for utterance of robot.

II. RELATED WORK

This paper refers to a few studies by J. cassell to analyze social dialogue strategies in a text dialogue conducted in Korean. J. cassell et al. studied SARA (Socially-Aware Robot Assistant) that analyses the user's visual, vocal and verbal (conversational strategies) behaviors to estimate its rapport level with the user.

In their studies, rapport is often used to elicit personal information from the user and it can improve the helpfulness and personalization of the assistant robot's responses [2]. Rapport also has powerful effects on performance in a variety of domains, including negotiation [3], counseling [4] and education [5][6]. To measure rapport, they used nonverbal feature like eye gaze and smiling, and conversation strategies including self-disclosure (SD), elicit self-disclosure (QE), reference to shared experience (RSD), praise (PR), and violation of social norms (VSN).

Therefore, the conversation topic of our study was set as a counseling environment, and conversation strategies was referred to the J. cassell study. We also attempted to grasp the elements of social dialogue more accurately by conducting verbal analysis.

III. SYSTEM COMPONENTS

A. Acquisition Dialogue Data

We conducted an experiment to acquire a data set using the 'automatic conversation data acquisition system'. The experiment was set up as a conversation between a robot counselor and a visitor, and participants played an automatically assigned role from the data acquisition server designed to obtain a large number of text-based conversation through internet. With this experiment, about 85 participants in the 20-30 age group were recruited online and about 650 conversations were acquired by conducting an acquisition experiment for a month.

TABLE I. DEFINITION OF SOCIAL CUES

Social Cues	Definitions
Greetings	Start of the conversation
Self-disclosure elicitation	Leading one/s interlocutors to provide information about themselves.
Self-disclosure	Revealing personal and private information about themselves.
Suggestion	An idea or plan to put forward for consideration.
General statement	Information or experiences heard from others
Simple yes/no answer	Simple answer(“yes”, “no”) for questions
Acknowledgement	Harmony or accordance in opinion or feelings, a position or results of agreeing
Praise	The expression of a favorable judgement of an attribute, behavior or product of other person.
Termination	End of the conversation

B. *Defining Social Cues*

After collecting the dialogue data set, the standards of social cue were set and the dialogue data was analyzed. Discourse analysis is required to represent large-scale communication in text communication. Therefore, this study set its own standards of social cue based on previous studies and analyzed dialogue data in order to conduct a discourse analysis, as shown in Table 1 [10].

TABLE II. EXAMPLE OF DIALOGUE WITH SOCIAL CUES

Role	Sentences in Dialogue	Tagging
Counselor	Welcome.	Greeting
	How are you feeling today?	Self-Disclosure Elicitation
Visitor	I just don’t feel so good.	Self-Disclosure
Counselor	You are not feeling well.	Acknowledgment
	Shall we begin the consultation?	Suggestion
	What are you worried about?	Self-Disclosure Elicitation
Visitor	I’m bored after work.	Self-Disclosure
Counselor	How about finding a hobby to enjoy after work?	Suggestion
Visitor	Do you know any hobbies to do?	Self-Disclosure Elicitation
Counselor	How about jogging?	Suggestion
Visitor	That’s a good idea!	Acknowledgment
	I know a good place to jog around the house.	Self-Disclosure
Counselor	Oh, that's great.	Acknowledgment
	Then I will end the consultation.	Termination

C. *Social Dialogue Data Tagging*

6 different people were recruited to tag 4,200 sentences with social cues (Example is shown in Table 2). To increase reliability, three coders were tagged for each utterance, and we divided them into two different groups. Each group tried to tag the each half of the dialogue with the pre-defined social cues. The reliability between coders was verified based on the Krippendorff's alpha, after tagging was completed (α = 0.817).

D. *HMM modeling*

Our model predicts the social cue sequence (hidden state sequence) of the counselor when the visitor’s social cue sequence is observed. As a method of predicting the hidden state, we used viterbi algorithm that finds the most likely hidden state sequence given the model and observed sequence. To build the social dialogue model by HMM, we used the open source package, Pomegranate [12].

After learning HMM with viterbi algorithm, performance evaluation was conducted with cross validation(K=7). The accuracy was calculated with the number of HMM prediction cues for the total number of turns in the conversation in permutation.

IV. RESULT

A. *Analysis Conversation Data*

The usage of social cues between the visitor and the robot counselor (Bao) was compared. As a result, visitors tend to use “self-disclosure” 4.8 times more than other social cues and robot consultants uses “Acknowledgement”, “Self-disclosure elicitation”, “Suggestion” more than the other social cues (Fig. 1).

We calculated a transition probabilities of social cues between robot counselor and visitor (Fig. 2). There are two results according to the visitor's social cue usage in (Fig. 1). First, counselor used "Acknowledgement" and "Self-disclosure Elicitation" as 40% as the response to “Self-disclosure”, the most frequently used social cue by visitor. Second, “Self-disclosure Elicitation”, “Suggestion”, and “Simple yes/no” social cues, where the number of utterances by the visitor was small, showed a high probability that the counselor response with “Suggestion”, “Acknowledgement”, and “Praise”.

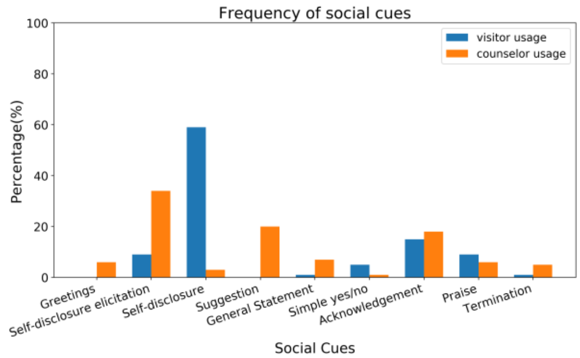

Figure 1. Percentage of social cues between a visitor and a counselor

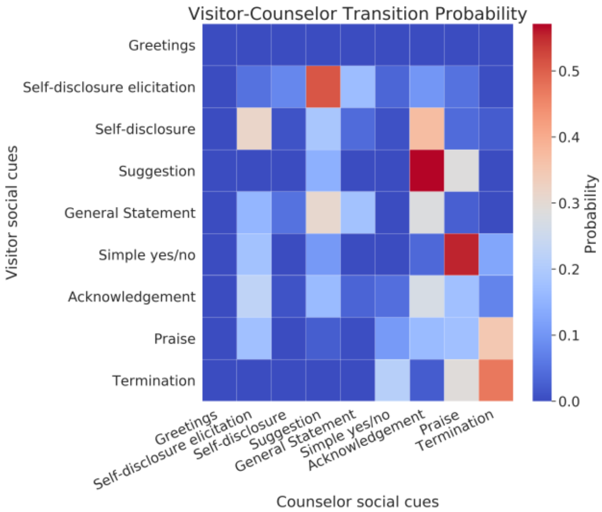

Figure 2. Transiton probability of social cues

B. HMM prediction accuracy rate

We evaluated the performance of the HMM model trained with dialogue data. As a result, we can show an average accuracy of 50% using cross-validation divided into 7 folds (Fig 3).

V. Conclusion

We analyzed the tendency of social cues in the chatting data of visitor-counselor conversation. Visitor used the social cue of "Self-disclosure" for 60% of the conversation the most during the interaction, and the counselor used the "Self-disclosure elicitation" that induces the visitor's information the most. Current HMM model for predicting social cues is relatively low for real application. The next step is to develop a better predictive model for social dialogue model in the future. We are going to apply the developed model to a chatbot or AI speaker to conduct user evaluation. Through the experiment, we will judge how intimately the robot to which the developed model is applied and finally propose a basic social dialogue model.

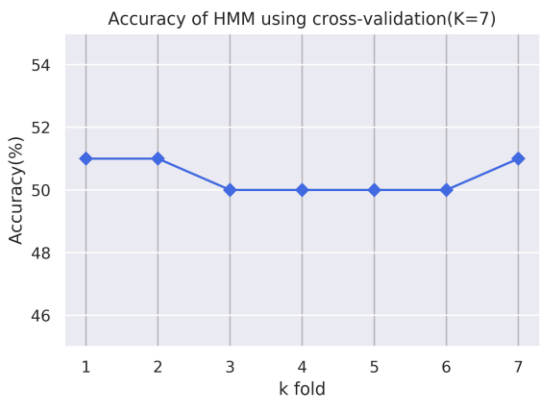

Figure 3. Accuracy of HMM model

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