Master's Thesis

Title

State estimation in collaborative learning for robot's control of multi-party dialogue

Supervisor

Professor Yasuhiro Minami

Author

Tadashi Hayamizu

February 12th, 2013

Department of Information Networking

Graduate School of Information Science and Technology

Osaka University

Master's Thesis

State estimation in collaborative learning for robot's control of multi-party dialogue

Tadashi Hayamizu

Abstract

As robotics recently advance, we will expect that robot should more prevail in human society. For this society, we have to tackle the most difficult and important problem, that is how to appropriatly build relationships between humans and robots. Currently, Human Robot Learning (HRL) deals with a part of this problem. However, HRL focuses on narrower relationships than those of the problem. HRL supposes that robots and human learn each other and performance of the robots are evaluated by both of learning effects. However, current robot systems cannot respond to humans without human's supports because the systems cannot perfectly recognize meanings of conversations and act autonomously. To act autonomously, robots have to recognize meaning of conversations correctly and decide the optimal actions depending on the situations.

Thus, we focus on robot's understanding of conversational situation to act autonomously. We apply conversational robot to the robot support in collaborative learning as a specific example of HRL. We first set up an experimental task as instance of collaborative learning and conducted a conversational experiment using the wizard of oz method. Then we defined conversational states as conversational situation in the task, investigateing the collected experimental conversational data. Finally, we proposed the method to understand conversational states using hidden Markov models, considering semiautomatic robot action generation. Estimation results showed that our proposed method attain 50% of state recognition accuracy, resulting in effectiveness of our proposed method.

Keywords

Hidden Morkov Model

State Estimation

Human Robot Learning

Contents

1 Introduction **5**

2 Related Work **7**

3 Collaborative Learning Scenario **8**

3.1 Yoyo Problem 8

3.2 Procedure 8

4 Data Collection for Collaborative Learning Scenerio **10**

4.1 Conversation Experiments for Data Collection 10

4.2 Dialogue Data 10

5 State Estimation of Multi-party Dialogues using Hidden Markov Model **14**

5.1 Conversation Models of Each Phase 14

5.2 Whole Conversation Model 15

5.3 State Estimation 16

5.4 Evaluation 17

5.5 Discussion 17

6 Conclusion and Future Work **21**

Acknowledgements **22**

List of Figures

1 yoyo problem 9
2 experiment image 13
3 the physical configuration of the system 13
4 conversation model of Phase1 18
5 conversation model of Phase2 18
6 conversation model of Phase3 19
7 conversation model of Phase4 19
8 whole conversation model 20

List of Tables

1 utterance label 11
2 example of labeling 11
3 number of states of conversation models of each phase 15
4 rate of concordance of the state estimation 17

1 Introduction

As robotics recently advance, we will expect that robot should more prevail in human society. For this society, we have to tackle the most difficult and important problem, that is how to appropriatly build relationships between humans and robots. However, most studies in this area only statistically confirmed the facts which had not investigated because relationship between human and robot is vague. To advance this study, it is important to refine vague relationship to more determinate relationship called Human Robot Learning (HRL).

HRL supposes that humans and robots learn each other and evaluate the performance of a robot by what humans and robots learn. Giving the objective of learning each other increases their research focuses and makes the researches practicable. HRL considers future society where robots join into human society states where humans and robots relay on each other and learn each other. Here robots will emerge intelligence and creative collaborative activities in the human society beyond their ordinary limited roles. They will take part in new roles that enforce the quality of interactions between humans. Existence of these robots extremely progresses mutual-understanding among humans.

Humans become smart in not only ”teaching-learning” relation but also”learning-each-other” relation. However, until now research techniques which disclose what kind of relations are effective in learning are limited in investigating emerged process in group activities. On the other hand, HRL can improve the effects of communication by controlling utterance contents and timing of robots that join in human conversations.

However, most robots used in HRL experiments are remotely controlled, and the robots cannot autonomously decide an action after understanding intentions in human conversational utterances. For example, Siri on iOS can estimate key words for search information from utterances in human-to-robot one-on-one conversations, but cannot understand human long term intentions in human conversations. Robots in HRL must be able to understand the human intentions in future so that they will prevail in educational fields.

We have researched dialogue processing to support human’s thinking, guide them, and evoke thier new ideas. In these researches, we implemented a natural speech interaction system using state of the art techniques such as large vocabulary speech recognition and text interactive processing. We aim at generating the communication strategy by which a robot performs appropriate actions to humans. To attain this aim, we propose a calculation model integrating various information and a statistical action generation model, which makes appropriate decisions using the calculation model.

2 Related Work

In this paper we model dialogue flow using HMMs. We note that HMMs have been used to model task oriented dialogues (Shirai, 1996) and casual conversation (Isomura et al., 2006). In contrast, this study uses HMMs to model and analyze multiparty collaborative conversations. There is not any similar studies in this area. In addition, while the two previous studies only modeled dialogue flows, the aim of the proposed method is to extend the HMMs to dialogue control. Recently Multi party dialogue system has been proposed(D. Bohus et al., 2009). However, in these systems, dialogue controls were made by conversation researchers. In contrast, the aim of the proposed method is to obtain dialogue control automatically.

3 Collaborative Learning Scenario

In this research, we use Yoyo Problem that is presented in Figure 1 for collaborative learning. The problem is proper for estimating conversation situation, it is because that the problem that occurs when we try to study construction of internal models is that the problem may include its own peculiar difficulties originating from the problem structure and the solver's knowledge. This section describes Yoyo Problem and procedure of the problem.

3.1 Yoyo Problem

Two persons practice the collaborative learning with Yoyo Problem[1] that is presented in Figure 1. The problem is multiple-choice, to predict the direction of movement of a yoyo placed on the floor and wound by a string, if the end of the string is pulled as illustrated in Figure 1. Answers to the problem are either that the yoyo ”rolls to the left,” ”rolls to the right,” ”does not move,” or others. The correct answer is that the yoyo ”rolls to the left,” since the direction of rotational momentum caused by the tension force in the string and the center of rotation at the yoyo's point of contact with the floor is to the left.

Robot joins in this learning and stimulate objective view of persons by repeating an utterance that is important meaning called ”revoice”.

3.2 Procedure

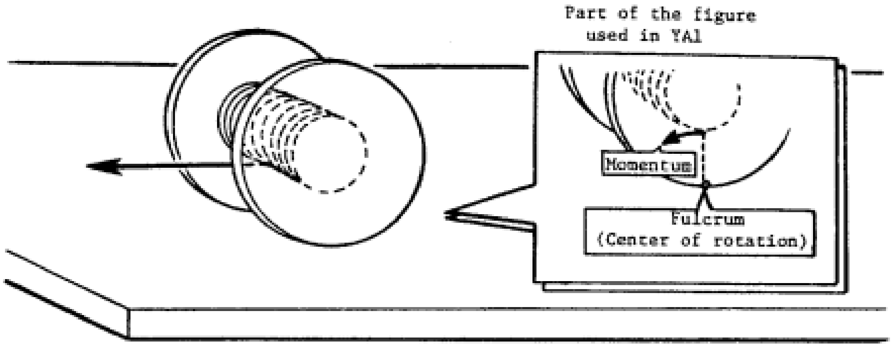
We practice the collaborative learning with Yoyo Problem that is presented in Figure 1 in the following steps.We split procedure into a phase and after that name each phase with this number.

Phase1. The first meeting (5 minites)

Robot and human practices the self-introduction each other before performing collaborative learning. The robot performs self-introduction and talks between a participant freely. Because it is important that a robot and persons relax the tension, the robot talks with persons positively.

Phase2. Solving The Yoyo Problem (10 minites)

After an explainer reading aloud of the problem, persons and robot discuss the problem and answer , as they watch the problem that is distributed.



The centers of two circular frames are interconnected by an axle, and a string is wound round it as illustrated in the figure below. What will happen if you pull the string as shown in the figure? The discs may roll, but never slide.

Mark the number that you think correct.

(1) The yoyo rolls to the left (counterclockwise).
(2) The yoyo rolls to the right (clockwise).
(3) The yoyo does not move.
(4) Others. (Write down your answer concretely.)

Figure 1: yoyo problem

Phase3. Confirmation of the result (5 minites)

The explainer distributes a real yoyo and robot let persons experiment to check a correct answer. And the explainer let persons write a correct answer and let persons and robot argue about a reason again.

Phase4. Confirmation of the reason about the result after an explanation (5 minutes)

After having heard the commentary about the correct answer, a robot asks about the understanding of contents and instructs it.

4 Data Collection for Collaborative Learning Scenerio

In this section, we explain the data collection and management to create a conversation model

4.1 Conversation Experiments for Data Collection

To collect the data that is needs to create a conversation model, we performed conversation experiments of collaborative learning that had explained in 3.1 section. There are about 40 dialogues between 80 persons and a robot on this corpus. The constitution of the system which we used for an experiment is presented in Figure 3. In addition, we explain the behavior of the robot in 4.1.1 sections.

4.1.1 Wizard of Oz

The behavior of the robot which intervenes as a listener when we collect dialogue data uses Wizard of Oz (WoZ) method. WoZ method is the effective simulation technique for dialogue system, it is what human who pretend the dialogue system called Wizard talks to persons. Wizard has understanding with Yoyo Problem and he behave to a robot.Because persons believe that he talks to a robot, Dialogue Data is close to the proper system.

4.2 Dialogue Data

To estimate the dialogue situation that is aim of our research, we give the dialogue data which had recorded in the experiments the two information which is utterance label and dialogue state. An utterance label is the symbol which extracted a characteristic every utterance of a user and the robot. A dialogue state is contents at each point of talks carried out. We can estimate a dialogue state from utterance label by using conversation model created by both utterance label and dialogue state. Utterance label is explained in 4.2.1 section, and dialogue state is explained in 4.2.3 section.

4.2.1 Utterance label

The utterance label is an attribute to give to utterance to distinguish content included in the utterance, for example table 1. Every utterance is given the utterance label, and one utterance may be given plural labels. In addition, one label is not given through more than two utterance. An utterance label has a type and contents, and contents become the hierarchical structure in the low rank of the type. The type classifies kinds of the utterance, and the contents classifies contents of the utterance. In the case of an unnecessary type to classify in contents, contents do not exist.

Table 1: utterance label

human's label				robot's label	
type	contents	type	contents	type	contents
Greeting		Explanation	slip	Greeting	
Description		Explanation	no-slip	Instruct	
Description	about robot	Explanation	Yoyo:rolls	Call	
Self-Disclosure		Explanation	Yoyo:rolls to the left	Question	
Self-Disclosure	place	Explanation	Yoyo:rolls to the right	Question	reason
Self-Disclosure	name	Explanation	Yoyo:does not move	Question	promote
Question		Explanation	Yoyo:shape	Revoice	
Question	place	Others		Revoice	name
Question	name	Others	utterance	Others	
Question	other	Others	reply	Others	reply

4.2.2 Labeling

Every utterance is given the utterance label like table 2. Two people give the label to use in this study to each dialogue data according to a manual which determined the rule that what kind of scene that you gives label.

Table 2: example of labeling

utterance	label1		label2	
	type	contents	type	contents
Hello.	Greeting			
Because this yoyo does not slip, the yoyo rolls.	Explanation	No-slip	Explanation	Yoyo:Roll

4.2.3 Dialogue state

Dialogue state is the state indicating the contents of the talks at each point of utterance, and it becomes the purpose of this study to estimate this. The dialogue state is divided into several kinds of contents every phase and changes by the flow of talks. A robot becomes able to estimate dialogue state at each point in time to be the state transition of the conversation model at each point in time from the input of the label by connecting transition of dialogue state with conversation model.

Figure 2: experiment image

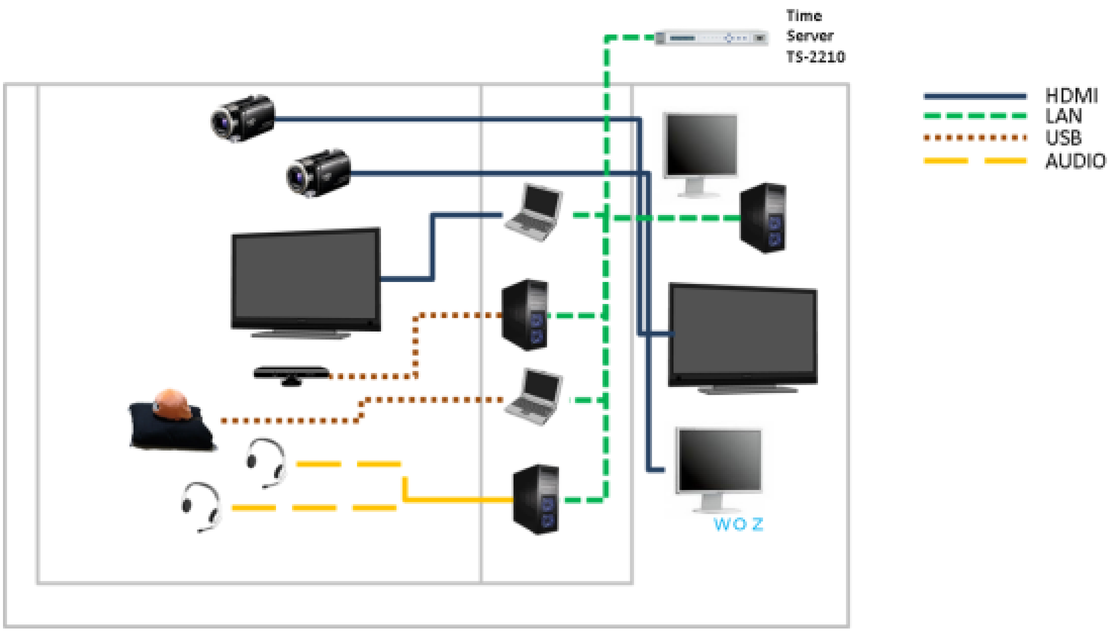


Figure 3: the physical configuration of the system

5 State Estimation of Multi-party Dialogues using Hidden Markov Model

This section describes the making of the conversation model using HMM (Hidden Marcov Model) and the dialogue state estimate technique, and the evaluation.

5.1 Conversation Models of Each Phase

The conversation model made it using the dialogue data which we explained in 4 section.I use Jahmm making a model using hmm.The models that we made are figure 4,5,6,7. To make the estimate of the dialogue state more highly precise, the conversation model fixed an initial state and a final state for every phase and made it separately. After having made the model of each phase, we unite each model and make one model through the whole talks. Each state of the model has initial state, an end state, dialogue state. The dialogue state is divided into a human dialogue state and robot dialogue state and assigns the dialogue state that we explained in 4.2.3 section to a human talks state. To estimate these human dialogue state is the purpose of this study, and what the action of the robot generates using robot dialogue state semi-automatically is the final aim.

5.1.1 Initial Parameters

For an initial value, we decided the number of the states, and in condition transition probability, and the utterance label generation probability in each state before making conversation model. The number of the states of each phase is initial state, an end state, the dialogue state total value. The state transition probability gives all transition except transition from the transition from initial state to an end state, dialogue state and an end state to initial state probability, and a value is all equal. The utterance label generation probability that is in each state gives the utterance label which may appear according to a human dialogue state and robot dialogue state probability every phase, and the value becomes equal. In addition, the label generation probability of the initial state and the end state sets it to the total of the human talks state and talks state of the robot.

Table 3: number of states of conversation models of each phase

	Phase1	Phase2	Phase3	Phase4
initial state	1	1	1	1
human's dialogue state	3	5	4	3
robot's dialogue state	3	4	4	2
last state	1	1	1	1
number of states	8	11	10	7

5.1.2 Learning for State Estimation

We explain the learning of the talks model here. The conversation model learns a utterance label line as input with the initial value that we set in 5.1.1 section. However, we cannot estimate dialogue state by having only input an utterance label line. Therefore we realize the estimate of the dialogue state by connecting the state of the model with the dialogue state that we want to estimate.

For example, in the case of Phase 2, the dialogue state that we want to estimate has initial state and human dialogue state that are six in total. When we give these dialogue state the initial generation probability of the utterance label, we distinguish an utterance label every dialogue state and initial generation probability and learn it, thus we can learn the generation probability that is in each state and the transition probability to each state definitely.

5.2 Whole Conversation Model

This section explains a model through the whole talks of the collaborative learning.

5.2.1 Model Meage

We make conversation model through the whole talks by connecting every conversation models of each phase by adding transition probability p from the end state of models of each phase to the initial state of model of next phase. After multiply $1-p$ and all state transition probability that an end state has, the end state is given the transition probability p that is from the end state to initial state of transition ahead.

5.2.2 Smoothing

Deflection occurs to the generation probability of the utterance label which each state has because there are few learning data. We prepared for the generation probability of the utterance label which each state should have for this correction and canceled the deflection by multiplying it and constant probability.

5.2.3 Flooring

When I make a model, I assumed the generation probability of the utterance label which is in each state 0 or a constant value, but unexpected label input of one makes an estimate impossible when I estimate a state as it is. The generation probability of the utterance label gave label generation probability of the pettiness on 0 labels to cope with the input of an unexpected label.

5.2.4 Model

The model that we made is figure 8. As for the double circle of the figure, initial state and the end are in a state, and, as for the circle, human dialogue state, and the square expresses robot dialogue state. In addition, state from 0 to 7 expresses a state of phase1, and state from 8 to 18 state a state of phase2, and state from 19 to 28 expresses a state of phase3, and state from 29 to 35 expresses a state of phase4, and state 36 expresses an end state of the whole model.

5.3 State Estimation

This section explains the state estimate technique using the conversation model which had made in 5.2 section. This model assigns the dialogue state that you should estimate to a human dialogue state and learns it. Therefore maximum likelihood state demanded at each point in time becomes state to be estimated each point in time by using Viterbi algorithm as input in an utterance label line for conversation model.

The evaluation method is a rate of concordance with the dialogue state that estimated that the talks that dialogue data are given are in a state from a utterance label. But I perform the rate of concordance only about human utterance and do not perform a state estimate about the utterance of the robot.

5.4 Evaluation

We evaluated a state estimation using ten dialogue data that is not used for learning. The evaluation result is table 4.

Table 4: rate of concordance of the state estimation

	average	max	min
Phase1	0.59	0.78	0.37
Phase2	0.45	0.88	0.16
Phase3	0.49	0.78	0.15
Phase4	0.62	0.97	0.22
Whole	0.51	0.76	0.35

5.5 Discussion

Confirming the error of the state estimate, there was a pair of state which had a relationship to often get a wrong estimate each other e.g. state 9 and 10 in figure 8. When I considered the wrong estimate of this pair to be concordance and calculated a rate of agreement, the rate of concordance grew from the value near min to the value near max of Phase2 of table 4. It is thought that this is because conversation model cannot distinguish these pair of dialogue state with the utterance label which I prepared soon substantially. Therefore we think that the rate of concordance can be improved if we can prepare an utterance label distinguishing these states well.

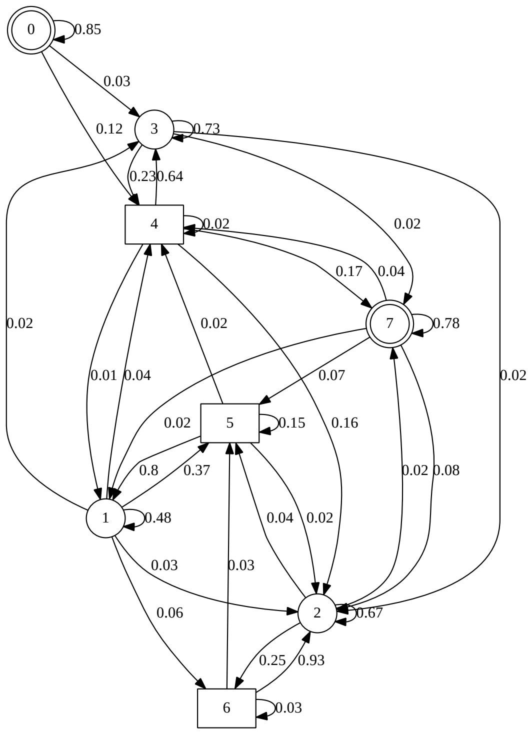


Figure 4: conversation model of Phase1

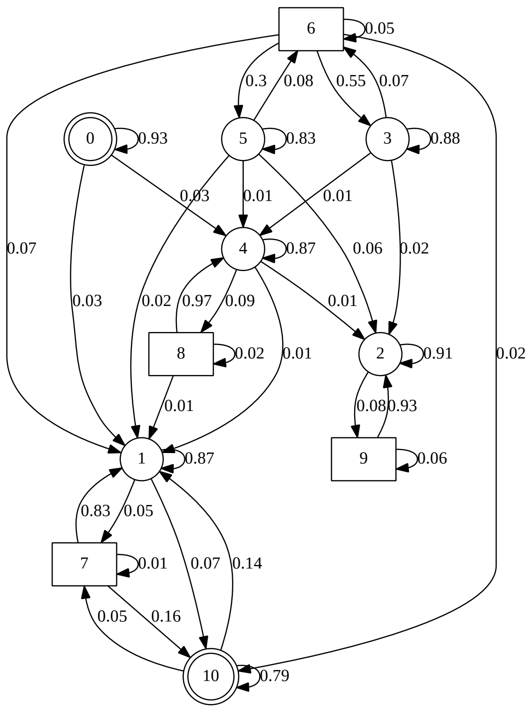


Figure 5: conversation model of Phase2

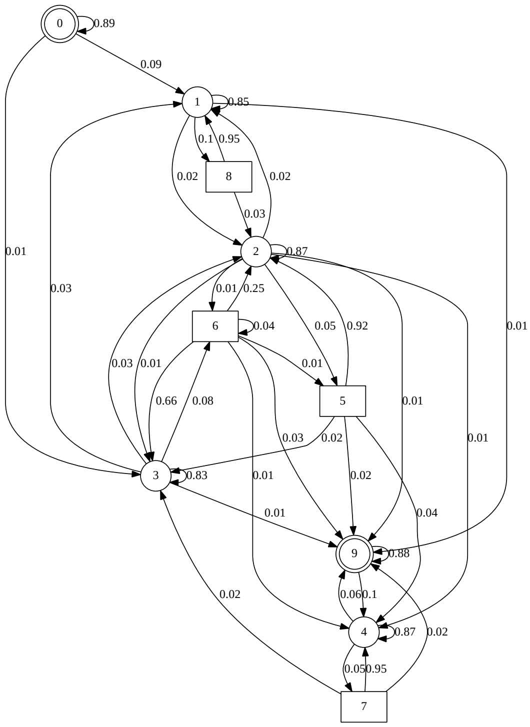


Figure 6: conversation model of Phase3

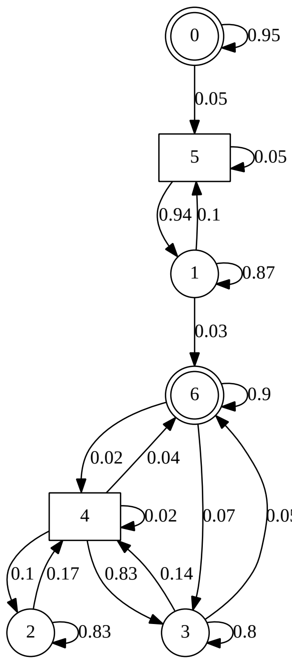


Figure 7: conversation model of Phase4

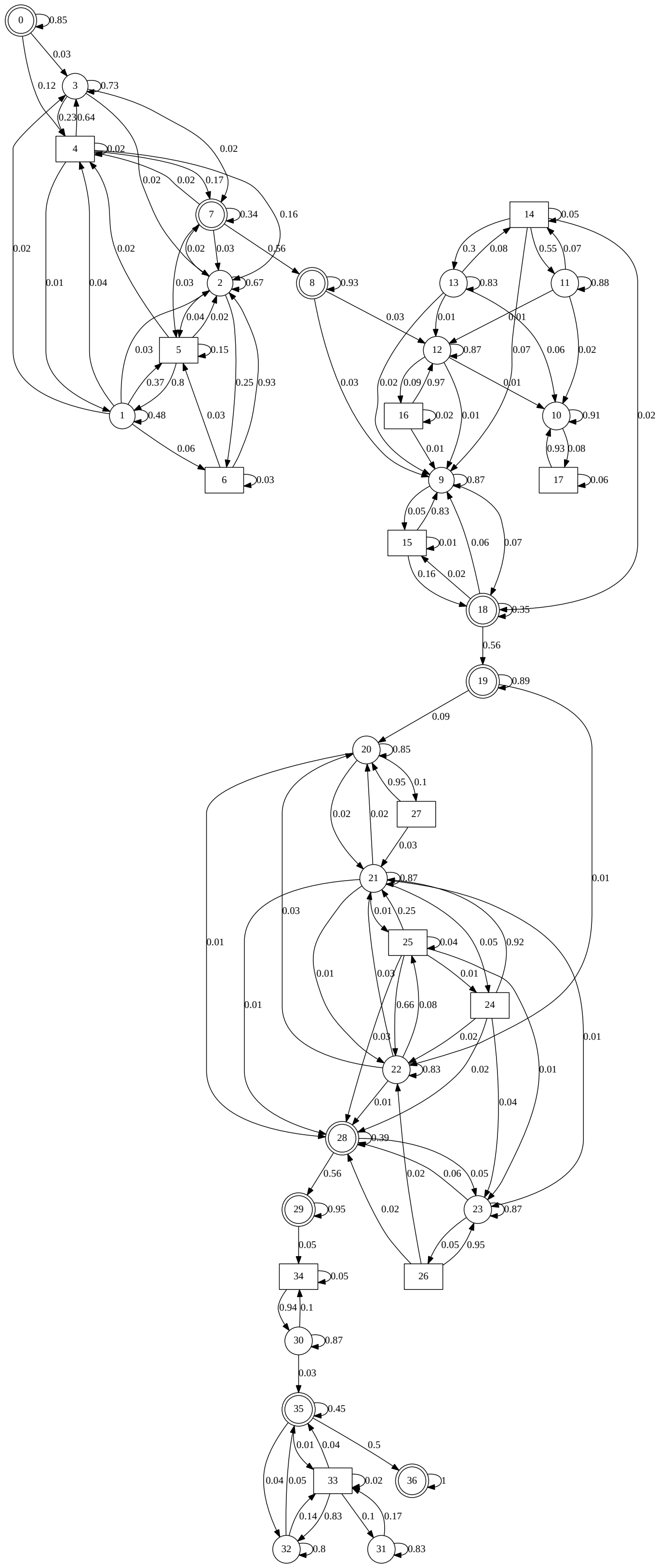


Figure 8: whole conversation model

6 Conclusion and Future Work

We had researched dialogue processing of supporting human's thinking , guiding, and rousing thought. These research incarnated a natural voice interaction that is possible in a current technical range by using technique of voice recognition and text interactive processing. This study proposed the method of state estimation by considering a calculation model and a generation model to incarnate a suitable interaction between humans and robot by using of an existing technique. By this, we are convinced that we were able to walk one step to build the relations that a person and a robot learn each other.

In the future work, we will set an utterance label which is to estimate the dialogue state more correctly or can estimate even if an utterance label has an error. We will complete the semiautomatic generation of the action of the robot by using the speech recognition and automated labeling and state estimation.

Acknowledgements

This thesis would not have been possible without a lot of grate supports of several people. First and foremost, I would like to appreciate to my supervisor, Professor Yasuhiro Minami of NTT Laboratory and Professor Kohji Dohsaka of Akita Prefectural University, for his pertinent advices, valuable and continual support. I express cordial gratitude to him for giving me a chance to receive a quality education. I'm also deeply grateful to Professor Masayuki Murata of Osaka University. He devoted a great deal of time for me and gave me an excellent guideline of my research and considerable supports. Also, I acknowledge Professors Koso Murakami, Teruo Higashino, and Hirotaka Nakano of Osaka University, for their appropriate suggestions on my study. Furthermore, I must appreciate to Associate Professor Shin'ichi Arakawa and Assistant Professor Yuichi Ohsita for valuable comments and suggestions on this study. In addition, I would like to express sincere appreciation to Mr. Daichi Kominami, who is my senior associate. I received a lot of advices from him and he kindly provided consultation for me. Finally, I would like to thank all the members of the Advanced Network Architecture Laboratory at the Graduate School of Information Science and Technology, Osaka University, and all the members of the NTT communication science laboratory for supports and fruitful discussion about my research and hearty encouragement.

References

[1] Y. Anzai and T. Yokoyama, “Internal Models in Physics Problem Solving,” in *Cognition and Instruction*, pp. 397–450, 1984.

[2] R. R. Shinsuke Higuchi and K. Araki, “A casual conversation system using modality and word associations retrieved from the web,” in *EMNLP ’08 Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pp. 382–390, 2008.

[3] F. T. Naoki Isomura and K. Ishii, “Evaluation method of non-task-oriented dialogue system by HMM,” in *the 4th Symposium on Intelligent Media Integration for Social Information Infrastructure*, pp. 149–152, 2006.

[4] D. Traum, S. C. Marsella, J. Gratch, J. Lee, and A. Hartholt, “Multi-party, Multi-issue, Multi-strategy Negotiation for Multi-modal Virtual Agents,” in *Proceedings of the 8th international conference on Intelligent Virtual Agents*, IVA ’08, pp. 117–130, 2008.

[5] W. Swartout, D. Traum, R. Artstein, D. Noren, P. Debevec, K. Bronnenkant, J. Williams, A. Leuski, S. Narayanan, D. Piepol, C. Lane, J. Morie, P. Aggarwal, M. Liewer, J.-Y. Chiang, J. Gerten, S. Chu, and K. White, “Ada and grace: toward realistic and engaging virtual museum guides,” in *Proceedings of the 10th international conference on Intelligent virtual agents*, pp. 286–300, 2010.

[6] D. Bohus and E. Horvitz, “Models for multiparty engagement in open-world dialog,” in *Proceedings of the SIGDIAL 2009 Conference: The 10th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, SIGDIAL ’09, pp. 225–234, 2009.

[7] K. Dohsaka, R. Asai, R. Higashinaka, Y. Minami, and E. Maeda, “Effects of conversational agents on human communication in thought-evoking multi-party dialogues,” in *Proceedings of the SIGDIAL 2009 Conference: The 10th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, SIGDIAL ’09, pp. 217–224, 2009.

[8] D. Klotz, J. Wienke, J. Peltason, B. Wrede, S. Wrede, V. Khalidov, and J.-M. Odobez, “Engagement-based multi-party dialog with a humanoid robot,” in *Proceedings of the SIGDIAL 2011 Conference*, SIGDIAL ’11, pp. 341–343, 2011.

[9] S. Fujie, Y. Matsuyama, H. Taniyama, and T. Kobayashi, “Conversation robot participating in and activating a group communication,” in *INTERSPEECH’09*, pp. 264–267, 2009.