Proceedings of the 17th IEEE International Symposium on Robot and Human Interactive Communication, Technische Universität München, Munich, Germany, August 1-3, 2008

A Barebones Communicative Robot Based on Social Contingency and Infomax Control

Fumihide Tanaka and Javier R. Movellan

***Abstract*— In this paper, we present a barebones robot which is capable of interacting with humans based on social contingency. It expands the previous work of a contingency detector into having both human-model updating (developmental capability) and policy improvement (learning capability) based on the framework of Infomax Control. The proposed new controller interacts with humans in both active and responsive ways handling the turn-taking between them.**

I. Introduction

Infomax control refers to the real time organization of behavior in a manner that maximizes the information gained about events of interests. Movellan [1] illustrated how an Infomax Control framework can be applied to the problem of detecting social contingency. A real time controller was developed that schedules its vocalizations in a closed loop manner so as to maximize the long term gathering of information about the presence or absence of responsive humans. The approach was applied to a simple social robot whose only goal was to detect responsive human beings. Although the robot was remarkably efficient at finding responsive humans using very simple sensors and actuators, it suffered from a major deficiency: The model used a very simplified model of human responsiveness, under which humans are not expected to spontaneously vocalize to the robot so as to initiate a communicative sequence. For example, when humans see the robot for the first time, they typically try to initiate the interaction by saying ”Hello, robot”, etc. In Movellan's [1] model, this is interpreted as an unexpected increase in the background response rate. As it turns out, when such background changes occur the optimal thing to do is to stay quiet, which turns out to be disruptive for the interaction with humans. This problem is not due to the Infomax Control framework itself but to the fact that the model of social agency was too simplistic. Another problem with the model was that it assumed stationary environments, i.e., on each trial a human is assumed to be either present or absent. Here we generalize the problem to non-stationary environments in which humans may spontaneously enter or leave conversational states.

II. Contingency Detection and Infomax Control

Watson proposed that contingency detection plays a crucial role in the social and emotional development of infants, and it is also a fundamental source of information for the definition and recognition of caregivers [2], [3]. Movellan modeled the problem of detecting the social contingency from the point of view of a barebones robot endowed with a single binary sensor (ex. a microphone) and actuator (ex. a speaker) [1]. The goal of the robot is to discover whether responsive social agents (ex. caregiver) are present. The robot estimates the belief about the presence of the social agents based on Bayesian inference over two possible contingency clusters (Fig. 1). The robot's action policy is determined by Infomax Control: set the robotic controller so that it maximizes the expected information return about the presence ($H_1 = 1$) or absence ($H_1 = 0$) of responsive social agents.

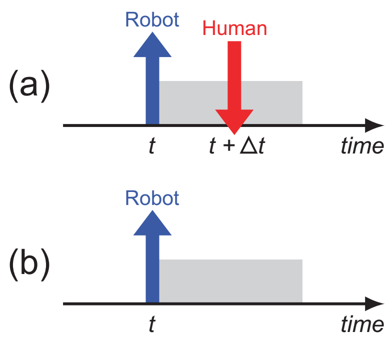

Fig. 1. (a) The case where responsive humans (social agents) present: $H_1 = 1$ (b) The case where there is no responsive human present: $H_1 = 0$

III. Two Hypotheses for a New Infomax Controller

In the original model of social contingency detection, humans were assumed to be responsive (Fig. 1). Usually a turn-taking process includes the opposite situation where humans initiate the interaction and the robot responds to them (Fig. 2). To handle the situation, we expand the structure of robot's hypothesis in the following way: In case of the original model, the robot had single hypothesis, H_1 describing whether there was a responsive agent or not. Here we introduce another hypothesis, H_2 denoting whether the agent believes there is a responsive robot (to the agent) or not. Then a new Infomax Controller can be designed based on the combination of two hypotheses, H_1 and $H_1 * H_2$.

IV. Modeling Human Dynamics using HMMs

As mentioned above, the original model of social contingency detection suffered two major limitations: (1) It

978-1-4244-2213-5/08/$25.00 ©2008 IEEE

F. Tanaka and J.R. Movellan are with the Institute for Neural Computation, University of California, San Diego, 9500 Gilman Drive, La Jolla, CA 92093, USA boom@mplab.ucsd.edu

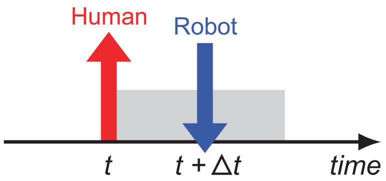

Fig. 2. The case where humans initiate the interaction.

assumed a very simple hand coded model of human social responsiveness, i.e., humans response to the robot but do not initiate interactions on their own. (2) Under the model humans are permanently in either a responsive or non-responsive state. To address these limitations here we propose to extend the Infomax Control approach so that human responsiveness can be directly learned from examples. Under this framework a social agent has two components: (1) An HMM that explains the observed sensory information in terms of some hidden state dynamics and, (2) An Infomax Controller in a manner that maximizes the gathering of information about the hidden states of the HMM.

More specifically the new approach works as follows: (1) During the development phase, an HMM is learned that describes the observed history of actions and sensory consequences to those actions. Due to the fact that the presence or absence of responsive humans has a critical effect on the consequence of the robot's actions, the HMM develops internal states related to the presence or absence of humans. (2) At run time the HMM computes the posterior distribution of the hidden states given the past history of observations and actions (Fig. 3). (3) The information gained after each action, i.e., the reduction in the posterior distribution of hidden states, is used as a reinforcement signal. Off-the shelf reinforcement learning methods, like value and policy iteration are used to develop an Infomax Controller. The role of the controller is to choose moment to moment actions that maximize the information gained about the hidden states.

V. Simulations

We are conducting a series of experiments to test the proposed approach both in computer simulations (Fig. 4) and in actual social robots interacting with humans [4]. Preliminary results show that the Infomax approach schedules vocalizations in a manner that match well at a qualitative level, the statistics of human interaction. For example, the controller produces turn taking-behaviors with vocalizations followed by periods of silence that last an average of 6 seconds. When implemented in a social robot, the system is capable of detecting humans in a very wide variety of conditions, including very noisy environments. Further results for the model combine the simultaneous learning of an HMM model of human dynamics and a controller that maximizes information gathering will be available in the near future.

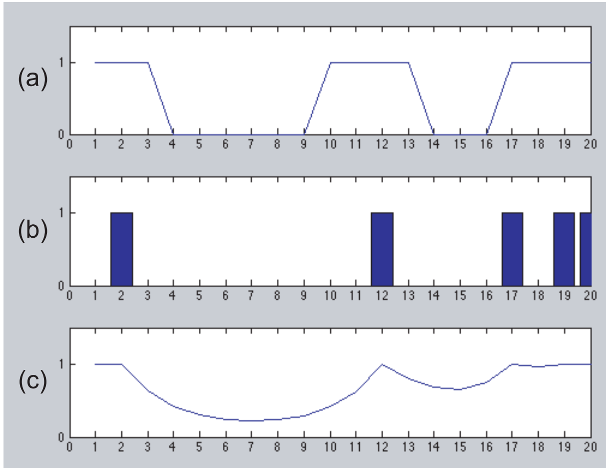

Fig. 3. An example of human modeling by HMMs: (a) A human's global dynamics of being present (H=1) and absent (H=0). (b) The human's behavior of making actions. (c) The posterior probability of the human being present (H=1) calculated by the HMMs.

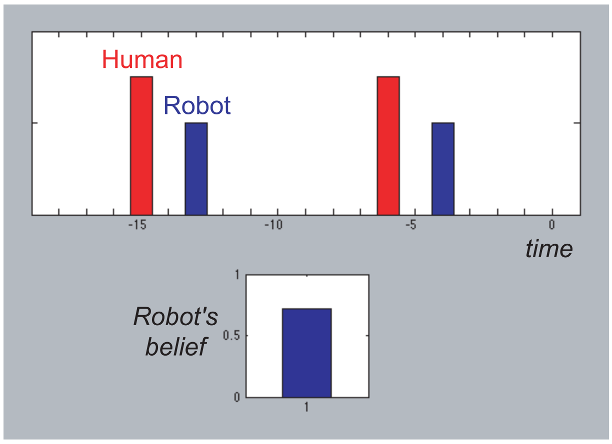

Fig. 4. An example sequence of the robot interacting with a human which is trying to initiate the interaction. Here, the robot is trying to be responsive to the human with its high belief about the presence of humans. This is a typical example of interaction which could not be dealt with the contingency detector presented in [1].

References

[1] J. R. Movellan, "An infomax controller for real time detection of social contingency," Proceedings of 2005 4th IEEE International Conference on Development and Learning, pp.19-24, 2005.

[2] J. S. Watson, "Smiling, cooing and 'the game'," Merrill-Palmer Quarterly, vol.18, pp.323-339, 1972.

[3] J. S. Watson, "The perception of contingency as a determinant of social responsiveness," In E. B. Thoman, editor, Origins of the Infant's Social Responsiveness, pp.33-64, LEA, New York, 1979.

[4] F. Tanaka, J. R. Movellan, B. Fortenberry and K. Aisaka, "Daily HRI Evaluation at a Classroom Environment: Reports from Dance Interaction Experiments," Proceedings of the 1st Annual Conference on Human-Robot Interaction, pp.3-9, 2006.