Towards Proactive Assistant Robots for Human Assembly Tasks*

Woo Young Kwon
Department of Electronics and Computer Engineering, Hanyang University
Seoul, Korea
wykwon@hanyang.ac.kr

Il Hong Suh †
Department of Computer Science and Engineering, Hanyang University
Seoul, Korea
ihsuh@hanyang.ac.kr

Categories and Subject Descriptors

I.2.3 [**Artificial Intelligence**]: Deduction and Theorem Proving—*Uncertainty, "fuzzy," and probabilistic reasoning*

General Terms

Algorithm

Keywords

Temporal Prediction, Proactive, Assistant Robots

ABSTRACT

In this paper, we propose a proactive assistant robot for human assembly tasks. In order to predict future events of human activities such as requesting parts for assembly, we use the temporal Bayesian network that can infer both causal probability and temporal distribution of an conditional event. Based on the temporal Bayesian network model of an human assembly task, we also show that the proactive assistant robot make human-robot-interaction quickly by temporal prediction of an event.

1. INTRODUCTION

When assisting others, humans often predict other's intentions and prepare several actions to respond quickly and effectively to the actions of others. Furthermore, humans can act proactively in order to assist others by predicting their intentions. In the case of an assistant robot in a manufacture line by human workers, the robot can predict a sequence of the assembling task. Therefore, the assistant robot can prepare parts and/or tools that will be required for the future. In human-robot interactions, these predictions and preparations play an important role in fast and effective interaction.

In order to predict human activities, robots are required to learn complex relationships among many stimuli in real-time; moreover, these relationships can change dynamically and non-deterministically. Therefore, a probabilistic method is required for the prediction of a future situation in real robotic applications. For an assistant robot to provide the right assistant at the right time, the robot should predict both what kind of assistant will be required and when the assistance should be provided. For these predictions, both a probability of an event and the temporal distribution of a requesting event of humans is required. In order to predict both the kind of a future event and the time of the event simultaneously, we use the temporal Bayesian network (TBN) by using the time as a random variable [1]. The TBN can infer both causal and temporal relationship between two events within one framework based on the independent assumption between the occurrence of an event and the start time of the event. By using the TBN, we design a probabilistic temporal prediction model of a human assembly task. Furthermore, we model a proactive assistant robot that can infer both the best proactive action and the best time to take the action in order to minimize the waiting time of human by using the temporal prediction of future events.

2. TEMPORAL BAYESIAN NETWORK

The temporal probability of an event A during a specific time interval (t_1, t_2) can be modeled as the joint probability of a static random variable corresponding to the frequency of the event and a temporal random variable corresponding to the start time point of the event; the temporal probability of an event is represented as $P(A = true, t_1 < T_A < t_2)$.

We assume that the temporal random variable T_A is independent of the static random variable A. Given the assumption of independence, the time interval probability can be given by

$$P(A = true, t_1 < T_A < t_2) \quad = \quad P(a) \int_{t_1}^{t_2} f_{T_A}(t_A)\, dt_A, \quad (1)$$

where $f_{T_A}(t_A)$ is the probability density function (PDF) of the temporal random variable of T_A, and t_A is a value of T_A. Using this equation of time interval probability of an event, we proposed the temporal Bayesian network [1] to infer both probability of a conditional event and temporal probability of the event. From the temporal Bayesian network, we can infer any time interval probability of a conditional event such as $P(A = true, t_1 < T_A < t_2 | B = true, T_B = t_B)$.

3. A PROACTIVE ROBOTIC ASSISTANT FOR A HUMAN ASSEMBLY TASK

Human assembly task needs various parts and tools. If an assistant robot proactively deliver a required tools and/or parts by predicting a task-sequence and human intention, the execution time of the human assembly task can be reduced. Moreover, an human worker may feel comfortable. Therefore, it is preferred to infer both which part will be requested future and when will be the time of the request for the proactive assistant robot. Figure 1 shows the part of

*This work was supported by the Global Frontier R&D Program on <Human-centered Interaction for Coexistence> funded by the National Research Foundation of Korea grant funded by the Korean Government(MEST) (NRF-M1AXA003-2010-0029744)

†All correspondence should be addressed to the author.

HRI'11, March 6–9, 2011, Lausanne, Switzerland.
ACM 978-1-4503-0561-7/11/03.

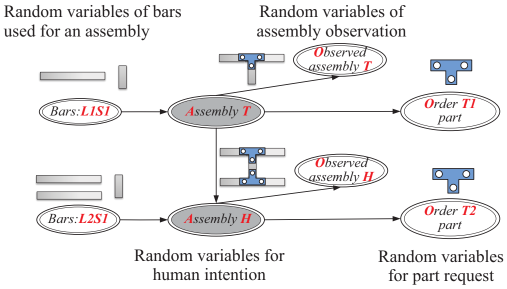

Figure 1: A temporal Bayesian network for T- and L-shaped assemblies.

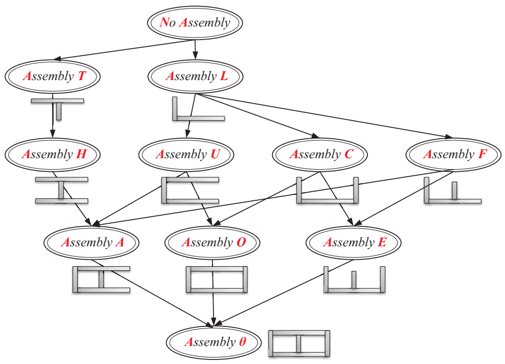

Figure 2: A temporal Bayesian network model of assembly sequences.

TBN model for a human assembly task. First, a person may pick up bars in order to make the target assembly, the θ-shaped assembly. After a worker decides how to combine two bars (the worker's intention), the worker will request a part to the assistant robot. If the worker's intention is to create a T-shaped assembly, the worker may request a T-part. After a T-shaped assembly is made, one possible next step will be a H-shaped assembly. From the TBN in Figure 1, any questions concerning what part will be requested at a specific time interval can be answered given temporal evidences. For example, given an evidence of picking up a long bar at t_0, the temporal probability of requesting a T-part by the worker is give by $P(OT1 = true, t_1 \leq T_{OT1} \leq t_2 | L1 = true, T_{L1} = t_0)$. The question can be answered by using the TBN in Figure 1. In the example, assembly-T and assembly-H are just interim states of the whole assembly sequences. In fact, there are many possible sequences in order to make the final assembly such as θ-shaped assembly. The overall assembly sequences can be modeled as in Figure 2. The next step for proactive assistance is to decide the best proactive action and the time to take the action in order to minimize waiting time. The waiting time is defined as $t_{Wa} = t_{Sa|\mathbf{E}} - t_{Ea} = t_{Sa|\mathbf{E}} - t_{Ba} - t_{Da}$ by the difference between the time of requesting part ($t_{Sa|\mathbf{E}}$) and the end time of a part-delivery action (t_{Ea}), where t_{Ba} is the start time of a proactive action and t_{Da} is duration of the action. The best time for taking the proactive action is given by minimizing the expectation, $E[T_{Wa}]$. Here, only start time of a proactive action t_{Ba} is free variable. Therefore, the best time of proactive action is given by $t_{Ba} = \mu_{Sa} - \mu_{Da}$

Considering only one proactive action, the best time of the proactive action can be easily obtained. To select the best proactive action among many candidates, however, a criterion is required to compare the usefulness of each proactive actions including several properties: an importance of a request ω_a, occurrence probability of the request $P(s_a|\mathbf{E})$, and the waiting time between the requesting time and the end time of deliver the requested part by a robot T_{Wa}. The temporal criterion is given by using expectation as

$$E\left[U\left(s_a, a|\mathbf{E}\right)\right] = E\left[\omega_a \cdot P\left(s_a|\mathbf{E}\right) \cdot \Phi\left(W\left(a|\mathbf{E}\right)\right)\right]$$
$$= \omega_a \cdot P\left(s_a|\mathbf{E}\right) \int_{-\infty}^{\infty} \Phi\left(t_{Wa}\right) \cdot f_{T_{Wa}}\left(t_{Wa}\right) dt_{Wa}, \quad (2)$$

where Φ is probability weighting function for the waiting time. Here, the standard normal distribution is used. By using the criterion, a proactive robot can select both a kind of proactive action and the time of the action.

4. EXPERIMENTS

We conducted an experiment in a human-robot cooperative assembly task, where two workers have to make a θ-shaped assembly, respectively. Two scenarios are in the experiment: on-demand assistance and proactive assistance. In the on-demand assistance scenario, a worker would pick up bars in order to make assembly. Next, the worker requests necessary parts (L-part or T-part) to combine the two bars. According the worker's request, an assistant robot deliver and hand over the requested part.

In the proactive assistance scenario, the assistant robot proactively deliver a part before the worker request the part yet. To give the right assistance at the right time, the robot has to know which bars and which parts have been taken. Moreover, the robot also has to know the progress of assembling task in the workspace. Therefore, four top down view cameras are mounted above the workbench. Shape-based visual object detection module is used for detecting bars and SIFT based object recognition software is used for detecting assembly. In order to model the TBN, we collected time interval data between events for every trial. Each trial is terminated when the worker successfully makes a θ-shaped assembly. We made CPTs by determining the frequencies of conditional events, and deduced the PDFs for the temporal intervals of conditional events for every trial, in which the means and variances of the Gaussian distribution were computed. With these causal and temporal data, a proposed TBN is constructed. To verify the effectiveness of the proactive assistant robot, we made a comparison of the task execution time between the proactive assistance and the on-demand assistance. From 30 trials, the task execution time of on-demand action selection is 371 s, while the time of proactive action selection is 240 s. From the result, we can see that there is a 33% improvement in task execution time when the proactive behavior selection method was used.

5. CONCLUSION

We have presented a proactive assistant robot that proactively deliver a part just when a worker has been predicted to request that part. The TBN enables the model to infer both causal and temporal probabilities using a single framework. Moreover, the temporal utility can provide a criterion to measure the usefulness of the proactive action using the criterion of human waiting time. By using these two probabilistic methods, an assistant robot can proactively act in order to assist others.

6. REFERENCES

[1] W. Y. Kwon and I. H. Suh. Probabilistic Temporal Prediction for Proactive Action Selection. In *IROS Workshop on Probabilistic Graphical Models in Robotics (GraphBot 2010), Taipei, Taiwan*, 2010.