2012 IEEE International Conference on Robotics and Automation
RiverCentre, Saint Paul, Minnesota, USA
May 14-18, 2012

A Temporal Bayesian Network with Application to Design of a Proactive Robotic Assistant

Woo Young Kwon and Il Hong Suh

Abstract— **For effective human-robot interaction, a robot should be able to make prediction about future circumstance. This enables the robot to generate preparative behaviors to reduce waiting time, thereby greatly improving the quality of the interaction. In this paper, we propose a novel probabilistic temporal prediction method for proactive interaction that is based on a Bayesian network approach. In our proposed method, conditional probabilities of temporal events can be explicitly represented by defining temporal nodes in a Bayesian network. Utilizing these nodes, both temporal and causal information can be simultaneously inferred in a unified framework. An assistant robot can use the temporal Bayesian network to infer the best proactive action and the best time to act so that the waiting time for both the human and the robot is minimized. To validate our proposed method, we present experimental results for case in which a robot assists in a human assembly task.**

I. Introduction

When humans assist each other, they often predict the other's intentions and prepare several actions for quick and effective response to their actions. Furthermore, humans are capable of acting proactively to assist others by predicting their intentions before actually request assistance. In the case of an assistant robot working in a manufacturing line alongside human worker, the robot can predict a sequence of the assembling tasks performed by the human, and can therefore prepare parts and/or tools that will be required in future. Due to these anticipations, the human worker can receive appropriate services from the assistant robot without explicit requests and waiting time. These temporal predictions and proactive action selection play an important role in fast and effective human-robot interaction [1]–[5], and vital in many robotic applications such as assistant robots [6]–[8] and mobile robot navgations [9], [10].

In general, robots are required to learn complex causal and temporal relationships existing between multiple events in real-time in order to predict human behaviors. Moreover, these relationships can change in a dynamic and non-deterministic fashion. A probabilistic method is therefore required to make future prediction in actual robotic applications. Several researchers have proposed probabilistic approaches to predict future events from both temporal and causal viewpoints [11] [12]. Among these many approaches, the dynamic Bayesian network (DBN) proposed by Dean and Kanazawa [13] is one of the most widely known methods to make predictions pertaining to sequential events. The DBN provides a method to represent and infer temporal sequences of events by discretizing time and creating an instance of each random variable at each point in time [14].

W. Y. Kwon is with the Department of Electronics and Computer Engineering, Hanyang University, Korea wykwon@hanyang.ac.kr

I. H. Suh is with the Division of Computer Science and Engineering, College of Engineering, Hanyang University, Korea. All correspondences should be addressed to I. H. Suh ihsuh@hanyang.ac.kr

DBN approaches are widely used for prediction of stochastic events. However, there are several difficulties in temporally predicting human behaviors. First, a standard DBN only works in the discrete time domain, where a uniform time granularity is allowed. However, many real applications require a different time granularity. For example, temporal prediction of human behavior in sport activities requires fine-grained time slice, while temporal prediction in daily life require more coarse-grained time slice. Therefore, finding the best time granularity in various situations is difficult problem. Second, first order Markov assumption in standard DBN approach restricts the expressive power of DBN to modeling exponentially distributed over time [15]; the holding times in each state are exponentially distributed in continuous Markov processes and geometrically distributed in discrete Markov processes. In fact, the exponential distribution is widely used for temporal distribution of an event because the time between consecutive events follows the exponential distribution under the independent assumption among events. However, there are many kind of events cannot be modeled as exponential distribution. For example, events related human behaviors are generally not independent. Therefore, the exponential distribution would not be appropriate to represent the time of conditional events related human behaviors.

Because DBNs have several limitations for representing a temporal distribution of an event, we need alternative temporal prediction methods. In order to predict both the kind of an future event and the time of the event simultaneously, we proposed a temporal prediction method in a continuous time domain by using the time as a random variable [6], which is based on separation between the occurrence of an event and the start time of the event. By using this approach, both causal and temporal relationship between two events can be represented within one framework. In this paper, we consider a temporal Bayesian network and its inference method that can infer the time of future events although there are any unobserved events based on the probabilistic temporal prediction method. Furthermore, we show that a proactive robot assistant can infer both the best proactive action and the best time to take the action in order to minimize the waiting time.

The rest of this paper is organized as follows: in Section II, we present the proposed temporal Bayesian network. Inference in the temporal Bayesian network is discussed in Section III. Section IV will present proactive behavior selection method based on the proposed temporal Bayesian network, and experimental results follow in Section V. We present the concluding remarks in Section VI.

II. A Temporal Bayesian Network

The temporal probability of an event occurring during a specific time interval 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. For example, the probability of lunch starting between 11 a.m. and 1 p.m. can be modeled as the joint probability of two random variables: the frequency of lunch happening every day and the start time of lunch.

More formally, the time interval probability of an event $X = true$ from t_1 to t_2—which has the same meaning as the temporal probability of an event at a specific time interval— is represented as $P(X = true, t_1 < T_X < t_2)$, where X represents the relative frequency of an event, and T_X represents the start time of the event X.

Next, the time interval probability can be reformed by

$$\begin{aligned} P(X = true, t_1 < T_X < t_2) &\\ = P(t_1 < T_X < t_2 | X = true) P(X = true) &\\ = P(X = true) \int_{t_1}^{t_2} f_{X_1}(t_X)\, dt_X & \quad (1) \end{aligned}$$

where $f_{X_1}(t_X)$ is the probability density function (PDF) of the temporal random variable of T_X when $X = true$, and t_X is a value of T_X. In the same way as above, the time interval probability that an event X has the value of $false$ between time interval t_1 and t_2 can be defined as follows:

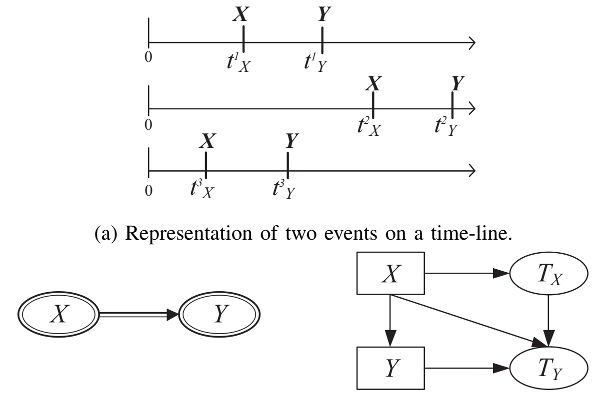
$$\begin{aligned} P(X = false, t_1 < T_X < t_2) &\\ = P(t_1 < T_X < t_2 | X = false) P(X = false) &\\ = P(X = false) \int_{t_1}^{t_2} f_{X_2}(t_X)\, dt_X & \quad (2) \end{aligned}$$

If an event has more than three states, its time and frequency of occurrence is given by

$$P(X = x_i, t_1 < T_X < t_2) = P(X = x_i) \int_{t_1}^{t_2} f_{X_i}(t_X)\, dt_X. \quad (3)$$

For now, we defined the time interval probability of an event in the absolute time domain. In practice, however, it is difficult to identify the origin in the absolute time domain, and therefore, it is preferable to use relative time, which is represented as the time interval between two events.

If two events X and Y occur sequentially, there can be a causal relationship such that X is the cause and Y is the effect as shown in Fig. 1(b), where the double-lined circle notation represents compound random variables with both causal and temporal probability. There is no meaningful temporal information in the absolute time domain as shown in Fig. 1(a); meaningful temporal information can be found only during the time interval between two events. Although the absolute starting time of each event is randomly distributed, the intervals of time between events can have a regular distribution.



(a) Representation of two events on a time-line.

(b) conceptual network (c) representation as a hybrid Bayesian network

Fig. 1. Causal and temporal relationship between two events.

These time intervals can be derived from the conditional probability of two events. Given observations of the temporal event, $X = x_i$ and $T_X = t_X$, the temporal probability of $Y = y_i$ from t_1 to t_2 can be represented as

$$\begin{aligned} P(Y = y_i, t_1 \le T_Y \le t_2 | X = x_j, T_X = t_X) &\\ = P(Y = y_i | X = x_j) P(t_1 \le T_Y \le t_2 | T_X = t_X, Y = y_i, X = x_j) &\\ = P(Y = y_i | X = x_j) \int_{t_1}^{t_2} f_{Z_k}(t_Y - t_X) dt_Y, & \quad (4) \end{aligned}$$

where Z_k is a temporal random variable of the time-interval between T_X and T_Y given $X = x_j$ and $Y = y_i$ [1], and f_{Z_k} is a PDF of Z_k. This causal and temporal relationships in (4) can be represented as a hybrid Bayesian network in Fig. 1(c). Here, we use conditional linear Gaussian distribution as the PDF of $f_{Z_k}(t_Y - t_X)$.

In a hybrid Bayesian network with conditional linear Gaussian models, a discrete node cannot have continuous parents. Furthermore, the CPD of a continuous node is a conditional linear Gausssian; For every combination of the discrete parent the node is a weighted linear sum of its continuous parents with some Gaussian noise [17].

Conditional linear gaussian in this paper is defined as follows: Let T_X be a continuous node in a hybrid Bayesian network, $\mathbf{U} = \{U_1, \cdots, U_N\}$ be its discrete parents, and $\mathbf{T_U} = \{T_{U_1}, \cdots, T_{U_M}\}$ be its continuous parents, conditional Linear Gaussian in hybrid Bayesian network have the form

$$P(T_X | \mathbf{U}, \mathbf{T}_U) \sim N(w_{\mathbf{u},0} + \sum_{i=1}^{M} w_{\mathbf{u},i} \cdot t_{U_i}, \sigma_{\mathbf{u}}^2), \quad (5)$$

where $\mathbf{u}$ and $\mathbf{t}_U$ are a combination of discrete and continuous states of the parents of T_X. In this formula, $\sigma_{\mathbf{z}}^2 > 0$, $w_{\mathbf{y},0}$ and $w_{\mathbf{y},i}$ are real numbers, and $w_{\mathbf{y},i}$ is defined the

[1] In [16] it was shown that the conditional PDF for two events that are generated sequentially is given by the PDF of a random variable of the difference between the two events.

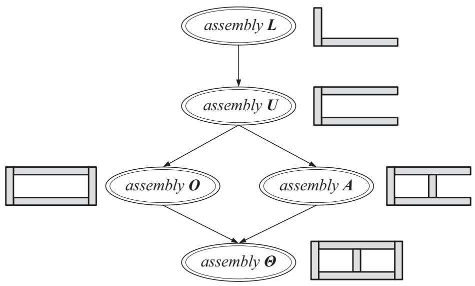


Fig. 2. An example of a temporal Bayesian network for a manual assembly task.

i-th component of a vector of the samedimension as the continuous part $\mathbf{T}_U$ of the part variables.

III. Inference in The Temporal Bayesian Network

To predict both the temporal and causal probability of an event in a complex situation, we designed a novel temporal Bayesian network using conditional temporal probabilities as described in Section II. The probabilities of when and whether an event occurs can be inferred from the temporal Bayesian network in a similar fashion to Bayesian networks. In this section, we introduce inference examples in the proposed temporal Bayesian network using temporal marginalization.

Given a set of discrete evidences $\mathbf{e} = \{e_1, e_2, \cdots, e_N\}$ and temporal evidences $\mathbf{t_E} = \{t_{E_1}, t_{E_2}, \cdots, t_{E_N}\}$, probability of an event $Q = q_i$ between a specific time interval (t_1, t_2) is represented as $P(Q = q_i, t_1 < T_Q < T_2 | \mathbf{e}, \mathbf{t_e})$, which is a typical query. For probabilistic temporal inference, all continuous and discrete random variables that don't belong to a query or evidences should be marginalized in HTBN.

Thus, the query is reformulated as

$$P(Q = q_i, t_1 < T_Q < T_2 | \mathbf{e}, \mathbf{t_e}) = \sum_{\mathbf{h} \in \mathbf{H}} \int_{\mathbf{t_H}} P(Q = q_i, t_1 < T_Q < T_2, \mathbf{h}, \mathbf{t_H} | \mathbf{e}, \mathbf{t_E}) d\mathbf{t_H}, \quad (6)$$

where $\mathbf{H}$ is a set of discrete random variables for unobserved events, and $\mathbf{h}$ is combination of discrete state of the random variables. Moreover, $\mathbf{t_H}$ is times of unobserved temporal events. Marginalization over a continuous random variable is obtained by the integral over the whole space of the random variable. Therefore, $\mathbf{T_H}$ over an infinite time range should be given for marginalization.

Fig. 2 shows an example of a temporal Bayesian network for an assembly task. A human worker assembles a θ-shaped assembly using three types of bars: long bars, medium bars, and short bars. If they start from an L-shaped assembly using a long bar and a medium bar, two sequences are possible to make the θ-shaped assembly. These two sequences are modeled in the temporal Bayesian network in Fig. 2.

When assembly-U is observed, the time interval probability of assembly-θ between times t_1 and t_2 can be inferred using the temporal Bayesian network model in Fig. 2. The conditional time interval probability is given by $P(\theta, t_1 \le T_\Theta \le t_2 | U = true, T_U = t_U)$, where t_U is the observation time of assembly-U. Here, we will use a short-term expression of the time interval as:

$$T_{\Theta t_1}^{t_2} := t_1 \le T_\Theta \le t_2, \quad (7)$$

$$P(\theta T_{\Theta t_1}^{t_2} | u, t_U) := P(\Theta = true, T_{\Theta t_1}^{t_2} | U = true, T_U = t_U). \quad (8)$$

Thus, the query is given by

$$P(\theta, T_{\Theta t_1}^{t_2} | d, t_D) = P(\theta, T_{\Theta t_1}^{t_2}, d, t_D) / P(d, t_D). \quad (9)$$

By marginalizing unobserved random variables, the numerator and denominator are given as follows:

$$P(\theta, T_{\Theta t_1}^{t_2}, u, t_U) = \sum_O \sum_A P(u) P(O|u) P(A|u) P(\theta | A, O) \cdot \int_{t_O} \int_{t_A} P(t_U|u) P(t_O|O, u, t_U) P(t_A|A, u, t_U) \cdot P(t_\Theta | \theta, O, A, t_O, t_A) dt_S dt_A \quad (10)$$

, and

$$P(u, t_U) = \sum_\Theta \sum_O \sum_A P(u) P(O|u) P(A|u) P(\Theta | A, O) \cdot \int_{t_\Theta} \int_{t_O} \int_{t_A} P(t_U|u) P(t_O|O, u, t_U) P(t_A|A, u, t_U) \cdot P(t_\Theta | \Theta, O, A, t_O, t_A) dt_S dt_A. \quad (11)$$

Here, random variables L and T_L are conditionally independent given U and T_U from network structure in Fig. 2. Therefore, random variables L and T_L can be ignored in the inference example.

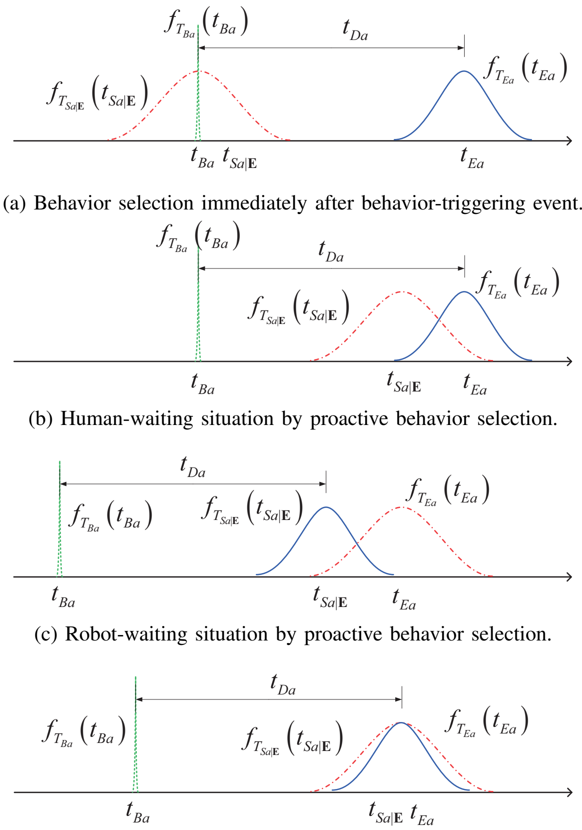
Because of U and T_U is observed, distribution such as $P(t_U|u)$ is given as a normal distrubiton with zero variance, $N(t_U; t_u, 0)$. If U and T_U is not observed, $P(t_U|u)$ is give as a normal distribution with zero mean and infinity variance $N(t_U; 0, \infty)$. Other conditional distribution such as $P(t_A|A, u, t_U)$ is given by conditional linear Gaussian as in (5).

After marginalizing out with respect to both continuous and discrete hidden random variables, the time interval probability of θ between t_1 and t_2 given an evidence u at t_U is a mixture distribution comprising PDFs for all possible paths from the evidence node to the query node; all possible paths are "$U \to O \to \Theta$" and "$U \to A \to \Theta$".

IV. Proactive Behavior Selection

Two important issues faced in proactive action-selection are deciding on the best proactive action to take and the best time to perform the action in order to minimize the waiting time by using the temporal prediction. To accomplish this, a robot should know the best time in order to minimize the waiting time for both the human and the robot.

If we consider a single proactive behavior, a robot must identify the best time so that waiting time for both the human and the robot is minimized. Fig. 3 shows an example of a PDF for a proactive behavior given a behavior-triggering event, where $Si|\mathbf{E}$ is a behavior-triggering event



(a) Behavior selection immediately after behavior-triggering event.

(b) Human-waiting situation by proactive behavior selection.

(c) Robot-waiting situation by proactive behavior selection.

(d) Minimum-waiting situation by proactive behavior selection.

Fig. 3. PDFs of proactive behavior given a behavior–triggering event.

corresponding to a behavior a given a set of evidences $\mathbf{E}$, $T_{Sa|\mathbf{E}}$ is a temporal random variable of the event, T_a is a temporal random variable corresponding to the starting time distribution of the proactive behavior related to behavior-triggering event, T_{Ea} is a random variable corresponding to the end time of the proactive behavior, and T_{Da} is a random variable corresponding to the duration of the behavior. As shown in Fig. 3(a), without temporal prediction, a behavior will be executed immediately after the behavior-triggering event is presented. In this situation, the person waits until the behavior of the robot is finished. If the robot starts the behavior early, as shown in Fig. 3(b), the waiting time may decrease. However, if the robot starts the behavior too early, as shown in Fig. 3(c), the robot waits until the person requests a part. The best time for the proactive behavior to be performed is when the waiting time of both the human and the robot is minimized, as shown in Fig. 3(d).

The waiting time is defined by the difference between the start time of an action-triggering event $t_{Sa|\mathbf{E}}$ and the end time of an action t_{Ea} as in the following:

$$t_{Wa} = t_{Sa|\mathbf{E}} - t_{Ea} = t_{Sa|\mathbf{E}} - t_{Ba} - t_{Da}. \tag{12}$$

In this situation, the person would wait for the robot to serve them. The waiting time of the person is given by $t_{Hw} = t_{Ea} - T_{Sa}$. The expectation of the waiting time of the person is given by

$$E[T_{Hw}] = \int_{-\infty}^{\infty} t_{Hw} f_{T_{Hw}}(t_{Hw}) dt_{Hw}. \tag{13}$$

The best time for performing the proactive action is calculated by minimizing the expectation, $E[T_{Hw}]$. Using only a Gaussian function and a Dirac delta function for the PDFs, the expectation for the waiting time is given by $\mu_{Sa} - \mu_{Ba} - \mu_{Da}$.

Considering a single proactive action, the best time of the proactive action can be easily obtained. However, to select the best proactive action among many candidates, a criterion is required to compare the usefulness of each proactive actions in terms of several properties: the importance of the action in relation to the priority of an action-triggering event corresponding to the action, the probability of the occurrence of the action-triggering event, the waiting time of both the human and the robot, and the cost of the proactive action. To compare the usefulness of actions per a criterion, we define a temporal payoff function corresponding to these properties given by

$$E\left[\Phi(T_{Wa})\right] = \int_{-\infty}^{\infty} \Phi(t_{Wa}) \cdot f_{T_{Wa}}(t_{Wa}) dt_{Wa}, \tag{14}$$

where $f_{T_{Wa}}(t_{Wa})$ is the PDF of waiting time of both the human and the robot, and $\Phi(t_{Wa})$ is the probability weighting function for the PDF of the waiting time.

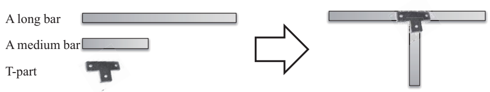
In this paper, we use a standard normal distribution as the temporal payoff function to minimize waiting time since the temporal payoff has several characteristics which are as follows:

- If the waiting time is zero, the temporal payoff is at a maximum.
- If the waiting time increases, the temporal payoff should decrease.
- If the waiting time is infinite, the temporal payoff of the waiting time is zero.

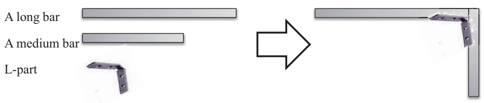
V. EXPERIMENTS

To evaluate our proposed temporal Bayesian network, we performed experiments that involved a human-robot cooperative scenario, in which a person has to make a θ-shaped assembly using three types of bars and two types of parts. There are two methods for combining two bars using one part: The first method is to combine the middle of a bar and the end of a bar using a T-shaped part, and the second approach is to combine the ends of two bars using an L-shaped part. Combining these two methods, various assemblies can be made.

As shown in Fig. 5(a), a person picks up a bar on the left side of the workspace and makes an assembly. When the person requests an L-part or T-part, a robot with a 5 degree of freedom (DOF) arm hands the part to the person. To provide the right assistance at the right time, the assistant robot has to know the progress of the assembly task in the workspace. Therefore, top down view cameras are mounted



(a) Assembling using the T-part.



(b) Assembling using the L-part.

Fig. 4. Illustrations showing assemblies the T-and L-part.

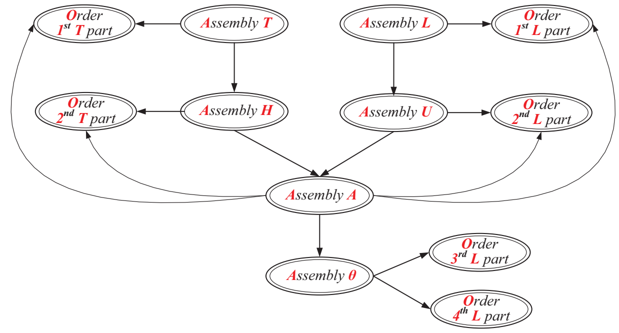
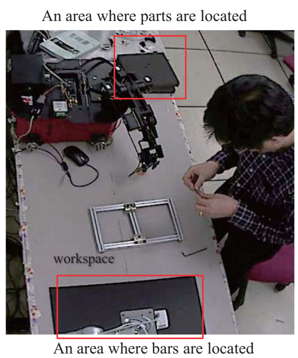
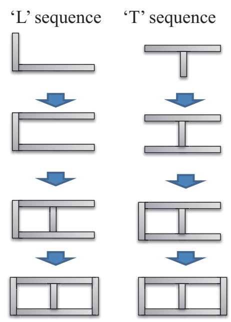


Fig. 6. Modeling data for the Bayesian network.



(a) Experimental setup.



(b) Two typical assembling sequences.

Fig. 5. Illustration of human-robot cooperation task and the experimental setup.

above the workbench. Shape and texture-based visual object recognition software is used for detecting the assembly.

There are many possible sequences to construct a θ-shaped assembly using three types of bars and two types of parts. Fig. 5(b) shows the two typical sequences used to make the assembly: the L-sequence and T-sequence. Fig. 6 shows the TBN model of the scenario. We provide random variables to represent the assembly types, such as AT, AL, AU, AH, AA, and $A\theta$. For example, AT indicates a T-shaped assembly.

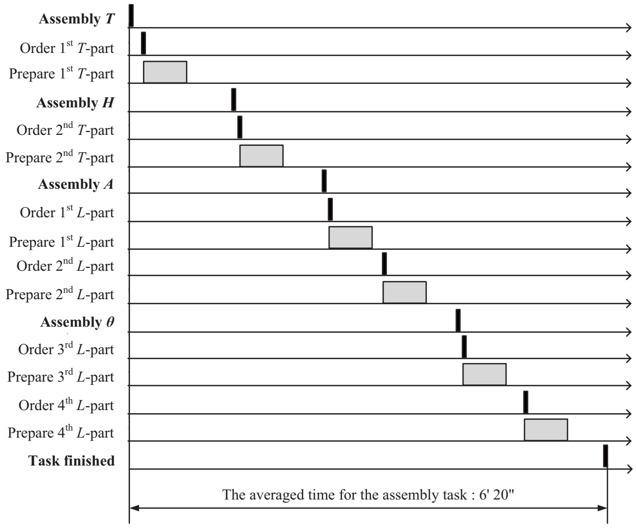
In the experiment, an assistant robot delivers T-parts or L-parts just at the point when it is predicted that the person will request the part. In other words, the robot has to predict both the time and type of future event such as requesting a part, and has to provide the appropriate part depending on the predicted behavior-triggering event before the person actually requests it. After the person picks up the bars, the person will then order a T-part or an L-part to combine the two bars. The events of order-T or L parts are also classified as different events as follows: *Order-1st-L-part, Order-2nd-L-part, Order-3rd-L-part, Order-4th-L-part, Order-1st-T-part*, and *Order-2nd-T-part*.

In this experiment, the robot must anticipate the types of parts and the timing of requests using the TBN and the proactive behavior selection method. To model the TBN in Fig. 6, CPTs and PDFs must be provided for the inference of causal and temporal probabilities. Therefore, we collected time interval data between events for every trial, such as the time interval between *Assembly-T* and *Assembly-H*. Each trial is terminated when the human successfully makes a θ-shaped assembly. We made Conditional Probability Tables (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 mean and variance of the Gaussian distribution were computed. We performed a demonstration in two ways as shown in Fig. 6: T-sequence and L-sequence. With this causal and temporal data, a proposed TBN is constructed.

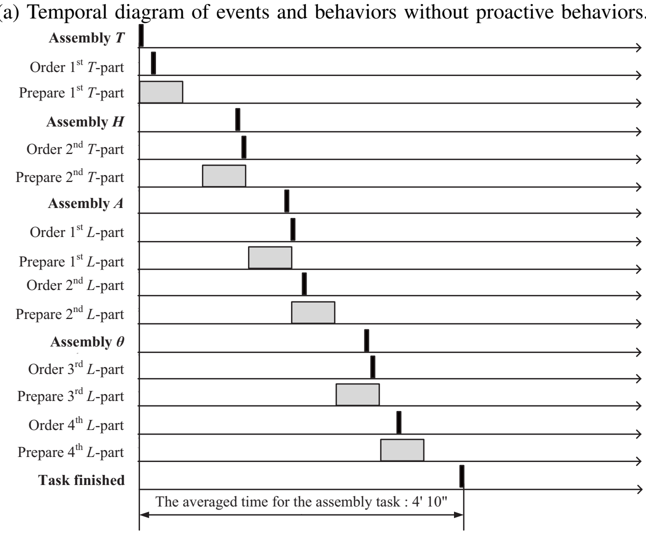
Moreover, the durations of the behaviors, *preparing-L-part* and *preparing-T-part*, are given by a normal Gaussian distribution with $N(19, 0.2)$ and $N(18.5, 0.3)$, respectively.

By temporally predicting behavior-triggering events, *order-T-part* and *order-L-part*, a robot can select the best proactive behavior and the best time to perform the behavior, given temporal evidence. To illustrate proactive behavior execution effectively, Fig. 7 shows a temporal diagram of the T-type assembly sequence, including the times of events, the start times and the end times of the behaviors.

Fig. 7(a) shows a temporal diagram of events and behaviors that occur when no proactive behavior is used for the assistant robot. In this case, the assistant robot starts delivering a part only after the person requests it. As a result, the person will have to wait until the assistant robot finishes a delivery behavior. The averaged task-execution time is 6min 20s for this situation. Fig. 7(b) shows an averaged temporal diagram of events and behaviors that occur when a proactive assistant robot is involved. The proactive assistant robot predicts the kinds of parts that will be requested and the times at which they will be requested, and therefore, can prepare the required part even though the person has not yet requested the part. As a result of these proactive behaviors, the averaged task-execution time is 4min 10sec. To verify the effectiveness of our proposed prediction and the behavior selection methods, we compared the task execution time with proactive assistance and on-demand assistance. The task execution times and improvement ratios are shown in Table I. We can see that there is a 33% improvement in the task execution time when the proposed proactive behavior selection method is used.



(a) Temporal diagram of events and behaviors without proactive behaviors.



(b) Temporal diagram of events and behaviors with proactive behaviors.

Fig. 7. Temporal diagrams of events and behaviors.

Assembly method	On-demand	Proactive assistance	improvement
$T-sequence$	6’ 20”	4’ 10”	34%
$L-sequence$	4’ 40”	3’ 25”	32%
Total	5’ 30”	3’ 50”	33%

TABLE I

AVERAGED TIME ELAPSED FOR THE ASSEMBLY.

VI. CONCLUSION

In this paper, we have proposed a novel temporal Bayesian network for human-robot interaction, where an assistant robot proactively delivers a part just when it is predicted that a person request that part. Our key contribution is that our proposed model is able to infer both causal and temporal probability using a single framework by explicitly representing time as a random variable. Employing temporal prediction of human behavior based on the proposed temporal Bayesian network, a robotic assistant can infer the best proactive behavior to assist a person and the best time to perform the proactive behavior. Our experimental results show that the proposed method decreases the total task execution time by anticipating preparatory actions via the prediction of human behaviors.

ACKNOWLEDGEMENT

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-M1AXA003-2011-0028353)

REFERENCES

[1] Y. Demiris, “Knowing when to assist: Developmental issues in lifelong assistive robotics.” in *Conference proceedings:... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, vol. 1, 2009, p. 3357.

[2] A. Schmid, O. Weede, and H. Worn, “Proactive Robot Task Selection Given a Human Intention Estimate,” in *Robot and Human interactive Communication, 2007. RO-MAN 2007. The 16th IEEE International Symposium on*, 2007, pp. 726–731.

[3] L. Craighero, F. Bonetti, L. Massarenti, R. Canto, M. F. Destro, and L. Fadiga, “Temporal prediction of touch instant during observation of human and robot grasping,” *Brain Research Bulletin*, vol. 75, no. 6, pp. 770–774, 2008.

[4] G. Hoffman and C. Breazeal, “Cost-based anticipatory action selection for human-robot fluency,” *IEEE Transactions on Robotics*, vol. 23, no. 5, p. 952, 2007.

[5] A. Bannat, J. Gast, G. Rigoll, and F. Wallhoff, “Event analysis and interpretation of human activity for augmented reality-based assistant systems,” in *Intelligent Computer Communication and Processing, 2008. ICCP 2008. 4th International Conference on*. IEEE, 2008, pp. 1–8.

[6] W. Kwon and I. Suh, “Towards proactive assistant robots for human assembly tasks,” in *Proceedings of the 6th international conference on Human-robot interaction*. ACM, 2011, pp. 175–176.

[7] M. Huber, M. Rickert, A. Knoll, T. Brandt, and S. Glasauer, “Human-robot interaction in handing-over tasks,” in *Robot and Human Interactive Communication, 2008. RO-MAN 2008. The 17th IEEE International Symposium on*, 2008, pp. 107–112.

[8] P. Basili, M. Huber, T. Brandt, S. Hirche, and S. Glasauer, “Investigating Human-Human Approach and Hand-Over,” *Human Centered Robot Systems: Cognition, Interaction, Technology*, p. 151, 2009.

[9] K. M. Krishna, R. Alami, and T. Simeon, “Safe proactive plans and their execution,” *Robotics and Autonomous Systems*, vol. 54, no. 3, pp. 244–255, 2006.

[10] B. Johansson and C. Balkenius, “An experimental study of anticipation in simple robot navigation,” *Lecture Notes in Computer Science*, vol. 4520, p. 365, 2007.

[11] S. F. Galán, G. Arroyo-Figueroa, F. J. Díez, and L. E. Sucar, “Comparison of two types of event bayesian networks: A case study,” *Appl. Artif. Intell.*, vol. 21, no. 3, pp. 185–209, 2007.

[12] S. Haider and A. Zaidi, “Transforming Timed Influence Nets into Time Sliced Bayesian Networks*,” *Journal of Approximate Reasoning*, vol. 30, pp. 181–202, 2002.

[13] T. Dean and K. Kanazawa, “A model for reasoning about persistence and causation,” *Computational Intelligence*, vol. 5, no. 2, pp. 142–150, 1989.

[14] G. Arroyo-Figueroa and L. Sucar, “Temporal Bayesian network of events for diagnosis and prediction in dynamic domains,” *Applied Intelligence*, vol. 23, no. 2, pp. 77–86, 2005.

[15] U. Nodelman, C. Shelton, and D. Koller, “Continuous time Bayesian networks,” in *Proceedings of the Eighteenth International Conference on Uncertainty in Artificial Intelligence*, vol. 378–387, 2002.

[16] D. Bertsekas and J. Tsitsiklis, *Introduction to probability*. Athena Scientific Belmont, Massachusetts, 2002.

[17] U. Lerner and R. Parr, “Inference in hybrid networks: Theoretical limits and practical algorithms,” in *Proc. UAI*, vol. 1. Citeseer, 2001, pp. 310–318.