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Planning of proactive behaviors for human–robot cooperative tasks under uncertainty

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A B S T R A C T

For seamless human–robot cooperation, a robot may need to take several steps proactively to minimize unnecessary delays between the human's intention and the robot's corresponding reactions. By predicting exogenous events from human intention and generating proactive plans based on the predicted events, a robot can reduce delays and significantly improve interaction. In this paper, we propose a decision-theoretic proactive planning framework that selects best proactive actions and the best times for those actions as a means to improving human–robot interactions. To this end, we developed a composite node temporal Bayesian network as an extension to handle both the nature of an event and its time of occurrence within a single framework. We also developed a composite node temporal influence diagram that combines a composite node temporal Bayesian network with a limited memory influence diagram to solve proactive planning problems. Experimental results obtained using a robot assistant in a manual assembly task demonstrate the effectiveness of our proposed framework.

1. Introduction

When humans interact with one another, they usually predict the intentions of others and synchronize their reactions accordingly [1,2]. For example, when dancing, people need to continuously predict the intentions of their partners, and on the basis of those predictions, proactively respond with the correct motion at the correct time. Proactive responses to predicted human intentions result in seamless interactions among people.

Conversely, many human–robot interactions follow a request-and-react pattern that evolves into a rigid turn-taking pattern with induced delays that disrupt seamless interactions. These delays retard the overall speed of human–robot interactions. Moreover, many people become frustrated and annoyed when many delays occur in a robot reaction. Therefore, seamless interactions between humans and robots are important in human centered robotic applications. To reduce delays and thereby facilitate seamless interactions between humans and robots, a robot should be able to predict future events based on observed human activities. Predictive abilities facilitate anticipation and smart decision-making by allowing a robot to determine which actions to perform proactively to obtain or avoid a predicted situation and minimize delays for both the human and the robot.

For example, robot assistants used on a manufacturing line that includes human workers can predict human assembly tasks and anticipate the components and/or tools required for future work. Another example is a smart robot assistant in the kitchen that can predict events during the cooking process. Based on the predicted human related events that occur during the cooking process, the robot can then infer the kinds of utensils and/or ingredients that will be needed and when. The next step for a seamless interaction is to make a plan providing the proper assistance at the proper time. To achieve this, a robot should perform several preparatory actions prior to the expected time of the human-related events to minimize the wait time between the human and the robot. Consequently, plans for seamless interaction describe the proactive execution of robotic actions. We call seamless human–robot interactions "proactive human–robot interactions" and the act of planning for proactive interactions "proactive planning".

Proactive planning has the following requirements: First, the planner needs to work in a dynamic environment. Most existing planners assume a static environment that only changes when the robot performs an action, i.e, there are no exogenous changes from the viewpoint of the robot. However, changes in the real world are caused not only by robot actions but also by exogenous events generated from human activities. Several temporal planning methods deal with predictable exogenous events that are not

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under the planning agent's control but occur instead at known times. Examples of these include the arrival and departure times of planes at an airport and entries in a railway timetable. However, exogenous events from human activities cannot be treated in such a simple manner because humans act based on their intentions and understanding of a particular situation. As a consequence, there is no such thing as a simple timetable of human activities. Instead, events from human activities have complex causal–temporal relationships. Therefore, exogenous events should be estimated using the complex causal–temporal relationships among the events.

Second, the uncertainty in both the nature and time of an event has to be considered during a planning stage. In the real world, exogenous events from human activities are not perfectly predictable because a robot cannot fully observe the human intention behind the events. In addition, the effects of a robot's actions in the real world also have a certain degree of uncertainty. The uncertainty in human–robot interaction involves a combination of both the nature of the events and when they occur. However, despite the time of occurrence and nature of an event being two side of the same coin, such issue have been dealt with independently in both planning and scheduling problems [3]. For proactive planning, these two uncertainties need to be modeled simultaneously.

Third, proactive planning methods have to handle problems with an uncertain duration of actions and events. In many planning problems, including human–robot interactions, it is natural to consider durative actions and events with uncertainty. However, many existing methods, such as classical planning and Markov decision processes, assume instantaneous transitions of actions and events.

Finally, the modeling of a time-dependent utility is required for proactive planners. Proactive planning requires that human intentions and the outcomes of robot actions are synchronized in the context of both event types and their occurrence times. For instance, when a person has the intention to use a service, a smart robot should provide the robot service at the proper time. If a planner uses only hard temporal constraints, only an exact synchronization can be modeled. However, in many cases, not all pairs of robot actions and human intentions may be synchronized exactly. If a robot has an insufficient amount of time to prepare two services that are expected to be required in a future human–robot cooperative task, the robot should decide whether to prepare the first service; if the robot skips the first service, the robot can have sufficient time to prepare the second. Therefore, there is a trade-off between the delay in the two services and skipping the first altogether. In this case, it is necessary that the penalty for a delay be modeled using a time-dependent utility.

However, existing planners do not fully satisfy the above four requirements. To satisfy the requirements of proactive planning problems, we developed hybrid temporal influence diagrams [4,5] as an extension of hybrid temporal Bayesian networks [6]. Hybrid temporal Bayesian networks represent the time of an event as an explicit random variable in a continuous time domain. As a result, both the explicit time and nature of an exogenous event can be inferred within one framework, and a robot can decide on the best type of proactive actions and their occurrence times corresponding to the exogenous events based on human intention. However, the computational complexity of a hybrid temporal influence diagram is too high even when the number of decision variables is small because the simultaneous global optimization of the types of proactive actions and their occurrence times is a very time-consuming process.

In this paper, we propose the use of composite node temporal influence diagrams (CNTIDs), based on limited information influence diagrams (LIMIDs) [7], as an improved proactive planning method that has computationally feasible solutions to the planning problem. We also improve hybrid temporal Bayesian networks to be computationally effective using a composite node with a combination of the event types and time of occurrence, instead of using hybrid Bayesian network frameworks.

The remainder of this paper is organized as follows. Related works are first presented in Section 2. Next, Section 3 describes the composite node temporal Bayesian network used to predict both the causality and time of occurrence of a future situation in a probabilistic manner. Section 4 then presents the CNTIDs used in the proposed proactive planning framework to simultaneously determine the nature and time of a proactive action. Next, Section 5 presents a method for solving CNTIDs. Experimental results are then provided in Section 6. Finally, Section 7 ends this paper with some concluding remarks.

2. Related works

As mentioned in the previous section, there are four requirements to the planning problem for proactive human–robot interactions: dynamic environments, causal and temporal uncertainty, durative actions, and time-related cost functions. Obviously, these requirements are related to temporal planning problems, and are partially satisfied in the existing temporal planning methods. In this section, we introduce related works to determine the relationship between the requirements of proactive planning problems and existing temporal planning methods.

Many researchers have addressed the problem of planning with temporal information as an extension of classical STRIPS planning [8]. Classical planning problems assume that the environment is deterministic and fully observable. They also assume a static environment that only responds to the agent's actions [9]. Further, actions and their outcomes in classical planning are assumed to be instantaneous. These assumptions create problems when dealing with real-world planning problems are being dealt with because, in reality, the results of actions and their outcomes have uncertainties and, each action takes a different duration.

Earlier research studies, e.g., parcPLAN [10], ZENO [11], and TLPlan [12], relaxed the assumption of instantaneous actions and events by explicitly modeling durative actions and temporal constraints. They relied on temporal constraint satisfaction for the temporal aspect of different actions and events.

A number of more recent planning methods have also relaxed the assumption of a static environment, e.g., CRIKEY [13], SGPlan [14], LPG-TD [15], TGP [16], and TPSYS [17]. They are capable of handling predictable exogenous events from the context of a timed initial literal, which describe exogenous events occurring at a given absolute time independently of the plan execution [18]. Planning domain description language 2.2 (PDDL2.2) [19] supports predictable exogenous events in the context of a timed initial literal. Although a timed initial literal represents a dynamic environment in part, it is insufficient to represent all aspects of exogenous events in human–robot interactions. A timed initial literal only supports predictable exogenous events in a deterministic manner, whereas there are many unpredictable exogenous events in many cases of human–robot interactions.

Recently, several planners, such as OPTIC [20] and SGPlan5 [21], support temporal planning with time-dependent continuous costs, while many previous temporal planners primarily support exact synchronization among events and actions based on the disjunctive temporal problem, in which only hard temporal constraints can be modeled. These recent methods can handle time-related soft constraints. Planning domain description language 3.0 (PDDL3.0) [22] supports these time-dependent soft constraints in the form of logical expressions.

Uncertainty is another important aspect of real-world planning problems. For probabilistic temporal planning, researchers have mainly focused on decision theoretic approaches. Influence