State-of-the-Art of Intention Recognition and its use in Decision Making

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Intention recognition is the process of becoming aware of the intentions of other agents, inferring them through observed actions or effects on the environment. Intention recognition enables pro-activeness, in cooperating or promoting cooperation, and in pre-empting danger. Technically, intention recognition can be performed incrementally as you go along, which amounts to learning. Intention recognition can also use past experience from a database of past interactions, not necessarily with the same agent. Bayesian Networks (BN) can be employed to dynamically summarize general statistical evidence, furnishing heuristic information to link with the situation specific information, about which logical reasoning can take place, and decisions made on actions to be performed, possibly involving actions to obtain new observations. This situated reasoning feeds into the BN to tune it, and back again into the logic component. In this article, we provide a review bearing on the state-of-the-art work on intention and plan recognition, which includes a comparison with our recent research, where we address a number of important issues of intention recognition. We also argue for an integrative approach to intention-based decision-making that uses a combination of Logic Programming and Bayesian Networks.

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1. Intention Recognition

We consider intention recognition in a dynamic, real-world environment. An important aspect of intentions is *future-directedness*, i.e., if we intend something now, we mean to execute a course of actions to achieve something in the future (Bratman, 1987; Cohen and Levesque, 1990; Singh, 1991; Roy, 2009). Most actions may be executed only at a far distance in time. During that period, the world is changing, and the initial intention may be changed to a more appropriate one or even abandoned (Bratman, 1992; Geib and Goldman, 2009). An intention recognition method should take into account these changes, and, when necessary, be able to reevaluate the intention recognition model, depending on some time limit; in addition, as new actions are observed, the model should be reconfigurable to incorporate them. In other words, the model should be incremental and, furthermore, the intention recognition prediction is available at anytime.

Generally, *intention recognition* (also called *goal recognition*) is defined as the process of becoming aware of the intention of another agent and, more technically, as the problem of inferring an agent's intention through its actions and their effects on the environment (Charniak and Goldman, 1993; Tahboub, 2006; Heinze, 2003; Armentano and Amandi, 2007). For the recognition task, the distinction between my model of me and my model of another should be mentioned, though I can use my model of me to imagine the same model for the other. This is known as the "Theory of Mind" theory (Premack and Woodruff, 1978; Whiten, 1991; Cheney and Seyfarth, 2007), which neurologically reposes in part on "mirror neurons" as supporting evidence, since low-level intentions in the form of gesture goals can be recognized automatically and, it is argued, deeper-level intentions recognized on top of mirror-neurons layers (Iacoboni et al., 2005; Rizzolatti and Craighero, 2004; Nakahara and Miyashita, 2005).

Plan recognition is closely related to intention recognition, extending it to also recognize the plan the observed agent is following in order to achieve his intention (Sadri, 2011b; Armentano and Amandi, 2007). Mere intention recognition is performed in domains in which it is preferred to have a fast detection of mere user goal/intention rather than a more precise but time consuming detection of the complete user plan, e.g., in the interface agents domain (Armentano and Amandi, 2007; Horvitz et al., 1998; Madani et al., 2009).

Generally, the input to both intention and plan recognition systems are a set of conceivable intentions and a set of plans achieving each intention, given in terms of a plan library (Charniak and Goldman, 1993; Geib and Goldman, 2009) or a plan corpus (Blaylock and Allen, 2003, 2004; Armentano and Amandi, 2009)). Intention recognition is distinct from planning, as goals are not known a priori, and presumed goals are subject to defeasibility. There are also generative approaches based on planning algorithms, which do not require a plan library/corpus (e.g., see (Ramírez and Geffner, 2010)).

Intention and plan recognition have been applied and shown to be useful in a wide range of application domains (Sadri, 2011b), including story understanding (Charniak and Goldman, 1990), human-computer interaction and interface-agents systems (Lesh, 1998; Hong, 2001; Armentano and Amandi, 2007), traffic monitoring (Pynadath and Wellman, 1995), assistive living (e.g. Elder Care, Ambient Intelligence) (Geib, 2002; Haigh et al., 2004; Tahboub, 2006; Roy et al., 2007; Pereira and Han, 2011a,b; Han and Pereira, 2010c) and military settings (Mao and Gratch, 2004; Heinze, 2003).

The future-directedness of intentions also means that, once an agent intends something, he has settled on a particular course of action (Bratman, 1987; Cohen and Levesque, 1990; Singh, 1991; Roy, 2009). This makes the intentions relatively stable, pending new information. An agent who made the decision to act in a certain way commits to sticking to this decision for the reasons which led to it, unless counterbalancing reasons meanwhile appear and trigger further deliberations. In other words, intentions are relatively resistant to reconsideration unless there are pondered reasons to do so (Bratman, 1992, 1987; Roy, 2009). Following this, any attempt to tackle the issues of intention change or abandonment cannot solely be based on the observed actions. The reasons why the intention is changed or abandoned must be taken into account. The reasons can be changes in the environment (possibly made by other agents) that impel the observed agent to refrain from following his initial intention. And here the context-dependent modeling appears to be unavoidable.

Sometimes Bayesian Networks (BNs) are used as the intention recognition model. The flexibility of BNs for representing probabilistic dependencies and the efficiency of inference methods for BN have made them an extremely powerful and natural tool for problem solving under uncertainty (Pearl, 1988, 2000). The directed acyclic graph structure of the network contains representations of both conditional dependencies and independencies between the random variables represented by the graph nodes. The probabilistic information is compactly given by conditional probability distribution tables for each and every node. To perform intention recognition, we constructs a three-layer BN (Pereira and Han, 2009c, 2011b)—justified based on Heinze's causal intentional model (Heinze, 2003; Tahboub, 2006)—and use it for evidential reasoning from observations to intention hypotheses.

One may surmise a knowledge representation method to support incremental BN model construction for performing intention recognition during runtime, from an initially given domain knowledge base. As more actions are observed, a new BN is constructed from the previous one reinforcing some intentions whilst ruling out others. This incremental method allows domain experts to specify knowledge in terms of small and simple BN fragments, which can be easily maintained and changed, and which are used to compose the situated ongoing BN model. Alternatively, these fragments can be easily learned from data. More rarely, one proposes a method to represent relationships among intentions, when considering the case of agents that may pursue multiple intentions simultaneously. This is an indispensable aspect, but mostly omitted in prior work, which however allows to sometimes significantly decrease the com-

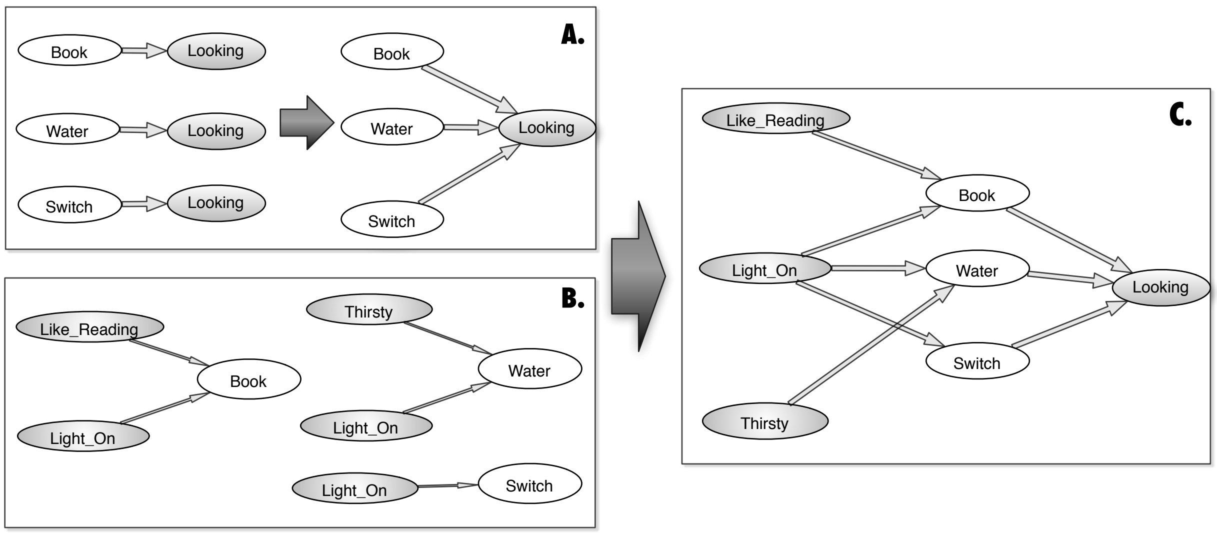

Fig. 1. Incremental intention recognition method via dynamic selection and construction of Bayesian Network. **(Box A)** (Context-dependent) selection of fragments for the currently observed action, so as to then perform Noisy-OR combination for the action node (*Looking*); **(Box B)** Selection of Bayesian Network fragments for the intentions; **(Box C)** Constructing a three-layer Bayesian Network, upon which intention recognition is performed.

plexity of the probability inference (Gogate and Dechter, 2011).

Some methods are generally motivated by the fact that knowledge experts often consider a related set of variables together, and organize domain knowledge in larger chunks. An ability to represent conceptually meaningful groupings of variables and their interrelationships facilitates both knowledge elicitation and knowledge base maintenance (Laskey and Mahoney, 1997). To this end, there have been several methods proposed for BN construction from small and easily maintained network fragments (Pearl, 1988; Pfeffer et al., 1999; Mahoney and Laskey, 1996; Laskey and Mahoney, 1997; Xiang and Poh, 2005; Natarajan et al., 2008; Laskey, 2008). In essence, a combination of BNs is a graph that includes all nodes and links of the networks, where nodes with the same name are combined into a common node. The main issue for a combination method is how the influence of different parents of the common node can be combined in the new network, given the partial influence of each parent in the corresponding fragment. The most extensively used and popular combination method is Noisy-Or, firstly proposed by (Pearl, 1988) for BNs of Boolean variables, and generalized by (Srinivas, 1993; Diez, 1993) for the general case of arbitrary domains.

As such, in our work (Han and Pereira, 2010a, 2011b,a; Han, 2012), we have developed an intention recognition method that possesses several important features: (i) The method is *context-dependent* and *incremental*, enabling incremental construction of a three-layer Bayesian Network model as more actions are observed, and in a context-dependent manner, which, in addition, relies on a logic programming knowledge base concerning the context; (ii) The Bayesian Network is composed from a knowledge base of readily specified and readily maintained Bayesian Network fragments with simple structures, thereby enabling an efficient acquisition of the corresponding knowledge base (engineered either by domain experts or else automatically from a plan corpus); and, (iii) The method addresses the issue of intention change and abandonment, and can appropriately resolve the issue of the recognition of multiple intentions.

To illustrate some important aspects of our method, let us consider the following example.

Example 1.1 (Elderly person's intention recognition) *An elder stays alone in her apartment. The assistant system (with the capability of intention recognition) observes that she is looking for something in the living room. In order to assist her, the system needs to figure out what she intends to find.*

The first step is to select, from a given knowledge base of BN fragments, the fragments for action

Looking, which consist of a single intention connecting to the action (Fig. 1, Box A). This process is context-dependent, in the sense that whether an intention may give rise to an action depends on the situation the action is observed in. Suppose that the selected intentions are: something to read (*Book*); something to drink (*Water*); and the light switch (*Switch*). They are then combined using the Noisy-OR method, resulting in a single BN with a common action node (Fig. 1, Box A).

Next, the fragments for each intention are selected from the given knowledge base (Fig. 1, Box B). These fragments are then plugged into the combined network in Box A, resulting in a three-layer BN in Fig. 1, Box C, upon which intention recognition is performed. This consists in computing the probability for each intention in the current network, conditional on current observations (e.g. the state of the light, and the observed action *Looking*). Recall that to perform intention recognition, we construct a three-layer BN (Pereira and Han, 2009c, 2011b)—justified in being based on Heinze's causal intentional model (Heinze, 2003; Tahboub, 2006). For further details and examples see (Han, 2012, Chapter 2)(Han and Pereira, 2011a).

As mentioned earlier, the advantage of this dynamic and context-dependent construction of the model is that the obtained BN usually has a significantly reduced size, compared to when a large and general network is built and used for all foreseen cases. The context-dependent selection of the fragments can sometimes lead to the final solution without having to perform probabilistic inference; for instance when there is a single conceivable intention giving rise to the current observed actions given the situation at hand. Furthermore, from the design point of view, it is easier and usually much cheaper to construct the small fragments (and then combine them) than to construct the whole BN (Pearl, 1988; Laskey, 2008).

2. Decision Making with Intention Recognition

Given the crucial role that intentions play in a diversity of decision making processes (Bratman, 1987; Meltzoff, 2005; Woodward et al., 2009; Roy, 2009; Searle, 2010), one would expect intentions to occupy a substantial place in any theory of action. But surprisingly, in one of the most influential theories of action—the rational choice theory (Russell and Norvig, 2003; Binmore, 2009)—including the theory of decision making—explicit reference is made to actions, strategies, information, outcomes and preferences, but not to intentions.

This is not to say that no attention has been paid to the relationship between rational choice and intentions. Quite the contrary, a rich philosophical and Artificial Intelligence (AI) literature has developed on the relation between rationality and intentions (Bratman, 1987; Cohen and Levesque, 1990; Singh, 1991; van Hees and Roy, 2008). Some philosophers, e.g. in (Bratman, 1987, 1999; Roy, 2009), have been concerned with the role that intention plays in directing rational decision making and guiding future actions. In addition, many agent researchers have recognized the importance of intentions in developing useful agent theories, architectures, and languages, such as Rao and Georgeff with their BDI model (Rao and Georgeff, 1995), which has led to the commercialization of several high-level agent languages, e.g. in (Burmeister et al., 2008; Wooldridge, 2000, 2002). However, to the best of our knowledge, there has been no real attempt to model and implement the role of intentions in decision making, within a rational choice framework. Intentions of other relevant agents are always assumed to be given as the input of a decision making process; no system that integrates a real intention recognition system into a decision making system has been implemented so far.

In our work, we have set forth a coherent Logic Programming (LP) based system for decision making—which extends the existing work on Evolution Prospection for decision making (Pereira and Han, 2009a,b)—but taking into consideration now the intentions of other agents. Obviously, when being immersed in a multi-agent system, knowing the intentions of other agents can benefit the agent in a number of ways. It enables the recognizing agents to predict what other agents will do next or might have done before. Hence, they can plan in advance and take the best advantage from the prediction, or act to take a remedial action. In addition, an important role of recognizing intentions is to enable coordination of your own actions and in collaborating with others (Bratman, 1987; Kaminka et al., 2002).

The Evolution Prospection (EP) system is an implemented LP-based system for decision making (Pereira and Han, 2009a,b, 2011b). It is implemented on top of XSB Prolog (XSB, 2009), a full account of which can be found in (Pereira and Han, 2009b). An EP agent can prospectively look ahead a number of steps into the future to choose the best course of evolution that satisfies a goal. This is achieved by designing and implementing several kinds of prior and post preferences, and several useful environment-triggering constructs for decision making. In order to take into account the intentions of other agents in decision making processes, we integrated into EP a previously and separately implemented, but also LP-based, intention recognition system (Pereira and Han, 2009c, 2011b; Han and Pereira, 2011b).

The obtained integrated system can perform intention-based decision making (Han and Pereira, 2011c; Han and Pereira). It takes into account recognized intentions of other agents within different constructs of the decision making system, notably intention-triggering goals (e.g. upon recognizing intentions of a friend, the goal of helping him/her is provoked, while upon recognizing intentions of an enemy, the goal of preventing his/her achievement of the recognized intention is triggered) and different kinds of intention-triggering preferences (e.g. upon recognizing an intention of a friend, one may prefer an action to another one if it provides more support to achieve the intention; in contrast, if it is an enemy, the ones providing greater support are disfavored).

The system has been applied for providing appropriate assistance for elderly people in the Ambient Intelligence domain (Han and Pereira, 2010c,b; Pereira and Han, 2011a) (e.g. upon recognizing the intention of an elderly person staying alone in his apartment, the system derives suggestions on how to achieve his intentions appropriately, taken into account his profiles and different aspects of the living environment); for deriving morally acceptable decisions in moral dilemmas (Han et al., 2012c; Han and Pereira) (it is known that a key factor in legal and moral judgments is actual intention, which for instance can distinguish murder from manslaughter (Hauser, 2007; Young and Saxe, 2011)).

Furthermore, our recent work has paid much attention to the problem of intention-based decision making in large-scale multi-agent systems (Han et al., 2011a,b, 2012a,b). We study the performance of agents which are capable of intention recognition within a population of interacting agents—in order to investigate what is the role of intention recognition in the evolution of cooperative behaviors (Nowak, 2006; Sigmund, 2010). Interestingly, we find that such recognizing agents can learn to cooperate with each other in an environment where cheating is favorable. Therein intention-based decision making is applied in the course of social dilemmas (e.g. the famous Prisoner's Dilemma (Sigmund, 2010)). Note that this work significantly diverges from the existent AI literature on intention recognition (see below), wherein the study is carried out at small, local settings: how to efficiently and correctly recognize particular agents' intentions. As such, our work has contributed not only to the evolutionary and philosophical studies of intention recognition (Pereira et al.), it has suggested an approach to study and evaluate intention recognition methods in large-scale social and biological complex systems.

Example 2.1 (Intention-triggering goal: elder care) *Suppose in the previous example the intention recognition system predicts that the elder intends to find something to drink. The assistant system provides a suggestion on what kind of drink the elder should take.* Tea *or* coffee*? The following (simplified) EP program targets that.*

```
on_observe(suggest)<- has_intent(elder,drink).
suggest <- tea.       suggest <- coffee.
expect(tea).          expect(coffee).
expect_not(coffee) <- blood_high_pres(elder).
coffee   <|  tea    <- sleepy(elder).
```

The first line reads: if it is recognized that the elder has the intention of finding something to drink, then the goal of suggesting an appropriate drink is triggered. The second line says, tea and coffee are the possible suggestion options. The third line states, both options are always to be expected. An exception is that coffee is prohibited when the elder has high blood pressure (fourth line). Furthermore, coffee is preferred to tea—when both options are still available after considering all other constraints—provided the elder is sleepy (fifth line).

Example 2.2 (Intention-triggering preferences) *Being thirsty, I consider making tea or coffee. I realize that my roommate, John, also wants to have a drink. To be friendly, I want to take into* *account his intention when making my choice. This scenario is represented with the following preference rules in EP.*

```
tea    <| coffee <- has_intent(john,tea).
coffee <| tea    <- has_intent(john,coffee).
```

For further details, and more complete and extended examples, see (Pereira and Han, 2011a; Han and Pereira).

3. Related Work on Intention Recognition

Work on intention and plan recognition has been paid much attention for more than thirty years, and a large number of methods have been applied. They can be roughly categorized into two main groups: *Consistency* and *Probabilistic* approaches (Armentano and Amandi, 2007; Singla and Mooney, 2011; Geib and Goldman, 2009; Sadri, 2011b).

Consistency approaches face the problem by determining which intention is consistent with the observed actions, i.e. whether the observed actions match with at least a plan achieving the intention. The earliest work on plan recognition belongs to this group (Schmidt et al., 1978; Wilensky, 1983; Kautz and Allen, 1986; Hong, 2001; Sadri, 2010). More recent work can be found in a rather comprehensive survey by Sadri (2011b). The problem with the consistency approaches is that they cannot handle well the case where the current observed actions enable more than one intention—they cannot directly select between those intentions.

Probabilistic approaches, on the other hand, are mainly based on Bayesian Network and (Hidden) Markov models (Charniak and Goldman, 1993; Pynadath and Wellman, 1995; Forbes et al., 1995; Albrecht et al., 1998; Forbes et al., 1995; Albrecht et al., 1998; Bui et al., 2002; Huber and Simpson, 2004; Tahboub, 2006; Schrempf et al., 2007; Geib and Goldman, 2009; Pereira and Han, 2009c, 2011b; Armentano and Amandi, 2009). An advantage of the probabilistic approaches is that they can directly address the above issue of the consistency approaches—by finding the most probable intentions given the set of current observations, on the basis of accumulated statistical evidence, or simply on the basis of subjective beliefs encoded in a Bayesian Network or Markov model.

Bayesian approaches have been one of the most successful models applied to the intention/plan recognition problem (Charniak and Goldman, 1993; Pynadath and Wellman, 1995; Goldman et al., 1999; Geib, 2004; Geib and Goldman, 2009). The first model was built by Charniak and Goldman (1991, 1993). Depending on the structure of plan libraries, a knowledge-based model construction is employed to build BNs from the library—which is then used to infer the posterior probability of explanations (for the set of observed actions). This approach, mostly advanced by Goldman et al. (1999) and especially in the more recent work (Geib and Goldman, 2009) [1], addresses a number of issues in intention/plan recognition, e.g., when the observed agent follows multiple intentions or interleaved plans simultaneously; fails to observe actions; addresses partly ordered plans. However, there are some important aspects not yet explored therein, partially for the sake of computational efficiency. First, prior probabilities of intentions are assumed to be fixed. This assumption is not always reasonable because those prior probabilities should in general depend on the situation at hand (Bratman, 1992, 1987; Pynadath and Wellman, 1995; Brown, 1998), and can justifiably be captured by causes/reasons of the intentions, as in our method (Pereira and Han, 2011b; Han et al., 2011a; Tahboub, 2006; Heinze, 2003). Indeed, Geib and Goldman (2009) also highlighted the need to account for contextual information or state of the world as a potential extension to their plan recognizer. In (Pynadath and Wellman, 1995), a similar context-dependent Bayesian approach is used, though the model therein is not incremental. The authors demonstrated that taking into account contextual information is important to appropriately recognize drivers' intention in the traffic monitoring domain (Pynadath and Wellman, 1995).

Second, intentions are assumed to be independent of each other. This is not generally the case since the intentions may support or exclude one another, leading to the need to reconfigure the model. Hence, those works might not appropriately address multiple intentions recognition. Pynadath and Wellman (1995) proposed to combine, in their BN model for plan recognition, the mu-

[1] Note that this work is based on Bayesian inference, though they do not build Bayesian Networks as in (Charniak and Goldman, 1991, 1993).

tually exclusive plan nodes into a single variable. As a step further, we formally define how that can be done appropriately, so as to guarantee consistency in the obtained BN. This latter assumption must always, explicitly or implicitly, be made by the approaches based on (Hidden) Markov models, e.g. (Armentano and Amandi, 2009; Bui, 2003), or statistical corpus-based machine learning (Blaylock and Allen, 2003, 2004). Generally, in those approaches, a separate model is built for each intention; thus no relations amongst the intentions are expressed or can be expressed. These works were restricted to the single intention case. The method developed in our work attempts to tackle the multiple case more appropriately. We plan on further experimentation for evaluating it. In any case, note that although there were some previous attempts, e.g., in (Geib and Goldman, 2009) and (Pynadath and Wellman, 1995), no experiments have been carried out.

Different from most above mentioned works, our model is *context-dependent*, which is achieved by including in it causes/reasons of intentions. This way, our model can appropriately deal with the abandonment/changes of intentions—when the causes/reasons do not support or force the intending agent to hold those intentions anymore—in an *integrated* manner. In contrast, in (Geib and Goldman, 2003), the authors build a *separate* model to recognize when the observed agent abandons its current intention, which may then trigger revision of the intention recognition model. To the best of our knowledge, this is the only work addressing the abandonment issue. However, the system presented therein is only evaluated with a rather small benchmark (with three intentions), and only for the accuracy of the abandonment recognition itself. The benefit from having this additional intention abandonment recognition module for enhancing intention/plan recognition performance has not been studied, as the authors themselves mention in their recent study (Geib and Goldman, 2009). We also address this issue in our work.

In line with our recent work is our own prior work, a context-dependent incremental intention recognition model (Han and Pereira, 2010a). But there we only deal with the single intention case, and it has exponential complexity. Our latest model is more general and efficient, being able to deal with the multiple intention case, and has linear complexity for the single intention case (Han and Pereira, 2011a).

The method is performed by dynamically constructing a three-layer BN model for intention recognition (IRBN), from a prior knowledge base consisting of readily maintained and constructed fragments of BN. Their simple structures allow easy maintenance by domain experts and also facilitate automatic construction from available plan corpora. The three-layer IRBN follows a *causal* intentional structure (Heinze, 2003; Tahboub, 2006), from causes/reasons (of intentions) to intentions (as causes of actions), then to (actually observed) actions. This causal structure enabled us to appropriately capture different aspects of context-dependent intention recognition, from context-dependent selection of intentions for model construction, to sensitizing prior probabilities of the intentions already in the model.

In our work we have provided several operators for constructing as well as simplifying the BN model dynamically, highlighting the importance of taking into account contextual information – an aspect usually omitted in previous approaches (Pynadath and Wellman, 1995; Geib and Goldman, 2009). In addition, we have shown experimentally that contextual information is crucial for recognition accuracy when the observed agents might change or abandon their initial goals/intentions. It is apparently an unavoidable aspect of real agents, clearly pointed out in (Geib and Goldman, 2003, 2009). Taking into account such information enables to account for the reasons why the agents change or abandon their goals/intentions.

We have also attempted to tackle the problem where an observed agent may follow multiple intentions simultaneously, in a more appropriate manner. We have formally described how to represent relationships amongst intentions in the Bayesian Network for intention recognition, particularly in order to maintain its consistency when one needs to combine mutually exclusive intentions (Pynadath and Wellman, 1995). This aspect is indispensable in multiple intentions recognition, but mostly omitted in previous work. However, the scalability of our method remains to be seen. For its evaluation, we still need to gather an appropriate plan corpus allowing for the possibility that users pursue multiple intentions simultaneously.

A limitation of the current formalization in the multiple intentions recognition case is that we need to assume that the intentions to be combined are perfectly mutually exclusive. This assumption can be relaxed by utilizing a latent variable for any subset of perfectly mutually exclusive intention nodes. The latent variable figures in the BN, either as a child or parent of the nodes, whichever works better for inference. We are exploring this direction to provide a more general method for representing relationships amongst intention nodes.

Another limitation of our current method is that it did not explicitly take into account temporal evolution of domain variables in the BN. It is usually done using Dynamic Bayesian Networks (DBNs) (Pynadath and Wellman, 1995; Forbes et al., 1995; Albrecht et al., 1998), where the state of each variable is represented by a series of nodes. In our method, the time evolution, to some degree, is implemented by means of updating the IRBN from time to time. For example, the states of the cause/reason nodes are updated using an external logic program which represents the evolving world. In this way not only can one significantly reduce the size of the BN, and thereby its inference complexity (as LP inference is significantly less expensive), but the declarative representation and reasoning of LP techniques (Baral, 2003) could be important when the states of a node cannot be easily represented in an explicit manner. However, in domains where the states of the nodes might constantly change, the explicit time series representation of DBNs is apparently necessary. We envisage to bring in, to some degree, the time series representation of DBNs (Dean and Kanazawa, 1992; Forbes et al., 1995; Albrecht et al., 1998), to improve our method.

One future direction area we aim at is the real deployment of our intention recognition method to tackle different real application domains, e.g., Ambient Intelligence (Han and Pereira, 2010c; Sadri, 2011a) and Care of the Elderly (Pereira and Han, 2011a), where intention recognition has been of increasing importance (Sadri, 2011b,a; Han and Pereira, 2010c).

4. Related Work on Intention Recognition for Decision Making

Many issues concerning intentions have been widely discussed in the literature of agent research. Some philosophers, e.g., Bratman (Bratman, 1987, 1999) have been concerned with the role that intention plays in directing rational decision making and guiding future actions. Many agent researchers have recognized the importance of intentions in developing useful agent theories, architectures, and languages, such as Rao and Georgeff with their BDI model (Rao and Georgeff, 1995), which, as we said above, has led to the commercialization of several high-level agent languages (e.g., see (Burmeister et al., 2008; Wooldridge, 2002)).

However, to the best of our knowledge, there has been no real attempt to model and implement the role of intentions in decision making, within a rational choice framework. Intentions of other relevant agents are always assumed to be given as the input of a decision making process; no system that integrates a real intention recognition system into a decision making system has been implemented so far.

The ongoing work of Han and Pereira (2010c); Pereira and Han (2011a,b) also attempts to combine the two systems, Evolution Prospection and Intention Recognition, but in a completely different manner. There we use an intention recognition system to recognize the goal of the observed agent (e.g., an elder (Pereira and Han, 2011a)), which the evolution prospection system then uses to derive appropriate courses of actions to help achieve.

Our recently published approach is more general and genuinely integrated: the intention recognition system is employed also to evaluate other different kinds of information being utilized, within an EP program (Han and Pereira, 2011c; Han and Pereira). It summarizes the existing work on Evolution Prospection and Intention Recognition and shows a coherent combination of them for decision making. The Evolution Prospection system has been proven to be a useful one for decision making, and now it has been empowered to take into account intentions of other agents—an important aspect that had not been explored so far. The fact that both systems are LP-based has enabled their easy integration.

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