Proactive Intention Recognition for Home Ambient Intelligence

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Abstract We explore a coherent combination of two jointly implemented logic programming based systems, namely those of Evolution Prospection and Intention Recognition, to address a number of issues pertinent for Ambient Intelligence (AmI), namely in the home environment context. The Evolution Prospection system designs and implements several kinds of well-studied preferences and useful environment-triggering constructs for decision making. These enable a convenient declarative encoding of users' preferences and needs, as well as reactive constructs like goal triggering rules. The other system performs intention recognition by means of Causal Bayes Nets and a planner. This approach to intention recognition is appropriate to tackle several AmI issues, such as security and emergency. We also present a novel method for collective intention recognition to allow tackling the case where multiple users are of concern. We exemplify our methods with examples in the elder care domain as it is one typical concern in the home environment context.

Keywords. Evolution Prospection, Preferences, Intention Recognition, Ambient Intelligence, Logic Programming

1. Introduction

One of the key issues of Ambient Intelligence (AmI), which has not been well studied yet, and reported as an ongoing challenge [3], is that AmI systems need to be aware of users' preferences, intentions and needs. Undoubtedly, respecting users' preferences and needs in decision making processes would increase their degree of acceptance w.r.t. the systems, making them more friendly and thoughtful. Furthermore, an ability to recognize intentions of assisted people as well as other relevant concerns such as intruders, would enable to deal with a combination of several issues, e.g. pro-activeness, security, emergency, etc. in a more integrated and timely manner.

In this paper we set forth a coherent formulation of logic based implemented systems, Evolution Prospection (EP) [9] and Intention Recognition (IR) [8], to tackle those challenges, showing how they are applied to a number of issues of AmI in home environment. The first one designs and implements several kinds of well-studied preferences, with formal semantics given in [4,5], and several useful environment-triggering constructs for decision making. These enable it to provide rational decisions, taking into account users' preferences and health conditions, as well as information about the external environment provided, e.g. by networked sensors. EP system is described in Section 2.1.

The latter is a two-stage IR system (described in Section 2.2). In the first stage, it uses Causal Bayes Nets (CBN) [16] to identify conceivable intentions and compute their likelihood based on the very first observations, then filter out the much less likely ones. Then, in the second stage, the retained intentions are validated by more observations which comply with plans for those intentions generated by a plan generator (or simply with those of a library of plans). This approach exhibits several advantages important for addressing AmI issues. Firstly, based on the initial observations, the likelihood of intentions can be computed by the CBN, from which the recognizing agent can gather which intentions are more likely and worth addressing, so that, in case of having to make a quick decision, it can focus on the most cogent ones first. This feature is important for security and emergency issues of AmI where decisions must be timely made to be useful. Waiting until observing the very last actions of a plan, e.g. of intruding or of endangering life, may be too late to engage in a useful action.

The approaches based solely on BNs (e.g. [15]) just use the available information for constructing the networks. For complicated tasks, e.g. in recognizing hidden intentions, not all information is observable. Our approach of combining them with a planner provides a way to guide the recognition process: which actions (or their effects) should be checked whether they were or will be executed (maybe hiddenly) by the intending agent. This feature enables AmI assisting systems to always be prepared to deal with potential dangerous behaviors of the assisted people, as well as security issues such as intrusion.

However, since this IR system is only capable of recognizing individual intention, it is unable to deal with the problem domain where multiple users are of concern. As most researchers in philosophy [19,18] and multi-agent system [20] agree, collective intentions (or joint intentions; we-intentions; shared intentions) are not summative. A collective intention of a group of agents cannot be reduced to a mere summation of the individual intentions of the agents. It involves a sense of acting together and willing something cooperatively, thus some kind of "glue", e.g. mutual beliefs or mutual expectations, must exist amongst the agents. We will present a new method for collective intention recognition based on these philosophical accounts (Section 4).

2. Background

2.1. Evolution Prospection

The implemented EP system has been proven to be useful for decision making [9]. It has been applied for providing appropriate suggestions for elderly people, taking into account their preferences, health reports, future scheduled events as well as the information about the external environment [11]. The advance and easiness of expressing preferences in EP [4,5,9] enable to closely take into account elders' preferences. We next describe the constructs of EP, to the extent we use them here. A full account can be found in [9].

Language Let $\mathcal{L}$ be a first order language. A *literal* in $\mathcal{L}$ is a domain atom A or its default negation $not\ A$. The latter can express that the atom is false by default (Closed World Assumption). A *domain rule* in $\mathcal{L}$ is of the form: $Head \leftarrow Body$ (reading *Head if Body*) where *Head* is a domain atom and *Body* is a conjunction of literals.

An *integrity constraint* (IC) in $\mathcal{L}$ is a rule with an empty head, implying that its body must be false. A logic program P over $\mathcal{L}$ is a set of domain rules and ICs, standing for all their ground instances.

In this paper, we consider solely Normal Logic Programs (NLPs), those whose heads of rules are positive literals, i.e. positive atoms, or empty. We focus furthermore on abductive logic programs, i.e. NLPs allowing for abducibles – user-specified positive literals without rules, whose truth-value is not fixed. Abducibles instances or their default negations may appear in bodies of rules, like any other literal. They stand for hypotheses, each of which may independently be assumed true, in positive literal or default negation form, as the case may be, in order to produce an abductive solution to a query.

Definition 1 (Abductive Solution) *An abductive solution is a consistent collection of abducible instances or their negations that, when replaced by true everywhere in P, affords a model of P that satisfies the query true and the ICs – a so-called abductive model, for the specific semantics being used on P.*

Active Goals In each cycle of its evolution the agent has a set of active goals. The rule for an active goal AG is of the form: $on\_observe(AG) \leftarrow L_1, ..., L_t\ (t \geq 0)$, where L_1,...,L_t are domain literals. When starting a cycle, the agent collects its active goals by finding all the $on\_observe(AG)$ that hold under the initial theory without performing any abduction, then finds abductive solutions for their conjunction.

Similar to ECA rules (e.g. in [6]) and integrity constraints rules [7], rules for active goals in EP can be used to model reactive rules to provide reactive behaviors, as follows: $on\_observe(do(actions)) \leftarrow events\_expression, preconditions$, i.e. on detecting certain events, if certain preconditions are true, then certain actions should be executed. However, with additional background knowledge representing different kinds of information from different sources such as embedded network sensors, users' preferences, etc., EP system can deliberate on which actions to perform rather than simply react to observations, thereby making more rational decisions.

Preferring Abducibles An abducible A can be assumed only if it is a considered one, i.e. if it is expected in the given situation, and, moreover, there is no expectation to the contrary: $consider(A) \leftarrow expect(A), not\ expect\_not(A),\ A.$ This *consider*-rule is automatically added to an EP program for each abducible in it.

The rules about expectations are domain-specific knowledge contained in the theory of the program, and effectively constrain the hypotheses available in a situation. Counter expectation rules supplement expectation rules for the sake of representing defeasible conditions. These rules can be used to encode the pros and cons of the user towards some choice, represented by an abducible, which may trigger, e.g. the rule for an active goal.

Preference criteria among abducibles is employed by so-called *a prior* preferences, which are of the form: $a \vartriangleleft b \leftarrow L_1, ..., L_t\ (t \geq 0)$, where $L_1, ..., L_t$ are domain literals.

Example 1 (Solving Intrusion) *Consider a situation where the IR system recognized an intention of intrusion at night. The system must either warn the elders who are sleeping, automatically call the nearest police, or activate the embedded burglary alarm. If the elders are sleeping and ill, they do not expect to be warned, but prefer other solutions. Due to potential disturbance, the elders prefer simply activating the burglary system to calling the police as long as no weapon is detected and there is a single intruder.*

The situation is described by the program with three abducibles: $call\_police$, $warn\_persons$, $activate\_alarm$, and can be coded in EP as follows

1. $on\_observe(solve\_intrusion) \leftarrow at\_night,\ intruding\_intention\_detected.$
2. $solve\_intrusion \leftarrow call\_police.$ $\quad solve\_intrusion \leftarrow warn\_persons.$
   $solve\_intrusion \leftarrow activate\_alarm.$
3. $expect(call\_police).$ $\ expect(warn\_persons).$ $\ expect(activate\_alarm).$
4. $expect\_not(warn\_persons) \leftarrow ill,\ sleeping.$

5. $activate\_alarms \lhd call\_police \leftarrow no\_weapon\_detected,\ individual.$
6. $call\_police \lhd activate\_alarms \leftarrow weapon\_detected.$

Suppose it is night-time and an intrusion intention is recognized, then the active goal $solve\_intrusion$ (line 1) is triggered, and the EP system starts reasoning to find the most appropriate solutions.

This program has three abductive solutions: $[call\_police]$, $[warn\_persons]$, and $[activate\_alarm]$ since all the abducibles are expected and there is no expectation to their contrary. Note that for each abducible an *consider*-rule is added automatically [9]. Suppose it detects that the elders are sleeping and known to be ill, i.e. literals *ill* and $sleeping$ are factual. In this case, the elders do not expect to be warned (line 4), thus ruling out the second solution $[warn\_persons]$. And if no weapon is detected and only single intruder, the *a priori* preference in line 5 is triggered, which defeats the solution where only $call\_police$ is present (due to the impossibility of simultaneously abducing $activate\_alarm$). Hence, the only solution is to activate the burglary alarm. However, if weapons were detected, the preference in line 6 is triggered and defeats the $[activate\_alarm]$ solution. The only solution left is to *call the police*.

A Posteriori Preferences Having computed possible scenarios, represented by abductive solutions, more favorable scenarios can be preferred a posteriori. Typically, *a posteriori* preferences are performed by evaluating consequences of abducibles in abductive solutions. An *a posteriori* preference has the form:

$$A_i \ll A_j \leftarrow holds\_given(L_i, A_i),\ holds\_given(L_j, A_j)$$

where A_i, A_j are abductive solutions and L_i, L_j are domain literals. This means that A_i is preferred to A_j a posteriori if L_i and L_j are true as the side-effects of abductive solutions A_i and A_j, respectively, with no further abduction being allowed when testing side-effects. To give an example, let us extend the above with the following rules

7. $A_i \ll A_j \leftarrow holds\_given(not\_annoying, A_i),\ holds\_given(annoying, A_j)$
8. $annoying \leftarrow call\_police. \quad not\_annoying \leftarrow activate\_alarm.$

Suppose that no weapon is detected and there are more than one intruder. Then, no *a priori* preference is triggered, thus there being two abductive solutions $[call\_police]$ and $[activate\_alarm]$. Next, the *a posteriori* preference in line 7 is triggered. It means that the abductive solution leading to $not\_annoying$ is preferred to the one leading to $annoying$. Thus, $[call\_police]$ is ruled out, and $[activate\_alarm]$ is the only solution.

2.2. Intention Recognition

In [8], a method for individual intention recognition via Causal Bayes Nets (CBN) and plan generation was presented. The CBN is used to generate conceivable intentions of the intending agent and compute their likelihood conditional on the initially available observations, and so allow to filter out the much less likely ones. The plan generator thus only needs to deal with the remaining more relevant intentions, because more probable or credible, rather than all conceivable intentions. In the sequel the network structure for intention recognition is recalled. We assume the readers are familiar with the basic concepts of CBNs, which can be achieved from [16,8].

Network Structure for Intention recognition The first phase of the IR system is to find out how likely each conceivable intention is, based on current observations such as observed actions of the intending agent or the effects of its actions had in the environment.

A conceivable intention is the one having causal relations to all current observations. It is brought out by using a CBN with nodes standing for binary random variables that represent causes, intentions, actions and effects.

Intentions are represented by those nodes whose ancestor nodes stand for causes that give rise to intentions. Intuitively, we extend Heinze's tri-level model [14,10] with a so-called pre-intentional level that describes the causes of intentions, used to estimate prior probabilities of the intentions. However, if these prior probabilities can be specified without considering the causes, intentions are represented by top nodes (i.e. nodes that have no parents). These reflect the problem context or the intending agent's mental state.

Observed actions are represented as children of the intentions that causally affect them. Observable effects are represented as bottom nodes (having no children). They can be children of observed action nodes, of intention nodes, or of some unobserved actions that might cause the observable effects that are added as children of the intention nodes.

The causal relations among nodes of the CBNs (e.g. which causes give rise to an intention, which intentions trigger an action, which actions have an effect), as well as their Conditional Probability Distribution (CPD) tables and the distribution of the top nodes, are specified by domain experts. However, they might be learnt mechanically.

3. Intention Recognition and Evolution Prospection for AmI Issues

3.1. Proactive Support

One of the key features of AmI (particularly desirable in Elder Care) is that the assisting system should take initiative to help the people it assists. To this end, the system must be capable of recognizing their intentions on the basis of their observable actions, then provide suggestions or help achieve the recognized intentions. A suggestion can be, for example, what are the appropriate kinds of drink for the elder, considering the current time, temperature, or even future scheduled events such as going to have a medical test on the next day, upon having recognized that he has an intention to drink something. Or, a suggestion can simply be telling the elder where he put his book yesterday, having recognized that he might be looking for it.

The EP system is engaged to provide appropriate suggestions for the elders, taking into account the external environment, elders' preferences and already scheduled future events. Expectation rules and a priori preferences cater for the physical state (health reports) information of the elders to guarantee that only contextually safe healthy choices are generated; then, information such as the elders' pleasure, interests, etc. are then considered by a posteriori preferences and the like.

Example 2 (Elder Intentions) *An elder stays alone in his apartment. One day, the Burglary Alarm is ringing, and the IR system observes that he is trying to look for something. In order to assist him, the system needs to figure out what he intends to find. Possible things are: Alarm button ($AlarmB$); Contact Device ($ContDev$); Defensible Weapons (Weapon); and light switch ($Switch$). The CBN representing this scenario is in Figure 1.*

The nodes representing the conceivable intentions are *i(AlarmB), i(ContDev), i(Weapon)* and *i(Switch)*. The CBN has three top nodes in the pre-intentional level representing the causes of the intentions, which are $Alarm\_On$, $Defensible$ and $Light\_on$. The first and last nodes are evidence nodes, i.e. their values are observable. There is only one observable action, represented by bottom node $Looking$. It is a direct child of the intention nodes. The CPD tables are given. For example, the table of the node $Defensible$ says that

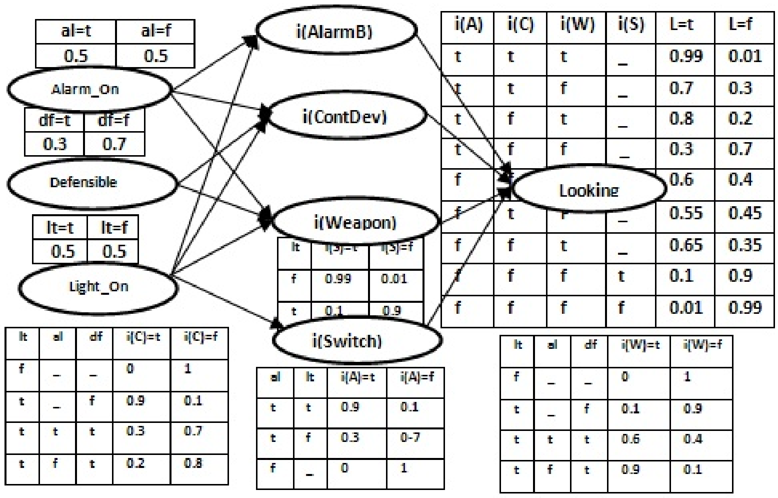

Figure 1. Elder's intentions CBN

the elder is able to defense himself (with weapons) with probability of 0.3 and not able to do so with probability 0.7 (**t** and **f** represent boolean values **true** and **false**, respectively). The table in the top-right corner provides the probability of the elder looking around for something conditional on the intentions. The readers are referred to [8] for the details of how to represent CBNs in P-log [13] and the computation of intentions' likelihood, and [10,11] for examples of using EP to provide suggestions.

3.2. Security and Emergency

Security is one of the key issues for AmI success [1], and particularly important in home environments [2]. It comprises two important categories : security in terms of Burglary Alarm systems and security in terms of health and well-being of the residents (prevention, monitoring) [2].

So far Burglary Alarm technology has been mainly based on sensing and recognizing the very last action of an intrusion plan, such as "breaking the door" [21]. However, it may be too late to provide an appropriate protection. Burglary Alarm systems need to be able to guess in advance the possibility of an intrusion on the basis of the very first observable actions of potential intruders. For example, it would be useful to find out how likely a stranger constantly staring at your house has an intrusion intention, taking into account the particular situation, e.g. if he has weapon or if it is night time. This information can be sent to the carer (or the elders if there is no carer available) to get prepared (e.g. turn on the light or sounders to scare off burglars or call relatives, polices, etc.). Our IR system appears to be appropriate. From the observed actions the CBN can be used to compute the likelihood of the conceivable intentions, and if it is big enough, the carer should be informed of a potential intrusion. To be sure, more observations need to be made and match with the scheme of plans library, but at least now the carer is ready to handle any potentially bad forthcoming situations. Waiting until being sure to get ready is too late to take appropriate actions. The EP system then can be used to provide suggestions on the appropriate course of actions to take (see Example 1).

Another security issue concerns health and well-being of the residents. AmI systems need to be able to prevent hazardous situations, which usually come from dangerous ideas or intentions (e.g. take a bath when drunk, drink alcohol while not permitted, or even commit suicide) of the assisted persons, especially those with mental impairments. To this end, guessing their intentions from the very first relevant behaviors is indispensable to take timely actions. In our IR, a situation-sensitive CBN can be employed to compute how likely there is a dangerous intention, and the carers should get informed in case it is likely enough, in order to get prepared.

Solving an emergency is also one of the important issues in AmI. There are a wide range of emergency situations, e.g. in security, when recognizing intrusion intention of a stranger or dangerous intentions of the assisted persons. They also can occur when detecting fire, unconsciousness or unusualness in regular activities (e.g. sleep for too long), etc. Emergency handling in EP can be done by having an active goal rule for each emergency situation. For solving the goal, a list of possible actions, represented by abducible enablers, are available to form solutions. Then, users' preferences are encoded using the different kinds of preference of EP: *a priori* ones for preferring amongst available actions, *a posteriori* ones for comparing solutions taking into account their consequences and utility, and *a posteriori evolution result* ones for comparing more-than-one-step consequences. Moreover, the expectation and counter expectations rules are used to encode pros and cons of the users towards each available action, or any abducible in general.

3.3. Discussion of Other Issues

We have shown how our IR and EP systems can be used to enable to provide proactive support for assisted people and tackle security and emergency issues. For lack of space, we here briefly sketch our approaches to some other important issues in AmI.

First of all, it is known that IR ability plays the central role in human communication [14]. In addition, an important aspect of intentions is future-directed, i.e. if we intend something now, it means we intend to execute a course of actions to achieve it in the future [17]. Most actions may be executed only at a far distance in time. Thus, we usually need to guess others' intentions from the very first clues such as their actions or spoken sentences, in order to secure a good conversation or cooperation. Perhaps we guess a wrong intention, but we need to be able to react in a timely manner; and that is also part of the conversation. We can simply attempt to confirm by asking, e.g. "is this (...) what you mean?". Our two-stage IR method can be used to design an *iFriend* that can react to human behaviors and speech, communicate with them to confirm their intentions so as to provide appropriate help when necessary, after having guessed their likely intentions using CBNs. *iFriend* has a list of actions and spoken sentences that, if any of them is enacted by the assisted person, there trigger an associated CBN to compute the likelihood of the intentions encoded by it.

Another issue is that, in order to be highly accepted by the users, an assistive system should be able to proffer explanations for the suggestions it provides. In EP, that can be easily done by keeping all the preferences, integrity constraints, expectation and counter expectation rules that were used both to consider and to rule out abductive solutions.

4. Collective Intention Recognition

The presented IR system only deals with an individual user. In many cases, an ability of collective IR is necessary, e.g. recognizing intrusion of a group of intruders. Or, in the Elder Care domain, there may be a couple of elderly staying alone, and they may intend to do things together. To provide appropriate help, recognizing their collective intention is important. In the following we describe a method for collective IR based on its mainstream philosophical accounts.

Most researchers agree that collective intentions are not summative, i.e. cannot be reduced to a mere summation of individual intentions [19,18]. Collective intentions involve a sense of acting and willing something together cooperatively. There must be some kind of “glue" supplementing the separate individual intentions in order for agents to partake in a collective intention, e.g. mutual beliefs [19] or mutual awarenesses [18]. In [19], the collective intention of a group of agents is defined as individual intentions of the agents plus their mutual beliefs. Following this, Kanno et al. presented a bottom-up approach to collective intention recognition [20]. To recognize the collective intention of a group of agents, the individual intentions and beliefs of the constituents are inferred first. Then, the collective intention is inferred by checking for consistencies amongst those inferred mental components. The main disadvantage of this bottom-up approach is that it is confronted with a combinatorial problem of possible combinations of individual intentions and beliefs to form collective intentions. Given the situation at hand, each agent may have several conceivable intentions and beliefs, but there are not many combinations of them forming conceivable collective intentions.

To tackle this issue, we propose a top-down approach to collective IR. The recognition process starts by inferring the possible collective intentions assuming that they were had by a virtual plural agent representing the group and abreast of all group activity. Then, we figure out which of them is a genuine one by checking whether there is any activity “glue" information linking the agents’ individual intentions. The above assumption is inspired and validated by Searle’s account of collective intention [18]. According to him, collective intentionality is non-summative, but remains individualistic. With the presupposition of mutual awarenesses, namely that each agent supposes the others are like himself and that they have similar awareness of him as an agent like themselves, it allows for the possibility of a single plural agent or “brain in a vat" having the collective intention of the group. Thus, if a group of agents had a collective intention, this intention could be recognized as if it was had by a single agent. For this we can use any existing individual IR methods. Next our presented IR method is used for illustration.

Example 3 (Elderly Couple’s Care) *A couple of elderly people stay alone in their apartment. The IR system observes that they are both now in the kitchen. The man is looking for something and the woman is holding a kettle. In order to assist them, the system needs to figure out what they intend to do. The possible collective intentions are: making a drink or cooking. The CBN for IR in this scenario is provided in Figure 2 .*

Confirming Collective Intention. Having recognized the intention, the next step is to confirm whether it is the genuine one. For intention recognition’s sake, what we are interested in (and actually all what we have got) are the actions or their effects in the environment resulting from the “glue" mental attitudes (mutual beliefs or mutual awarenesses) amongst the agents. An intermediate stage between having such mental attitudes and actual activity is that the agents form some mutual expectations between each other which reflect their attitudes. Thus, if and when having a collective intention, each agent in the group should act according to his expectations to other constituents. In this work we assume that a priori domain knowledge is specified in the form of a library containing the set of possible plans and expectation actions.

Briefly, the confirmation starts by grouping the agents that have the same first action from a plan achieving the recognized intention. Agents in a group are doing the same task

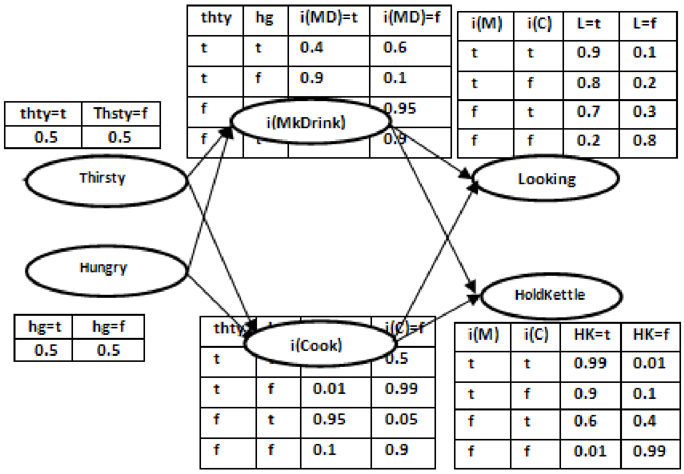

Figure 2. Elders Collective intentions CBN

(subplan) or at least some part together. Then, we only need to check for the expectation actions amongst agents in the same group and a single expectation action between two group responsible for consecutive subplans. This grouping method reduces the number of interactions between the agents that need to be checked (e.g. by an activity recognition system) and the number of possible expectation actions between two particular agents. Within a group, the expectation actions can be a "complain" action when a group member "deviates" from the task without an "inform" action; or a "help" action when an agent cannot manage his task (although we believe that this kind of action is mostly preceded by a "complain" action). For two consecutive groups—the second requires a result from the first as an input—the second has expectation actions of expecting some result ("expect result") from the first, or "complain" if the result is not delivered as expected; the first group in turn expects the second to use their result ("expect use"), or "complains" if the result is not used as expected. One expectation action observed between the two groups is enough to conclude they have a collective intention. The above example has two agents (elders) that are responsible for two different tasks—they have different first actions—illustrating expectation actions between two consecutive groups.

Example 4 (Confirming Collective Intention) *Suppose that "making a drink" was the collective intention recognized from prior step. We will check if it is a genuine one.*

Let us consider a simple plan achieving that intention *[take the kettle, fill it up with water, boil the water, look for tea or coffee, put it into the boiled water]*. Hence, the woman's subplan is *[take the kettle, fill it up with water, boil the water]* and the man's is *[look for tea or coffee, put it into the boiled water]*. The assigned result of the woman is to provide some *boiled water*. The man's expectation is that of *boiled water* from the woman, thus may have some "expect result" actions, e.g. ask whether the water is ready or get the water from the woman. Or, if after a while the if the woman could not boil the water or she was doing something else, the man would complain. If such "expect result" or "complain" action occurs, we can conclude that they really have a collective intention of making a drink. Otherwise, e.g., the man does not show any expectation of the water that the woman has boiled, then we can conclude that that is not their genuine collective intention, even if later he might use the boiled water for his own purpose. We emphasize that there are necessary actions showing the mutual expectations of results and usage of results when the agents have a collective intention towards achieving some task.

5. Conclusion and Future Work

Users' intentions, preferences and needs have been agreed by the AmI community to play an important role. However, they have not been sufficiently addressed, and considered as ongoing challenges. Here we have summarized our previous work on Intention Recognition and Evolution Prospection and shown how they can be useful for a number of issues of AmI, namely in the home environment, enabling to encode preferences and to recognize intentions. In addition, we have shown a top-down approach to collective IR in order to take care of problem domains where multiple users are considered. In the future, the IR system may make clear its own intentions and its recognition of others', so assisted persons understand what it is up to.

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