# A Novel Approach To Proactive Human-Robot Cooperation*

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*Abstract*— **This paper introduces the concept of proactive execution of robot tasks in the context of human-robot cooperation with uncertain knowledge of the human's intentions. We present a system architecture that defines the necessary modules of the robot and their interactions with each other. The two key modules are the intention recognition that determines the human user's intentions and the planner that executes the appropriate tasks based on those intentions. We show how planning conflicts due to the uncertainty of the intention information are resolved by proactive execution of the corresponding task that optimally reduces the system's uncertainty. Finally, we present an algorithm for selecting this task and suggest a benchmark scenario.**

## I. Introduction

Human centered computing is one of the most present topics in robotics today. A strong indicator for this is the large number of humanoid robotics projects world-wide. One example is the Collaborative Research Center SFB 588 on "Humanoid Robots" of the German Research Foundation [1].

One of the key challenges of human centered computing is the intuitive human-like interaction with robots. It requires the development of highly sophisticated approaches, since it involves the application of sensors and actuators in a real world scenario dealing with humans.

Our approach involves intention recognition, a discipline that is closely related to classical plan recognition. As we want to infer hidden user intentions, we are especially interested in the so called keyhole plan recognition [2]. A popular approach in this field is the application of Bayesian Networks. They provide a mathematical theory for reasoning under uncertainty and causal modeling. An example for the application of Bayesian Networks is the *Lumière* project [3] that tries to figure out the user's goals in office computer applications from tracking their inputs. A similar approach was successfully applied to affective state detection [4].

The other vital concept in our approach is proactive execution. Although many applications of proactive behavior are located in the realm of business and finances, there have been attempts to apply it to robotics. Proactive planning is mentioned in [5] in the case of probabilistic determination of the results of an action of a mobile robot. An architecture for autonomous agents that include a proactive behavior component is outlined in [6]. Achieving proactive behavior of agents through goal reprioritization is suggested in [7]. The unified planning and execution framework IDEA [8] allows agents to use the concept of proactive planner invocation in case the agents anticipate any problems.

The remainder of this paper is structured as follows: In section II we motivate the problem, followed by a general overview of our proposed system architecture in section III. The probabilistic approach to intention recognition is explained in section IV. Section V gives an introduction to the planner and its application to proactive cooperation. We propose a benchmark scenario in section VI and conclude the paper in section VII.

## II. Problem Formulation

We propose a system architecture that allows for intuitive human-robot cooperation in the sense of avoiding explicit clarification dialogs and explicit commands. The goal is to provide a more implicit interaction than what currently available systems offer and that resembles human-human interaction.

Humans are very good in mutual control of their interaction by reading and interpreting the affective and social cues of each other [9]. Hence, a robot system that is able to read the user's (non-)verbal cues to infer the user's intention is able to interact more intuitively from the human's perspective.

As humans try to figure out their interaction partner's goals or desires, they try to trigger reactions. Take for instance the waiter on a cocktail party who wants to know if somebody wants a refill. He presents the bottle, causing the guest to present his glass or to withdraw it. We call this action of the waiter *proactive*, since he acts without an explicit command from the guest, provoking a clarifying reaction from the guest and thus removing any uncertainty about the user's intention. As this example illustrates, humans are accustomed to perform intuitive cooperation. Thus, providing service robots with such a skill opens a new dimension in human-robot cooperation.

The crucial point of intuitive cooperation is the robot's ability to recognize the user's intention. Since even humans cannot do this perfectly, a probabilistic approach has to be used. This allows for stating how certain the recognized intention is. Proactive behavior of the robot can then be used to minimize uncertainty. The challenge for the planner is to select a robot action that urges the user to react in a way that unravels the user's intention. The corresponding robot actions need to be executed with care, since the recognized intention is uncertain. The human user is meant to close the loop of intention recognition and proactive action planning.

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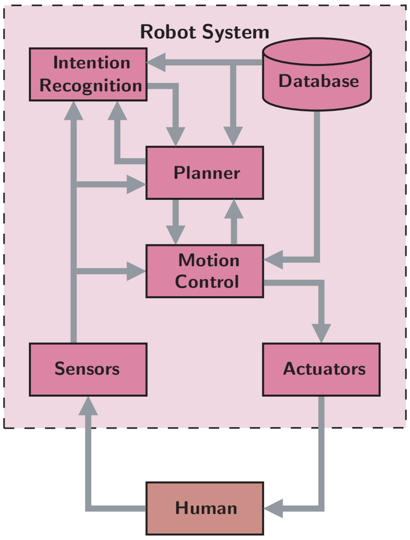


Fig. 1. System architecture.

## III. System Architecture

The system architecture defines the interface between a robot system and a human being that interacts with that robot. It also describes the basic building blocks that make up the robot system and the relations they have with each other. We suggest a robot architecture as depicted in Fig. 1.

A robot system's interface to the outside world is composed of its *Sensors* and *Actuators*. The *Actuators* may include arms, hands, a head, a torso, and a mobile platform or legs. On the *sensor* side we favor stereo cameras as visual sensors, a microphone array for auditory sensory information, and tactile sensors that cover a substantial part of the robot's surface as an artificial skin. Thus, all necessary information and features are provided to enable the robot to navigate in its environment, grasp objects or door handles, locate humans in its vicinity, and distinguish them by their faces and voices.

The central module of the system is the *Planner*. It uses the *Database*, the *Sensors*, and the *Intention Recognition* modules to obtain the current status of the world and itself as well as a list of the skills and actions that it is capable of. With this information the *Planner* decides on the execution of tasks, the allocation of resources to the individual modules, and the mode the system is running in. In order to execute tasks it issues commands to the *Motion Control* module.

The *Motion Control* module in turn receives these commands that describe the tasks that are to be executed and their corresponding parameters. It is responsible for decoding the commands and translating them into motion commands for the individual actuators. Subsequently it controls the motion of the actuators and the completion of the current task. The control loop is closed by the sensory information from the external world and the internal status through angle transmitters and strain gages.

The *Intention Recognition* fuses the information that is available from the *Sensors* and the *Database* using probabilistic methods. It strives to extract a hypothesis of the path that the human will move along in the near future and the type of interaction he desires to have with the robot. Thus the module makes an effort to understand as much of the non-verbal communication as possible that the human produces. The result is fed to the *Planner*. In case the information about the human intention is too uncertain the *Planner* is forced to execute tasks proactively.

The robot's model of the environment and the properties (such as shape and location) of the objects it knows about are stored in a *Database*. It also contains the actions derived through programming by demonstration that can be replayed with varying parameters. Furthermore, the *Database* will be used to store hard-coded finite state machines that control certain forms of human-robot cooperation, like the handing over of an object or guided robot motion through human touch.

## IV. Intention Recognition

Assisting a user based on implicit communications requires the knowledge of the user's aims, goals, or wishes. We summarize these as the user's *intention*. Since intention is a state of mind it cannot be measured directly. Nevertheless, humans are able to recognize intentions of their communication partners. This skill is extremely important, especially in non-verbal communications. Even though the estimation of a partner's intention is usually uncertain, the gained information is still of great value. Hence, we need a model that allows for estimating the user's intention from external clues while maintaining information concerning the uncertainty of the estimate.

The key to the hidden state of the user's intention are the actions performed by the user. It can be assumed, that actions are directly caused by the intention, as long as the user is not trying to cheat. Hidden intentions drive the observable actions, thus, the model must describe how the actions depend on the intention. We call this a forward model, since it captures the causal dependencies — actions depend on intentions, not vice versa.

To estimate the user's intention we propose a dynamic Bayesian network model what offers a lot of advantages. First, it is a probabilistic model, providing us the ability to reason under uncertainty. Second, it is a causal forward model and third, it allows for subsuming temporal information (successive measurements).

### A. Dynamic Bayesian Networks

Classically, Bayesian Networks are depicted as directed acyclic graphs with nodes representing variables and edges representing causal dependencies among these variables. The causal dependencies are modeled by means of conditional densities.

Dynamic Bayesian Networks (DBN) capture the development of the network over time. This is usually depicted by showing the network for two successive time-steps and connecting these models by means of edges representing the dependencies from time-step $t$ to time-step $t+1$.

Fig. 2 shows our DBN model for intention-recognition. We have one node in each time-step representing the user's intention, which is a hidden state that cannot be observed directly. For our application we assume this node to be discrete since there are distinct intentions that we want to distinguish. Nevertheless, it is possible to define continuous intentions.

User-intentions are often influenced by external circumstances. In other words, the intention is affected by the environment the user acts in. We cover these environmental influences by a node containing ”domain knowledge”.

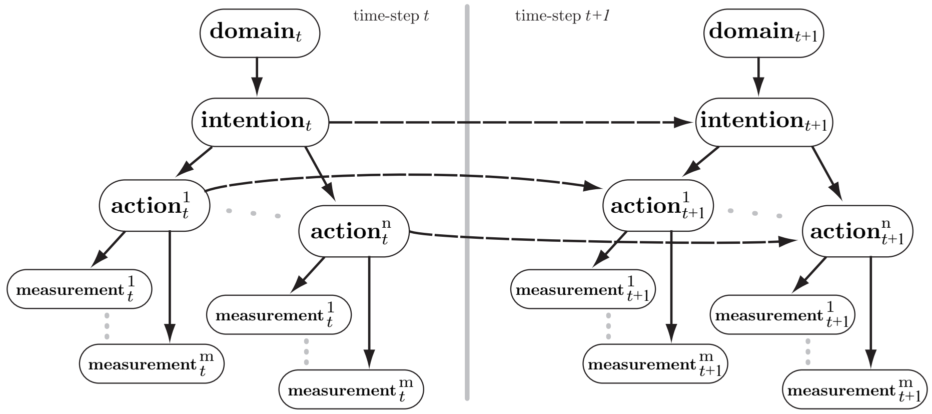


Fig. 2. The generic HDBN model for Intention-Recognition has one node for the hidden intention state in every time step. Possible actions are given as nodes depending on the intention.

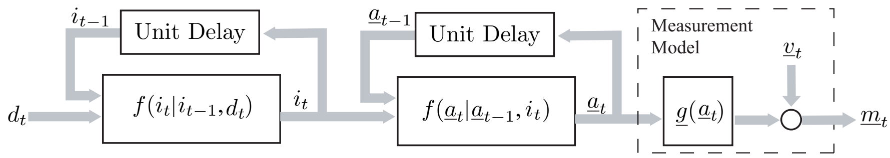


Fig. 3. Block diagram of intention forward model.

A user performs actions depending on the intention. These actions do not depend on other actions in the same time-step. This does not mean that these actions are mutually exclusive! As already pointed out, the actions depend causally on the intention and *not* vice versa. We cover this fact by the application of a probabilistic forward model $f(\text{action}_i|\text{intention})$ for every known $\text{action}_i$. Due to the power of probabilistic reasoning we are able to infer the intention from information on performed actions.

Humans can observe actions of other humans in a nearly direct way, although they may fail in some cases. Robots, on the other hand, have to reconstruct this information from sensor measurements. Hence, we need an additional layer (measurement nodes) in our network. Here we can apply standard measurement models known from dynamic systems theory.

To represent temporal behavior of a user, we introduce an edge from the intention node in time-step t to the intention node in time-step t+1. This enables us to cope with a user ”changing his mind”.

Actions depend on the actions performed in the preceding time-step. Hence, an edge from every action to its corresponding node in the next step is drawn. These edges contain information on how likely it is, that the same action is performed twice, given a certain intention.

Since sensor measurements depend only on the action in the current time step and not on previous measurements, no edges are drawn from a measurement in time step t to the corresponding measurement in time step t+1.

### *B. The Intention Estimator*

In order to explain the intention estimator, we introduce an alternative way to describe our model as shown in Fig. 3. In this blockdiagram $i_t$ is the intention variable, $\underline{a}_t$ a vector of actions, and $\underline{m}_t$ is the measurement vector. The domain knowledge is given by the variable $d_t$. The first and the second block depict the conditional densities for $i_t$ and $\underline{a}_t$. The vector representation of actions was chosen just for convenience. Since the actions are independent they could be modeled in multiple separate blocks. The dashed box at the end describes a standard measurement model for actions with additive noise $\underline{v}_t$. If the measurement function $g(\underline{a}_t)$ is not known, the dashed block can be replaced by a conditional density block like the first two blocks.

The estimator is shown in Fig.4. It computes a probability density over the intention $i_t$ given the measurement vector $\hat{\underline{m}}_t$ and the domain knowledge $\hat{d}_t$. The BF- and BB-blocks depict a Bayesian forward and Bayesian backward inference respectively. In this way the density $f(i_t)$ is calculated via intermediate densities $f(a_t)$, $f_1(i_t)$, and $f_2(i_t)$.

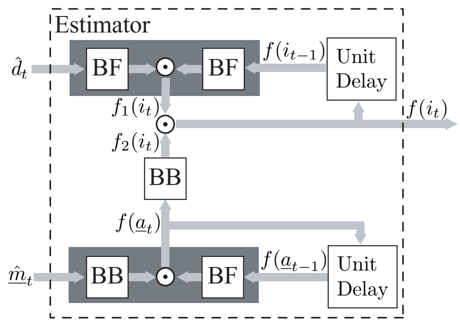


Fig. 4. The estimator computes a probability density over the intention $i_t$ based on the current domain knowledge $\hat{d}_t$ and the measurements $\underline{m}_t$ via intermediate densities $f(a_t)$, $f_1(i_t)$, and $f_2(i_t)$. It consists of Bayesian forward (BF) and Bayesian backward (BB) inference blocks.

The intermediate densities are multiplied, which is indicated by the dot in the circle. The dark blocks indicate the fusion of information from time-step $t$ with information from time-step $t-1$. This is to emphasize the fact that prediction- and filter-step are processed simultaneously.

A more in depth introduction to our approach to intention recognition can be found in [10].

## V. Planner

The planner constitutes the highest level of the organizational hierarchy of our robot system architecture. It is responsible for selecting the tasks that are to be executed, for making sure that all modules involved in the execution of the current task have the resources they need, and for selecting the current system mode. The tasks that are at the robot's disposal comprise the skills that the robot has learned through programming by demonstration and the skills that have been hard-coded by a programmer as finite state machines.

### A. Execution of Learned Skills

The database contains a selection of skills, especially manipulation tasks, that have been taught by the method of *programming by demonstration* [11]. In order to make these skills usable to our planner they will have to be described in some kind of task description language. Table I shows an example.

TABLE I
Sample task description of a grip command

| Task | *<id>* |
|---|---|
| Type | *grip, object, destination* |
| Preconditions | *object* $=$ *cup* $\vee$ *glass* |
| Effects | *hold object* |

Each task needs a unique identifier that can be used to retrieve the related data from the database. The *type* of the task needs to be an element of a set of known task types because in our real-world environment each task has different side effects (such as passing through a singularity) and dependencies on the environment (obstacles, for example), and the resources available (such as necessary specific sensory information). The preconditions list specifies the parameters that need to be satisfied to execute the task. The final task description entry states the effects the execution of the task has on the state of the robot and its environment. In the case of a complex task macro that consists of several elementary tasks the union of their effects needs to satisfy the goal.

### B. Execution of Hard-Coded Tasks

As a basis of elementary skills for human-robot cooperation we suggest to implement a set of simple tasks as hard-coded finite state machines. Examples are the handing over of an item to a human or a human leading the robot along a path by grasping its hand or lower arm. Fig. 5 shows the finite state diagram that can used to guide the robot.

By hard-coding a task we have full control over the execution and any specific settings necessary. Moreover, we can make sure that we use the full capabilities of the robot and take its limitations into account, especially regarding human safety. This is an inherent problem of a service robot, as its nature precludes safety mechanisms like a closed cage as used with industrial robots. Since it is the idea to use hard-coded tasks interchangeably with tasks learned through programming by demonstration we will describe these tasks in the same form of task description language.

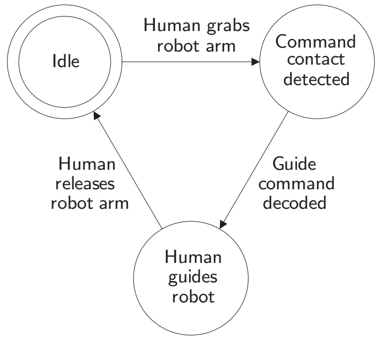


Fig. 5. Finite state machine for guiding the robot by a human.

### C. System Modes

It makes sense to provide several different modes of operation for the robot system. One of them should be an autonomous system mode including a planner that is able to plan and schedule tasks online and largely autonomously. It should be able to respond flexibly to any explicit commands or implicit intentions on the side of the human user.

We suggest another mode of operation where the course of robot action is predefined in a scenario (see section VI. Such a scenario, constructed from a number of elementary tasks, can be described conveniently by a high-level state machine. This mode allows for the specification of almost arbitrary complex scenarios and yet does not impose any implementation challenges.

### D. Interface Planner – Intention Recognition

Our concept of intuitive interaction between a robot and a human involves the tight interaction of the intention recognition module and the planner, see Fig. 1. The intention recognition provides the planner with a list of currently valid intentions and its probability density. These intentions must be well-known to both modules. In the other direction the planner returns the task that is currently being executed, which serves as an input for the calculation of the conditional intention probabilities in the intention recognition module.

### E. Proactive Execution of Tasks

When the robot is supposed to act in response to the intention of a human user, the planner takes all known and available tasks into account, any explicit action requests through a user interface and the input from the intention recognition. With respect to the intention recognition we have to distinguish several cases:

- The first case is that no intention can be inferred from the available sensor data. As a consequence, the probabilities of all intentions are equal, and no preferred intention can be determined.
- Another case with similar symptoms arises when there are many intentions that seem to be equally likely according to the observations. Again, the probabilities of those intentions will all have similar values, and it is again not possible to choose a clear winner unless there is another intention that has a higher probability.
- Assuming that there are two or three candidates as likely estimates for the human intention we have the chance to make a guess about the "true" intention. In this third

case of ambiguous results from the intention recognition we can choose an appropriate action and monitor the development of the probability density over all intentions.
- The last case happens when there is indeed one single intention that obviously dominates the rest. This is the ideal case, as it gives the planner a clear idea of what task to execute.

The last case is the easiest case to handle. The planner chooses the appropriate task and the robot thus acts according to the recognized intention. The other cases are a lot harder to deal with. In the cases where no intention was recognized with a sufficient certainty, the planner selects either an idle task or a task that tries to capture the human user's attention and communicate that the robot is idling and waiting for a command.

For the third case of two or three plausible intentions to choose from, we developed the concept of the *proactive execution* of a task. This means that instead of idling we pick an intention and pretend that this is the wanted intention, and select an appropriate task. Subsequently we start executing this task, closely monitoring how the values from the intention recognition develop. In case the similar probabilities tip in favor of our chosen intention we keep executing the task as usual. On the other hand, if it becomes clear that this task does *not* match the human's intention we stop execution, maybe roll back some movements, and start all over. Should there be no significant change of the confidence in these intentions we just keep executing the task.

The challenge here is the optimal selection of an intention from the two or three candidates. A practical strategy is to select the intention that triggers the execution of a task that lends itself to a segmentation into several parts naturally. This is true for most tasks that are specified by a finite state machine consisting of more than two states. Another strategy takes the issue of human safety into account and therefore the intention that triggers a robot action that is deemed the safest of all possible activities.

The strategy we propose here, however, is to pick the intention whose corresponding robot action will maximally decrease the uncertainty we have about the correct intention. If we denote the random variable for the intentions with $I$, we can specify this uncertainty as the entropy:

$$H(I) = -\sum_j p(i_j) \lg p(i_j) \ .$$

Let the random variable for the actions be $A$, then after picking an action the uncertainty of our system is reduced to the conditional entropy $H(I|A)$. We calculate $H(I|A)$ as

$$H(I|A) = -\sum_i p(a_i) \sum_j p(i_j|a_i) \lg p(i_j|a_i) \ .$$

Using Bayes' rule we can express the unknown $p(i_j|a_i)$ with the known $p(a_i|i_j)$ and thus obtain

$$\begin{aligned} H(I|A) &= -\sum_i p(a_i) \sum_j \frac{p(a_i|i_j)\, p(i_j)}{p(a_i)} \lg \frac{p(a_i|i_j)\, p(i_j)}{p(a_i)} \\ &= -\sum_i \sum_j p(a_i|i_j)\, p(i_j) \lg \frac{p(a_i|i_j)\, p(i_j)}{p(a_i)} \ . \end{aligned}$$

By computing this value for all possible actions and comparing the results, we are able to determine the action $\check{a}$ that has the lowest conditional entropy value and thus leaves us with the least uncertainty, that is

$$\check{a} = \arg_A \min\ H(I|A) \ .$$

Example: Consider the following probability values for 3 intentions $i_j$: $p(i_j) = \{0.4, 0.3, 0.3\}$ and 2 possible actions $a_i$. The selection of the action is done according to table II.

TABLE II
ACTION SELECTION DEPENDING ON INTENTIONS $\equiv p(a_i|i_j)$

| | $i_1$ | $i_2$ | $i_3$ |
|---|---|---|---|
| $a_1$ | 1 | 0 | 0 |
| $a_2$ | 0 | 1 | 1 |

The entropy of the intentions $I$ is $H(I) = 1.571$. Plugging in our values of $i_j$ and table II and using $p(a_i|i_j) = 0$ when $p(a_i) = 0$, we obtain $H(I|A) = 0.529$ when choosing action $a_1$ (i.e., $p(a_i) = \{1, 0\}$), and $H(I|A) = 1.042$ when choosing action $a_2$ (i.e., $p(a_i) = \{0, 1\}$). Hence we would pick action $\check{a} = a_1$ in this situation because it leaves us with the least uncertainty.

## VI. Benchmark Scenario

As a benchmark that can be used to effectively demonstrate and evaluate the proactive execution of tasks, we propose a scenario that involves two competing intentions and corresponding actions. Fig. 6 shows the rather complex state machine that describes this scenario.

It starts out with a dialog between robot and human where the human asks the robot to fetch a can. The robot then navigates to the can, grasps it and comes back to the human. Now the intention recognition comes into play. The human is holding a tray in one hand and a cup in another. By presenting the cup to the robot the latter should interpret this implicit communication as the human's intention of having himself a cup poured. As a consequence the robot should fill the cup. If the human moves the tray forward the robot should recognize that it is asked to place the can on the tray and release its grip.

When the user indicates neither desire, the intention recognition should realize this and present similar probability values for both intentions. The planner then switches to proactive execution, and the following three steps are performed in a loop: First, the planner selects a task to execute tentatively. Then the robot starts or continues to execute the given task. Lastly, after some short interval, the planner revisits the inputs it receives from the intention recognition and checks if the currently selected intention is still supported by the sensory evidence. After that the next loop iteration begins.

Upon successful completion of one of the tasks the robot should go back to the idle state. In that case of no recognized intention we intend to go back to the dialog state to receive an explicit command by the human. Should an error, fault or a dangerous situation arise we switch to the exception handler.

## VII. Conclusions

We have presented a new approach to human-robot cooperation that allows for the planning of robot actions even if the information about the human's intention is uncertain. This is achieved by introducing the concept of proactive

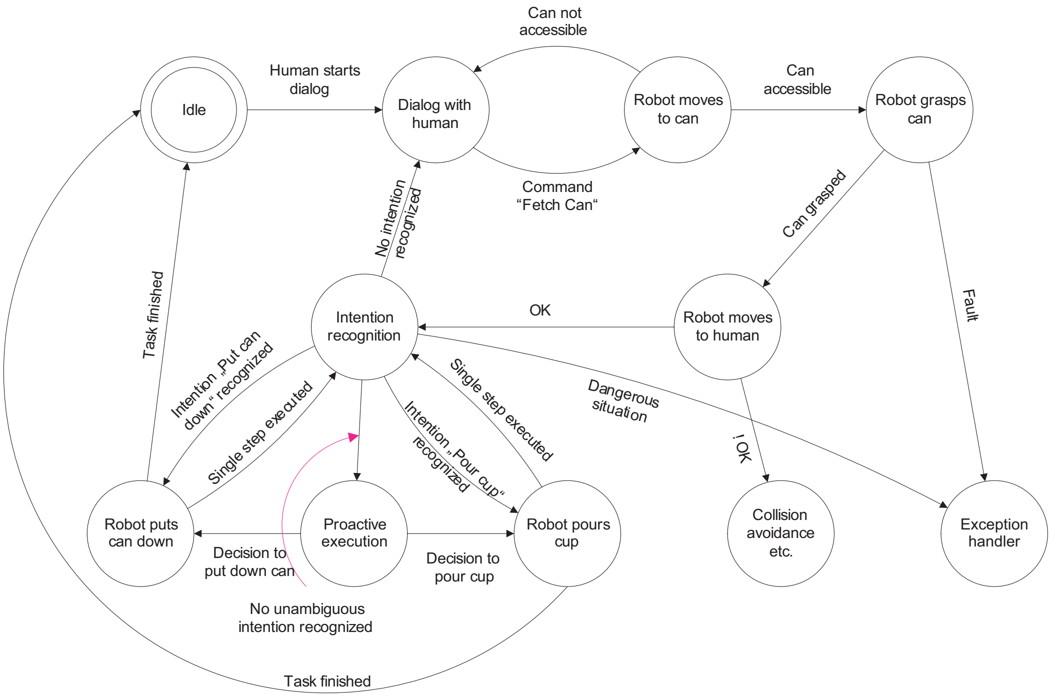


Fig. 6. Finite state machine for the demonstration of the proactive approach.

execution of tasks. As a result, we are able to close the loop involving human and robot by sensing the human's intentions and feeding back the findings through the robot's actions at any time and at any level of certainty.

The two modules we use to realize our concept are the intention recognition and the planner. The former facilitates communication between human and robot on an intuitive level, using affective and social cues rather than explicit commands. The latter selects the tasks to be executed according to the intentions the former has determined.

As the intention recognition process is likely to be ambiguous due to lack of hints from the human user or even his absence and noisy or missing sensor data, we use probabilistic methods for performing intention recognition and thus obtain a measure for the uncertainty of our findings. In the difficult case of high uncertainty we opt for the proactive execution of tasks rather than idling. Thus we display our information of the human's intentions back to him and provoke his reactions that we use in turn to confirm or disconfirm our choice for the correct intention. This intention is chosen such that we maximize the information we can obtain from the user's reaction and at the same time minimize our system's uncertainty. We have shown a suitable algorithm that allows for making this choice in a straightforward and easy-to-implement way.

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