Selection of Actions for an Autonomous Social Robot

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Abstract. Autonomy is a prime issue on robotics field and it is closely related to decision making. Last researches on decision making for social robots are focused on imitating humans' mind for taking decisions. Following this approach, we propose a motivational system for decision making using internal (drives) and external stimuli for choosing the right action. Actions will be selected from a finite set of skills in order to keep robot's needs within an acceptable range.

We present how our motivational decision making is applied to a social robot showing an improvement in robot's autonomy.

Keywords: motivations, decision-making, autonomy, social robot.

1 Introduction

Social Robots are intended for interacting with humans and assisting them in several tasks. During these tasks, it is desired that robots are able to accomplish such task by themselves without no surveillance. This idea implies a certain level of autonomy.

Autonomy is a term widely used in literature and its meaning ranges from very different values. [7] refers autonomy as *systems capable of operating in the real-world environment without any form of external control for extended periods of time*. But is it possible to achieve a full autonomous robot? Is it desirable? Absolutely autonomous robots are impossible to build. Robots are designed for achieving duties and it implies some kind of interaction with the world. Even human beings do not have this level of autonomy, they depend on others and their environment.

Some definitions of robots classify them as a especial kind of agents and being an agent entails making choices [14]. Consequently robots have to be endowed with some kind of decision making. We consider level of autonomy of robots as the amount of decisional mechanisms they are endowed with [11].

In this work we propose a motivational system for autonomous decision making which endows robots with the capacity to decide what to do and when to do it for satisfying its inner needs.

The rest of the paper is organized as follows. Next section presents some previous works about autonomy in robots and decision making. After that, our

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theoretical approach is explained and then how it has been implemented in a real platform will be shown. Finally conclusions are summarized.

2 Autonomy in Robots

Autonomy and more precisely autonomous robots have been extensively studied in the last years. More general researches have been focused on autonomous agents. As it is said at [2], agent autonomy is defined like the capability to interact independently, exhibiting control over its own internal state.In addition, [31] mentioned that autonomy is the degree in which one agent is independent with respect to another entity, the environment, other agents or even its own developer. Additionally, [3] consider autonomy as a measure and adjustable value.

Regarding robots, [1] and [10] present autonomy in robots as the capacity of producing plans for reaching a given goal. These plans could be modify on the fly and goals are given by users. At [13] adaptive autonomy is implemented in a tele-operation robot and the change in autonomy level is made dynamically.

As it has been mentioned before, autonomy in robots is very close to decision making. Different approaches have been used for decision making in robots. [28] implemented fuzzy decision making for navigation purposes in a robot. In contrast, [26] makes decisions computing goals priorities based on its importance and its urgency. Schermerhorn also remarks the importance of dynamic autonomy in the performance of a robot team. Scheutz [27] presents a decision making using likelihood of success, the benefit and the cost of an action. In [15], decisions are taken considering information gathered by humans and robots and operators are treated as perceptual resources of information; operators are queried depending of the amount of uncertainty in robot's beliefs.

As in many others scientific fields, researches try to imitate humans' brain and last investigations emulate humans' decision making. Accordingly, emotional and motivational models are suggested. As it has been exposed at [6], humans' decision-making is not affected only by the possible outcomes, but also emotions play a main roll. Emotions are applied as a biases mechanism for decision-making [30]. In view of it, other authors propose decision making systems based on motivations and drives. In this work, we follow this approach too where no specific goals are defined. Other motivational decision making system is proposed at [21] where selected actions depends on the behavioral state.

3 Our Approach

We proposed a decision making system based on motivations where no specific goals are given in advance; the objective of its life is to *survive* and to be *happy*, just as you and me.

In our decision making system the autonomous robot has certain needs (drives) and motivations. The goal is to keep these needs within an acceptable range. For the purpose of it, the system will generate goals (behaviors or actions) taking into account the state of the robot. The state of the robot is composed by internal state and external state. The process will be as follows:

1. Determine the internal state
2. Determine the external state
3. Choose the right action

Following, these steps will be explained.

The robot can be parametrized by several variables, which must be at an ideal level. When the value of these variables differs from the ideal one, an error signal occurs: the drive. These drives constitute urges to act based on bodily needs related to self-sufficiency and survival [9]. In this approach, the drives are considered as the internal needs of the agent.

Motivations are those internal factors, rather than external ones, that urge the organism to take action [25]. The motivational states represent tendencies to behave in particular ways as a consequence of internal (drives) and external (incentive stimuli) factors [12]. In other words, the motivational state is a tendency to correct the error, i.e., the drive, through the execution of behaviours.

In order to model the motivations of the agent, we use Lorentz's hydraulic model of motivation as an inspiration [16]. In Lorenz's model, the internal drive strength interacts with the external stimulus strength. If the drive is low, then a strong stimulus is needed to trigger a motivated behaviour. If the drive is high, then a mild stimulus is sufficient [8]. Therefore, the intensities of the motivations are calculated as shown in (1)

$$\begin{array}{l} \text{If } D_i < L_d \text{ then } M_i = 0 \\ \text{If } D_i \geq L_d \text{ then } M_i = D_i + w_i \end{array} \tag{1}$$

where M_i are the motivations, D_i are the related drives, w_i are the related external stimuli, and L_d is called the activation level. Motivations whose drives are below respective activation levels will not compete for being the dominant motivation. The general idea is that we eat when we are hungry and also when we have food in front of us, although we do not really need it.

Once the intensities of the motivations are calculated, the **internal state** of the robot is determined by the motivation with the highest value. This is the dominant motivation.

Then, the state of the robot in the world, i.e. the external state, has to be established. The world is modelled as objects and states related to them. Therefore the **external state** is defined as the states related to all objects in the world. Accordingly, the external state restricts the possible actions: for example, we can not eat if we do not have food.

The behavior at each moment will depend of the state of the robot (internal and external) and the potential actions. Tuples formed by the state and each action will have an associated value which represent the suitability of that action on that state. These values can be tuned by learning.

Actions affect the world and consequently the robot too. Hence robot's state varies dynamically during robot's lifespan. So actions will be selected accordingly to each configuration of the world.

4 A Decision Making System in Maggie

In this section, a first version of the decision making system is presented and how it interacts with the AD architecture is explained.

The intended decision making system will be developed and implemented on the social robot named Maggie [24] which is controlled by the Automatic-Deliberative (AD) architecture [5] [4]. Because of the lack of space, more detailed information is available in references. Summarizing, AD is a two levels architecture where communication is accomplished by Events, Short Term Memory and Long Term Memory (figure 1). Its essential component is the skill and its located in both levels [22]. An extensive example about how it is applied is presented at [23]. This paper presents how decision making system is added to the AD architecture.

The proposed decision making system has a bidirectional communication with the control architecture of the robot, the AD architecture (figure 1). On the one hand, the decision making system will generate the goal of the robot that may be translated into an action or behaviour. This behaviour will be taken by the AD architecture and the robot will fulfill the goal by activating the corresponding skill (deliberative or automatic one). On the other hand, the decision making system needs information from the environment in order to update the internal state of the robot. This information will be provided by the sensors of the robot.

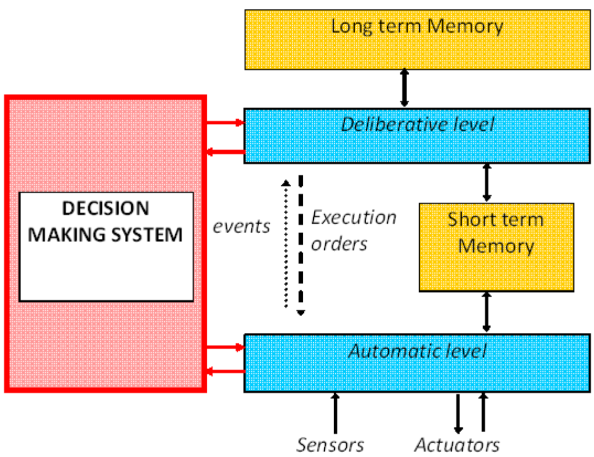

Fig. 1. AD architecture with the decision making system

The aim of the presented decision making system is to achieve a full autonomous robot. Therefore, the most appropriated action at each moment will be selected by the decision making module. Choosing the right action depends on the value of the motivations, previous experiences, and the relationship with the environment. All these elements have been modelled in order to be processed by the implemented decision making module.

The whole process can be summarized in the next steps:

1. Computing the dominant motivation (internal state)
2. Sensing the state in the world (external state)
3. Evaluating possible actions and selecting one of them

Following an example of how to apply our motivational decision making system is presented.

4.1 Internal State: Drives and Motivations

As expressed by equation (1), each motivation is represented by an integer value and it is affected by two factors: internal needs and external stimuli. Internal needs are the drives and their values depend on inner parameters. External stimuli are the objects situated in the environment altering the robot motivations. In addition, each motivation has the activation level: under it, motivations values will be set to zero and hence they will not be considered for the dominant motivation.

As mentioned, the internal needs, the drives, represent an internal value. Each motivation is connected to a drive. The selected drives are:

loneliness: the need of companion.
boredom: the need of "fun" or entertainment.
submissiveness: the need of obeying people orders.
energy: this drive is necessary for survival.

Since we want Maggie to be an autonomous social robot and based on past works and experiences, four non-conventional motivations have been defined:

social: it means the need of interaction with a human and its drive is *loneliness*.
recreational: this motivation is related to entertainment purposes. Its associated drive is *boredom*.
obedience: it is linked to respect others' wills and it is related to submissiveness drive.
survival: it refers to the energy dependence. This motivation is connected to *energy* need.

Since drives temporally evolve from scratch, motivations do as well. In our implementation, *loneliness*, *boredom*, and *submissiveness* drives linearly increase but with different parameters. It means that, as time goes by, these drives become bigger and bigger, and so do the corresponding motivations. *Loneliness* is the fastest drive since boredom and submissiveness evolve slighter. This is because in social robots, as ours, interaction with people is the most relevant aim and hence social motivation takes priority over the others two.

The most relevant inner need, due to the necessity of survival, is the *Energy* drive. If we want to achieve a full autonomous robot, power autonomy is the first step. Therefore, this drive will keep its initial value until a low level battery is detected. Then, its value will suffer a drastic raise becoming the most critical drive.

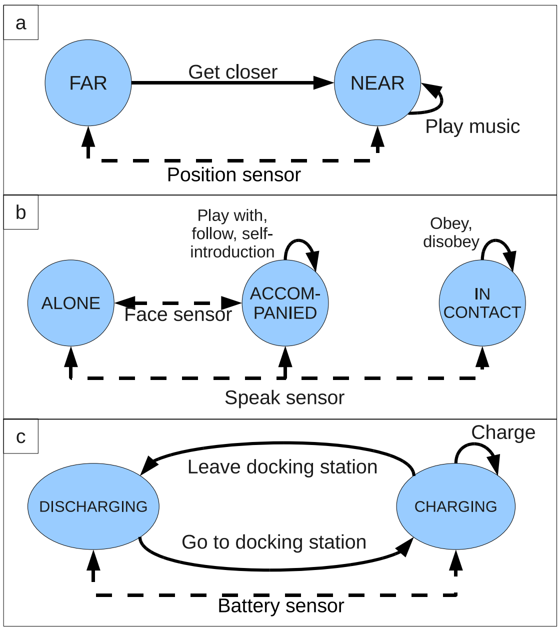

Fig. 2. States and actions for items: (a) TV, (b) person, and (c) docking station

After a drive is satisfied, it does not intermediately start evolving, there is a *satisfaction time* before it evolves again. The same idea occurs to you: once you have eaten, you do not feel hungry but it takes some time before you need to eat again.

4.2 External State: Sensing the World

The world is sensed by the robot in terms of objects and the related states to these objects. Objects are not limited to physical objects but abstract objects too. So, as a first approach, the world where Maggie is living in is limited to the laboratory and three objects have been defined: people living around the robot, a television/radio appliance and the docking station for supplying energy.Also relative states to all these items have to be presented and the transitions from one state to another is detected by several skills running on Maggie. More technical issues about how objects are sensed can be found in the references.

In Figure 2, objects, actions, and transitions from one state to another are shown. Dashed arrows represent skills monitoring the states, continuous ones mean actions executed with the objects, and circles are the states related to each item. If an action does not appear at one state, it means that it is incoherent to execute it from that state, e.g., Maggie cannot *play music* if it is *far* from TV or it cannot *follow* a person if it is *alone*.

External stimuli. Just like human beings can feel thirsty when they see water, the motivations are influenced by objects in the world and their states. That is called the external stimuli for motivations. These stimuli may have more or less influence: their values depend on the states related to the objects. In our implementation, all external stimuli values have been fixed empirically

4.3 Acting in the World: What Does Maggie Do Now?

Maggie interacts with the world through the objects and their potential actions. These actions are implemented as skills in the AD architecture. The actions cause effects over the drives. When the actions have ended, i.e. when the skill associated has been blocked because it has reached its goal, the effects are applied. If an error occurs during a skill execution or it is not successful, this situation is notified and its effect is not applied. In our experiments, most of the effects satisfy the drive, which becomes zero or decreases its value. Actions can also "damage" some drives of the robot increasing their values; i.e. *disobey* action increases *submissiviness* drive.

Next, once the world has been modelled, how the decision making system operates is explained. First of all, when the system starts, drives begin to evolve independently from their initial value zero, and skills start monitoring the related states to items. When a new state transition is detected, an specific event is emitted and the states are written in the short-term memory. The decision making module receives this event and states data are updated. Within robot lifetime, the action selection loop is executed in order to determine the next skill to be activated. At each iteration, the dominant motivation is computed as the maximum motivation whose value (internal needs plus external stimulus) is over its activation level. This parameter has been fixed to 10 for every motivation. Using the dominant motivation and the current states related to objects, the next action will be chosen.

This approach has already been implemented on virtual agents [18], [20], [19]. During these simulations and using reinforcement learning, Q-learning [32], the agent learnt the right q-values for maximizing its wellbeing. Currently, these ideas are being implemented in the social robot Maggie. At this work, we propose a set of values representing the best possible actions at each world configuration (the dominant motivation plus the state related to each object). The tuples formed by the dominant motivation, the object, the state related to the object, and the feasible actions will decide the selected action.

In some cases, the states and the actions are impossible. For example, for *playing with* people Maggie has to be *in contact* with a person. It does not make sense if *play with* action is activated when the robot is *alone*. At this point, values for these combinations are minimal and they will never be selected for execution.

During our first trials, after all values were fixed, the robot was programmed in such way that it always selected the best actions, it is those actions with the highest associated values. This leads to monotonous behaviours and the robot actions become very predictable. In order to allow *risky* behaviours, we have to face the dilemma of exploration vs. exploitation, several times refereed in the field of reinforcement learning [29]. Level of exploration represents the probabilities of executing actions different than those with the highest values. Using Boltzmann distribution, probabilities for selecting an action in a state is given by (2).

$$P_s(a) = \frac{e^{\frac{V(s,a)}{T}}}{\sum\limits_{b \epsilon A} e^{\frac{V(s,b)}{T}}} \tag{2}$$

where $V(s, a)$ is the given value for action a in state s and A represents all possible actions in state s; T is the *temperature* and it weights exploration and exploitation. High T gives the same likelihood of selection to all possible actions and the next action will be almost randomly selected; low T enforces actions with high values. As it is presented in [17], T value will be set according to equation 3.

$$T = \delta * \bar{V} \tag{3}$$

where $\bar{V}$ is the mean value of all possible values. In experiments, δ was set to 1.

5 Conclusions

In this paper we present a decision making system based on motivations where no predefined goals are provided in advance.

The robot's aim is to survive satisfying its needs. In order to achieve it, robot's actions are based on the state of the robot which it is formed by its inner state (the dominant motivation) and the external state, it is the state into its "world". The "world" is sensed by sensory skills and actions are accomplished by skills as well. Both are running in the AD architecture.

The motivations, the drives and other values have been set having in mind that Maggie is a social robot intended for human robot interaction. This values will define its personality. The experimental tests carried out show that the robot is able to select the most appropriate behaviour autonomously, as a function of its state (internal and external). In the future, this selection will be learnt by the robot through its interaction with the environment. This learning process will take into account the emotions as a reinforcement function (happiness, sadness), implemented as another motivation for the robot.

Trials running our motivational system have proven a great *initiative*, Maggie is proactive executing actions even without human's request. However, since a robot's behaviour is not easy to predict, human-robot interaction will be more interesting for users because robot can take the initiative.

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