

Why does an Agent Act: Adaptable Motivations for Goal Selection and Generation

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Abstract

We present a framework for active agents, that integrates both the goal achievement desire of traditional A.I. and the survival instinct of new A.I. This framework is based on "motivations" as (1) a control mechanism for internal and external goal selection and (2) a generative mechanism for internal goal generation (usually resulting in one-action plans). We present an architecture and an implementation of the framework, that enables the agent designer to preset the motivational profile of the agent, or the agent itself to change its own motivational profile on the fly, given *a priori* or perceived knowledge of the environment characteristics. Empirical results involving a mobile robot in various office environments are presented.

1. Introduction

The paper addresses the problem of acting in an environment: Given an environment (with its opportunities) and an autonomous agent (with its intellectual and physical capabilities), why should the agent act at all and under which principles?

Many approaches have been proposed in A.I. to tackle with this problem. A first approach ("traditional A.I.") suggests that the main activity of an agent is to achieve a goal: (1) *Planning approach*. A (possibly conjunctive) goal is given to the agent (the "program") by another agent (a "user"), the agent generates a plan and then executes it [Fikes & Nilsson, 71]. (2) *Reactive approach*. Desirable goal states are looked for in future possible worlds, a partial order on test-action pairs is generated, then the agent indefinitely reacts to its environment in the way prescribed by polling this structure [Schoppers, 87; Nilsson, 89]. The first approach provides useful tools for deliberating before acting (i.e., plan generation) but such agents lack reactivity which is necessary in dynamic and even unpredictable environments --- generating a plan is an NP-complete activity [Chapman, 87], which essentially means that a search has to be performed. The second approach provides a reactive structure for a given environment, but lacks reconfiguration capability (a different agent has to be built for each different environment) and avoids representing deliberation (e.g., limits the agent to perform already planned tasks).

A second approach ("new AI") proposes a situated view of the agent in its environment. (1) *Survival*. An agent can be considered as a society of smaller reactive agents, which together produce an emergent behavior that ensures the

actual survival of the agent and the achievement of given goals [Maes, 91]. (2) *Emotions*. The agent does not look for the achievement of goals, its behavior is determined by pursuing the satisfaction of the current strongest emotion (e.g., play, rest, escape) [Bates, 94]. These approaches extend the traditional reactive approach to provide agents with realistic ("believable") behaviors in unpredictable real environments, although the absence of deliberation still limits their reconfiguration capability (when new complex tasks must be performed).

Approaches have been proposed to extend the latter while retaining the deliberative aspect of the former [Pryor & Collins, 94]. The approach towards formulating and using principles for action, that we propose in this paper, is based on observations made by psychologists, which have identified an ordered list of factors that apparently drive human behavior. Maslow [54] observed that people first seek to meet their physiological needs (e.g., food, water, oxygen). With these needs satisfied, people seek to ensure their physical safety (e.g., by avoiding hazardous environments or predators). When satiated and safe, people turn their attention to affiliation needs (e.g., building and maintaining social bonds with one another). With strong social bonds in place, people are free to address needs for achievement (e.g., to achieve particular individual goals). Finally, when all of these more fundamental needs have been met, people can strive for self-actualization (e.g., a confident sense of personal development self-esteem). Then, faced with a continuing stream of potential goals, people selectively pursue those that are most compatible with their current motivations. Other things being equal, a hungry person will eat, a threatened person will seek safety, etc.

In comparison with the two A.I. approaches above, ours first acknowledge the fact that a deliberative & reactive agent in an unpredictable environment must cope with a stream of incoming goals [Rosenblatt & Vera, in press] --- goals are generated internally through deliberation (e.g., subgoalings) or are derived from percepts (e.g., unpredictable requests from other agents). We propose to introduce the concept of "motivation", as a principle of action, to (1) select the most relevant goals in this stream for the current situation, and (2) generate goals along several behavioral dimensions. By assuming that goals are turned into intended action via plan generation, the behavior of the agent is therefore oriented by motivations. We then note that motivations do not depend on the environment nor the inside of the agent's architecture, but that they can still be used for easily modifying the agent, or letting the agent

Physiological Safety Affiliation Achievement Learning	Battery level Avoiding stairways and hostile agents Achieving other agents' goals Achieving its own goals. Covering unknown areas
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Table 1: Motivations of human agents, and an interpretation for robots.

reconfigure itself, so as to adapt to new or changed environments.

In this paper, we first define a useful set of motivations for action; we provide an architectural mechanism for their integration in determining the agent's behavioral trajectory at any moment and we develop a theory of "motivational profiles" and their relationship to performance in particular classes of environments; we parametrize the architectural mechanism so that an agent can adapt its "motivational profile" so as to perform well in different classes of environments; we propose an implementation to evaluate the theory and architecture empirically.

2. Theory

2.1. Definitions

A motivation is anything that controls the focus of attention of the agent (i.e., that orients its current reasoning) [Simon, 79]. More precisely, psychological studies have found that very few motivations were sufficient to drive the whole behavior of agents. As a beginning we adapt the classic work of [Maslow, 54].

Table 1 summarizes the motivations empirically found in human agents, and, for each one, a possible interpretation in terms of agency (mobile robots in our case, see section 4). Roughly, the agent desires to respect its "body", stay away from aggression, collaborate/compete, finish its job and improve itself.

Motivation #4 (Achievement) corresponds to the one used in traditional A.I (achieving internal goals), although some aspects of motivations #3 (Affiliation, i.e. policies for collaboration) and #5 (Learning) have been studied per se (outside the agency framework). Motivations #1 and #2 have been studied in new A.I.

2.2. Motivational Profiles

A motivation is first a function of the state of the agent (e.g., its battery level, the time, its estimated activity) that produces a need (the strength of the motivation). This represents the interpretation of the motivation, and the agent has no control on it (e.g., for a human agent, not eating for one day creates a strong motivation to find some food).

We characterize the *relative importance* of each motivation (out of the others) by a weight: W_{phys} . W_{safe} . W_{aff} . W_{ach} . W_{learn} . To enable the agent designer to act upon the motivations, we allow the motivational profile (the list of these weights) to be changed/preset by the agent designer or the agent itself. This way, variously motivated classes of agents can be created.

For example, we can model the original hierarchy of needs ($W_{phys} > W_{safe} > W_{aff} > W_{ach} > W_{learn}$ [Maslow, 54]). A " $W_{phys} < W_{learn}$ " constraint models a "starving artist" (e.g., an agent more motivated in painting than in getting money to buy food). A " $W_{saf} < W_{ach}$ " constraint models a "tank on a battlefield" (e.g., an agent more motivated in destroying an enemy target than in protecting itself).

2.3. Profile and Environment

If goals can be selected by these motivations, then the behavior of the agent (resulting from the execution of actions that achieve these goals) can be oriented by its motivational profile.

For example in an environment with very few electrical outlets, it might be interesting to reinforce the physiological motivation of the agent, so as to produce a behavior in which the agent will take advantage of (i.e., make plans with) every available electrical outlet on its way. In an environment with many aggressive agents, it might be interesting to reinforce the safety motivation, so as to make the agent more "aware" of its own protection (i.e., make plans to avoid enemies).

These motivations can then be projected into the environment itself as an analysis tool (extracting the relevant features which interact with the agent's motivations). For example in our robotics world, relevant features of the environment are: number of electrical outlets, number of stairways, number of other agents (and their aggressivity), number of internal goals, size of the internal map. *A priori* evaluating the environment, given these features, can be used by the agent designer to set the motivational profile of the agent.

2.4. Adaptive Agents

If the agent is able to recognize these features in its environment, the agent can then modify its own motivational profile in an effort to adapt itself, i.e. get its optimal performances in each environment.

For example, when I want to take the highway 5 from San Francisco to Los Angeles, I might recognize this new highway environment, in which it is less possible to stop and rest. Therefore I might reinforce my physiological motivation to take more often advantage of any rest area (actually making a one-action plan).

Given the characteristics of an environment (its opportunities in terms of many/few electrical outlets, many/few stairways, many/few other agents,

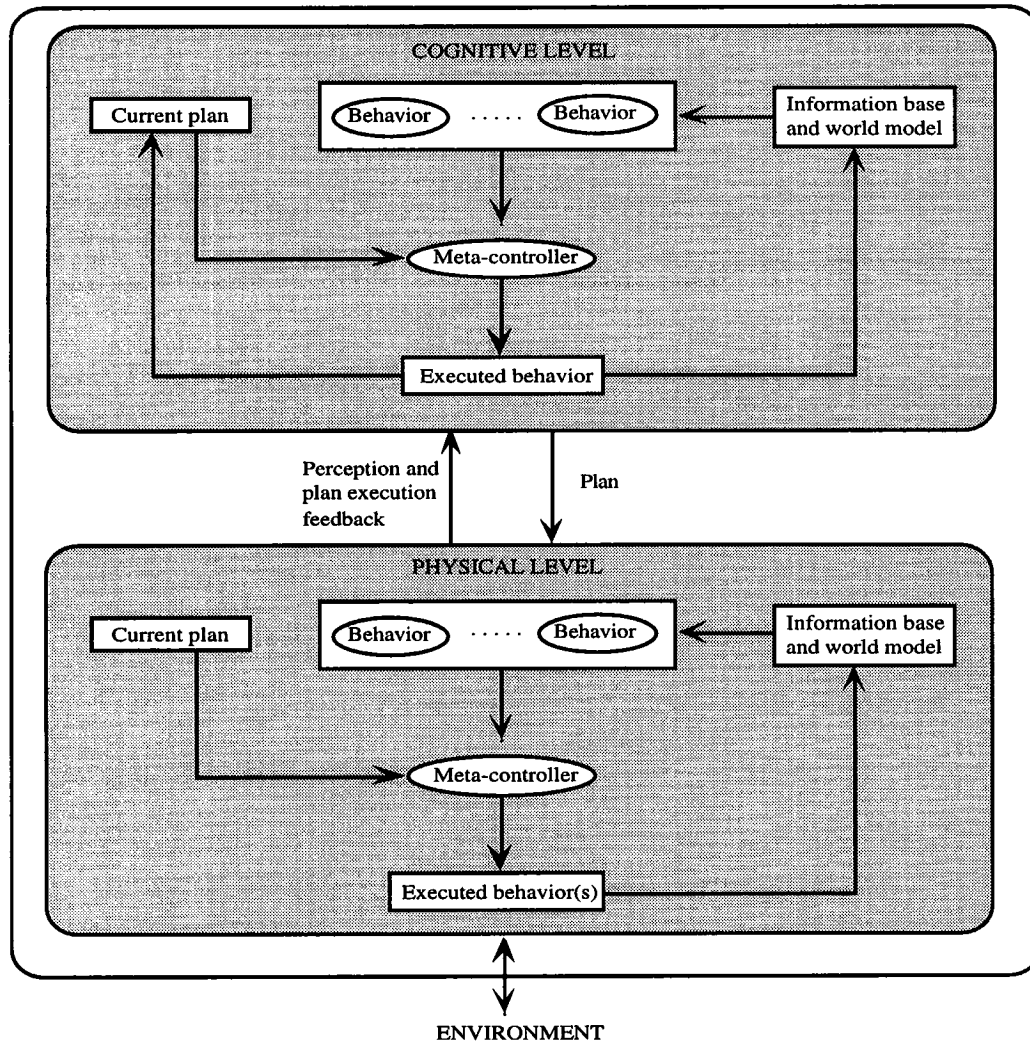


Figure 1: The two-level architecture of an Albot agent.

friendliness/aggressivity of other agents, own goals) the agent itself changes its motivational profile to get its optimal performances in this environment.

3. Mechanism

3.1. The Agent Architecture

Figure 1 describes the two-level architecture of our agent in which those motivations can be represented (Albots architecture, see [Hayes-Roth et al., 93; Hayes-Roth et al., 94] for full description). Briefly, a first level (physical) carries the code that is responsible for the motion and perception of the agent in its environment, thus representing the physical capabilities of the agent. A second level (cognitive) carries the code that is responsible for symbolic computations of the agent (reasoning, deliberation), thus representing the cognitive capabilities of the agent. These two levels both include a mechanism (meta-controller) to choose the next cognitive/physical capability to be executed next given the current

instantaneous plan of each level. For that, the plan of the physical level is given by the cognitive level; the plan of the cognitive level is reflectively set/modified by the cognitive level itself. Finally, the physical level, in direct contact with the environment, sends percepts back to the cognitive level.

In practice, the cognitive level is implemented by the BB1 blackboard [Hayes-Roth, 85], and the physical level is a rough simplification of it.

In the architecture's instantiation that we use, the cognitive capabilities of the agent include situation assessment (i.e., recognizing percepts), intention creation (i.e., turning percepts into intentions), goal merging (i.e., turning intentions into actual (possibly conjunctive) committed intentions), plan generation (i.e., turning conjunctive goals into actions [Morignot, 94]), plan monitoring (i.e., sending each action to the physical level). The physical capabilities of the agent include motion (path planning using a cell-decomposition and actual motion using potential field), perception and speech.

3.2. The Agent Motivations

Given this two-level blackboard architecture, the various reasoning capabilities of the agent are represented by Knowledge Sources. The content of a particular capability is agent-dependent and is not visible from the agent's control (its motivations); the only visible effect of using a KS is indirectly to create events, i.e. to create information inside the agent (thus the name "Knowledge Source"). At any point in time, some reasoning capabilities can be executed and a control mechanism is needed to choose among them: The Control Plan makes this choice by rating each one of them and executing the highest rated one [Hayes-Roth, 85]. Therefore, this control plan structure of the agent architecture is a natural place to insert the motivations defined above: each motivation is exactly one *focus* in the control plan, inside the global motivation *strategy*. The blackboard architecture then ensures that all¹ the available foci will be combined to choose the next executed KS [Hayes-Roth, 85]. More precisely, for each KS in situation and each motivation, a rate is defined by multiplying the motivational weight, the current motivational strength and the relevance of the (possibly conjunctive) goal of this KS to this motivation; the global rate of the KS is the sum of the local rates over the 5 motivations of Table 1. Thus identifying foci with motivations enables the blackboard architecture to focus the attention of the agent on the "best" reasoning capability (best = the agent chooses the right thing to its point of view).

As said above, each motivation is primarily a function turning *variables* into the value of a *need*. A motivational function is generally a decreasing function of the number of past events in each category. In practice, an event usually resets the function, which in turn increases when no event occurs. Then, a motivation is related to actions and goals: Some actions can reset a particular need (e.g., recharging its batteries is physiologically gratifying for the agent). When a need exceeds a particular threshold and when no current goal leads to satisfying this need, a goal (the survival instinct) is generated to lead the agent to satisfy this need (e.g., when the physiological need is too high, the agent will think about recharging its batteries).

More precisely, the semantics of the 5 motivations of table 1 is set by the following parameter values:

- *Physiology*: In the implementation, (1) the motivational function is an exponential function of the inverse of the battery level and (2) the action of recharging the batteries resets it.

- *Safety*: the motivational function is ideally an exponential function of the proximity of danger. In the implementation, it is constant over time.

- *Affiliation*: In the implementation, the motivational function is a decreasing function of the

¹ Since a control plan can be partitionned into different strategies [Hayes-Roth 85], other control mechanisms can coexist with the control mechanism described here (e.g., deadline oriented [Lalanda & Hayes-Roth 94]).

running average frequency of requests fulfilled --- a request is the fact that the agent knows that another agent has a particular goal. Namely (1) a request from another agent resets the function (through its variables) and (2) when no request is sent, the function increases linearly over time --- this models the willingness of the agent to respond *positively* to requests from other agents, i.e. to collaborate.

- *Achievement*: the motivational function is ideally a decreasing function of the running average frequency & importance of own jobs performed. In the implementation, the motivational function is a step-function of the nature of the procedure that runs at the cognitive level in order to plan the execution of these jobs.

- *Learning*: the motivational function is ideally a decreasing function of all possible knowledge already acquired. In the implementation, the motivational function is a decreasing linear function of the area covered by the robot, estimated by the number of visited locations out of all the locations that contain objects/people.

4. Analysis and Experiments

4.1. Domain

This motivational framework has been implemented to control a Nomadics 200 mobile robot [Zhu, 92] or its simulation. Physically, the robot can act on its environment by rotating its wheels, changing their direction, rotating a turret that supports a camera for image recognition, and using a voice synthesizer. It can sense its environment with sonars, infra-red, bumpers and a laser with its associated CCD camera.

The agent must perform some tasks requiring motion and communication in an indoor environment (actually the corridors and offices of the first floor of our laboratory). In the first scenario, the robot has to survey a floor of an office building and respond to alarms. A second set of scenarios involves assisting a secretary with daily tasks such as delivering documents, copying papers, sending email or verbally warning people.

4.1. Early Experiments

A first set of experiments demonstrates the effects of motivations on the behavior of the agent. The agent is capable of performing some office fac-totum tasks, reasoning about them (i.e., generating plans), and having the motivational characteristics of each defined goal.

Many scenarios are then possible: first if we let the agent alone for a long time without communicating with it (i.e., sending requests of actions), its physiology will tell it to recharge its batteries (i.e., a "recharge-batteries" goal is generated when the need exceeds the physiological threshold); then the agent will act spontaneously. If we send a request to the agent ("Could you bring such book to this person?"), the agent might generate a plan for it, and will start executing it (going to the library to pick up the book, going to an office). We might then send a second

request ("Could you give 5 copies of such paper to that other person?") that will make the agent replan to produce a longer plan. In the middle of an action, the physiological motivation will exceed its threshold again, in which case the agent will generate a one-action plan to go to the closest electrical outlet and spontaneously recharge its batteries. As a result the behavior of the agent will be changed because of its own physiology. With its batteries recharged, the agent can then switch back to its original plan and successfully give the book and the copies.

4.2. Planned Experiments

Since the agent follows its own motivations, it is always doing the right thing from its point of view. But there is no *a priori* guarantee that a particular motivational profile for a particular environment will produce good performances in others environments. To make this evaluation, we need first to define extrinsic criteria, i.e. a function from the environment only that will define the performances of the agent.

5. Conclusion

We have briefly presented a framework for active agents, that integrates both the goal achievement desire of traditional A.I. and the survival instinct of new A.I. This framework is based on motivations as (1) a control mechanism for internal and external goal selection and (2) a generative mechanism for internal goal generation (usually resulting in one-action plans). We have then presented an architecture and an implementation of the framework, that enables the agent designer to preset the motivational profile of the agent, or the agent itself to change its own motivations on the fly (if it is able to recognize certain features of its environment).

Our first experiments prove the feasibility of this approach. Our ongoing research involves defining the performances criteria of the agent in each kind of environment, and proving the quality of each motivation profile by statistically proving the optimality of the behavior of the agent in each one of them.

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