Agents with Anticipatory Behaviors: To be Cautious in a Risky Environment[1]

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Abstract. This work presents some anticipatory mechanisms in an agent architecture, modeling affective behaviours as effects of surprise. Through experiment discussion, the advantages of becoming cautious are presented and is shown how this approach increases not only opportunism and reactivity but also anticipatory capabilities for planning and reasoning. Cautious agents outcomes are analyzed in risky surroundings both on the basis of the environment features and of the internal model of caution. Expectation-driven and caution enabled agents are designed with the BDI paradigm.

1 CAUTIOUS AGENTS

This work is based on a general research framework whose objective is to claim how important is for an autonomous, cognitive system to exploit anticipatory behaviors, and in particular anticipatory representations of the world (predictions and expectations). Here we introduce anticipatory mechanisms in a BDI architecture, and model part of the short-term functions of surprise, in particular the advantages (in some kinds of environment) of becoming cautious. To have anticipatory representations, to experience surprise, and to exploit various functions of them will be crucial, not only for curiosity and exploration [5], but also for learning, attention, prudently adjusting behaviour, and for social relations: like trust [2], suspicion; coordination with the others and reliance; cooperation and competition etc. Without examining deep surprise sources and dynamics, we exploit some effects of surprise and their possible outcomes: in risky, unknown, harmful environments agent cautiousness can be a consequence of a kind of surprise that is due to -and a signal of- a mismatch between the agent expectation (internal state) and the actual perceived input (perceived data) [3]. Its internal signal alerts the agent and bring to mental and behavioural changes both with *Long term effects* like becoming more accurate and less self-confident in predictions, memorizing anticipatory signs of danger and different kinds of environment, learning more or less safe plans and purposive actions for a given goal in a certain condition and *Short term effects* like intention reconsideration, redirecting attention, searching for additional information, or becoming prudent. Hence, the anticipatory dimension of caution is strictly related to a form of expectation: like agents use and represent expectations to select best expected action from a set of available ones, so caution guides agent in the selection of less risky action between possible ones. Given this, it is possible to characterize agents with stable 'personalities' (a watchful and a rash agent, with locked capabilities [7]) and to experiment their performances in more or less dangerous environment. Moreover it is possible to build an adaptive agent able to run-time adjust its "degree" of caution to different environments or situations. This approach enhances anticipatory competences and increases the opportunism and the reactivity of BDI-like [6], planning and deliberative agents [1]. We do assume that the relevance of this problem is not only for theoretical modeling and for playing, but that will soon become important in virtual worlds and in the physical one, both for software cognitive agents and for autonomous robots.

2 SCENARIO DESIGN

A test bed scenario is designed as a simulation where entities and environment are represented as autonomous agents and artefacts. Environment is a 2D land map where sets of walls and gates (that can be open or closed) delimit rooms, corridors and areas where entities are able to move. A set of special locations seat symbolic reference points: these location of interest (LOI) contain noticeable world objects as *Repository, House, Tree*; two kinds of *Food* objects appear with modifiable frequencies, near to House and Tree: they rise at fixed location with a modifiable "reward" value; Harmful *Frozen puddles*, are located across rooms; *Fires* entities behave according to a two state cycle periodic function: in each period their first shape is a "Smoke" premonitory state, then they become real dangerous "Fire". For each period, fires change their location with discrete movements. Environment holds regularities as delimited risky areas where rise of fires can be related with agent presence.

At an high level of abstraction, we consider agents as mobile entities with sensors, reasoning and effectors components, characterized by the following tuple of bounded dynamic resources:

$$Ag =< En, r, Sr, s > \qquad (1)$$

En indicating the instant amount of energy, *r* the range of vision where sensors can retrieve data, *Sr* the sensor sample rate, and *s* the agent instant speed. Agents burn energy according to a combination of previous resource allocation (e.g. the more speed and sensor-rate is high, the more agent will spend energy) and they hold structured data sets representing knowledge and internal state.

In a Goal oriented fashion, first order objective for entities is to collect food items in the repository to obtain rewards and recharge energy. The task is composed of a recursive workflow of actions: 1) Look for Food with (supposed) best reward. Because agents know that each class of food rises near a proper LOI, this introduces agent explicit quantitative expectations about the possible food presence (and value). Each *lookForFoodPlan* is associated to a specific LOI and constantly monitored by a *subjective expected utility* function,

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determined merging both expectations on food reward and presence (near the LOI). 2) Go to the identified food location and pick it up. After identifying a set of food items, agent add them to the belief base and head for the nearest one, observing topology constraints and bounds. 3) Transport Foods (one at a time) from the original location to the repository and deposit them. Agents use belief modules referring to paths (defined as lists of locations to pass through) in order to routinize crossing rooms and LOI. By releasing foods in the repository, they obtain a reward calculated on the basis of the original food reward decreased with a decay factor strictly depending on the transport time interval. Along the presented workflow, agents run up against fires or frozen puddles: in these cases agents present a general short term reaction: actions and speed are obligate to reduce, furthermore a greater amount of energy has to be spent.
Starting from a traditional approach to the BDI systems[3], we developed an architecture dealing with 'the future', where intelligent agents build mental representations [4] for explicit expectations and risk avoidance. Stable 'personalities' have routinized intention-deliberation policies. To capture environment regularities (e.g. dangerous areas), watchful agents are enabled to choose those plans with the expected lower risk-value (and accordingly the higher safety) while rash agents prefer to choose the quickest and simplest ones. To deal with *adaptive* caution, an internal k-length buffer for registering events was constantly updated and monitored by adaptive agents: when the stored negative events exceed fixed threshold in a k-length history interval, they autonomously deliberate to increase the caution level. Adaptive agents shift among three kinds of more or less cautious behaviours (default, watchful and rash) adapting on the fly caution configurations to anticipate the dangerous risks of the crossing area. These caution competences can be reflected on the tuple of agent bounded resources (1), saying that an agent increasing caution level and becoming watchful has to reallocate resources: reducing speed s, increasing sensor rate Sr and increasing range of vision r. These adaptations heavily modify behaviour affecting the intentional stance and elicit trade-off in their performances. Note that relationships among different parameters characterizing these epistemic resources have to be analyzed with respect to the features of the different environments.

3 EXPERIMENTAL TEST

To measure agent effectiveness we considered environments with different levels of risk and evaluated agent energy in function of simulated time (fig. 1). **Experiment 1.** Safe environment (no Fires and

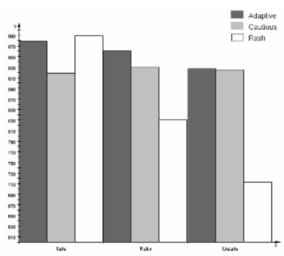

Figure 1. Adaptive, Cautious and Rash agent average energy comparison in safe, risky and unsafe environments.

no frozen puddles). We experience that to be cautious in safe worlds is a drawback: best mean performances are those of the rash agent, because of his quickness and no resource consumption for useless and costly attention/caution capabilities (fig.1). **Experiment 2.** Risky environment (2 Fires and 2 frozen puddles). In the same time interval, adaptive agent outperforms the others: a stabilized cautious agent looks ahead and prevents accidents, while adaptive agent (with a modifiable caution) is able to minimize negative effects until its buffer reach the threshold to be watchful. On the contrary, rash agent is unable to react in safety mode because of its fixed low level of Caution. **Experiment 3**. Unsafe environment (4 Fires and 3 frozen puddles). It is interesting to note the different slopes of the functions (caused by the different energy consumption). Peaks indicate goal achievement while precipitous changes of slopes indicate unexpected accidents (agent near Fire or near a Frozen puddle) (fig. 2). Best energy performances come from adaptive agent that is able to optimize damages and resource consumption. Energy trend for the rash agents falls with deep peaks. Mean performances of cautious and adaptive agents are comparable (fig. 1): even if the adaptive agent continuously tries to modify its behaviours during the simulation (adapting it to the environment) at the end its global performances result comparable with the ones of the watchful agent that, in some sense, is "built" for well performing in a highly unsafe world.

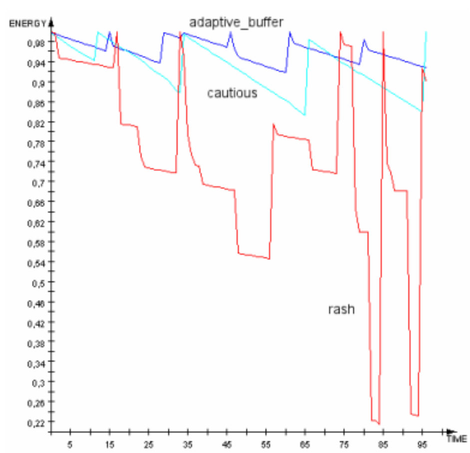

Figure 2. Agent comparision in unsafe environment shows best performance for adaptive agents.

[3] System was built upon Jadex: see http://vsis-www.informatik.uni-hamburg.de/projects/jadex/.

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