A Coherence-Driven Action Selection in Dynamic Environments*

(Extended Abstract)

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ABSTRACT

In this paper, we propose a coherence-driven approach to action selection in agents. The mechanism is inspired by the cognitive theory of coherence as proposed by Thagard. Based on a proposal to extend BDI agents with coherence, we interpret, how action selection can be viewed as a coherence-maximising problem. Contrasted against the classical BDI approach to action selection where actions are selected against a pre-determined set of beliefs and desires, this method provides us with a reasoning formalism that incorporates uncertainty and dynamism in the world model without loosing the type of formal qualities that make BDI-like architectures so attractive for testability and reliability reasons.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Intelligent agents*

General Terms

Coherence theory

Keywords

Action selection, Deductive coherence, Adaptation

1. INTRODUCTION

Autonomous robotic agents situated in dynamic environments must continuously select appropriate actions against a continuous input of sensory information. This paper aims to propose a novel approach to the problem of action selection in this context. Popular cognitive architectures such as BDI [2] have a representation limited to a set of cognitive elements. A coherence-based architecture in addition represents associations among cognitive elements [1] which helps understand constraints among these elements and hence prioritise goals and intentions based on a global maximisation of constraints. That is, the model is essentially dynamic, where beliefs, desires and intentions are subjected to the criterion of coherence maximisation. Here we propose to incorporate such a reasoning in autonomous robots. We do so over the basic BDI architecture, but the process of action selection is based on coherence maximisation inspired by Thagard's theory of coherence [3].

2. COHERENCE FRAMEWORK

We use the coherence framework introduced by Joseph et al [1], based on Thagard's formulation of the theory of coherence as maximising constraint satisfaction [3]. The core notion is that of a *coherence graph* whose nodes represent pieces of information and whose weighted edges represent the degree of coherence or incoherence between nodes. Every coherence graph is associated with a value called the *coherence of the graph*. Based on Thagard's formalism, this can be calculated by partitioning the set of nodes of the graph in two sets, containing the accepted and the rejected elements respectively. The aim is to partition the set of nodes such that a maximum number of constraints is satisfied, taking their values into account. A constraint is satisfied only if it is positive and both the end nodes are in the same set, or negative and the end nodes are in complementary sets.

The degree of coherence or incoherence is calculated from an underlying relation between pieces of information such as explanation, deduction or deliberation. Here we use deductive coherence where this relation between pieces of information arises from logical deduction. A *coherence function* to determine the degree of coherence or incoherence is defined based on Thagard's principles on deductive coherence: 1) *deductive coherence is a symmetric relation* 2) *a proposition coheres with propositions that are deducible from it,* 3) *propositions that are used together to deduce something cohere with each other,* 4) *the more hypotheses it takes to deduce something, the less the degree of coherence,* 5) *contradictory propositions are incoherent with each other*. A semi-formal definition is given below (Formal definition can be found in [1]) :

1. the size of the smallest set of formulas that is needed to make α and β satisfy principle 2 (i.e. such that $\mathcal{T}^1, \alpha \vdash \beta$ but not $\alpha \vdash \beta$);
2. the size of the smallest set of formulas that is needed to make α and β satisfy principle 3 (i.e. $\mathcal{T}, \alpha, \beta \vdash \gamma$ but not $\alpha, \beta \vdash$);
3. the larger the $\mathcal{T}$, the lower the coherence between α and β (principle 4). Contradiction is treated as in 2 with contradictory propositions together implying falsehood ($\perp$).

*This work is supported by the Generalitat de Catalunya grant *2009-SGR-1434* and the Agreement Technologies Project *CONSOLIDER CSD2007-0022, INGENIO 2010*

Cite as: A Coherence-Driven Action Selection in Dynamic Environments (Extended Abstract), S. Joseph, C. Sierra and M. Schorlemmer, *Proc. of 9th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2010)*, van der Hoek, Kaminka, Lespérance, Luck and Sen (eds.), May, 10–14, 2010, Toronto, Canada, pp. 1497-1498

[1] $\mathcal{T}$ is a theory presentation of the agent

4. The greater the truth value of β (in case 1) or γ (in case 2), the higher the coherence between α and β.
5. To obtain the final, symmetric strength (principle 1) between α and β, the highest of the two directional strengths is taken.

3. COHERENCE-DRIVEN ACTION SELECTION

A coherence-driven agent is based on the multi-context specification (MCS) of agents which is a group of interconnected contexts and bridge rules to make inferences across contexts. An agent will further have a function that maps a context to its corresponding coherence graphs. And another function that maps a set of bridge rules to a graph-composition function. This extension is required because contexts are expressed as coherence graphs and agents will need both coherence and graph-composition functions to reason within and between graphs. For the BDI agents considered here, the contexts are belief, desire and intention, which determine a belief graph, a desire graph, and an intention graph respectively. A coherence-driven agent always work with the composition of belief, desire and intention graphs, formal details can be found in [1].

An agent at any time can either perceive the external environment or make a decision about a future action. In the case of choosing among a number of alternatives, an action with the highest preference from the accepted set of the coherence maximising partition is chosen. To incorporate a new piece of information an agent re-evaluates its theory, hence re-computes the coherence graphs, their composition and the coherence maximising partition. If the new information falls in the accepted set then it reinforces the theory and the theory becomes more coherent. However, if it falls in the rejected set, then it contradicts elements of the accepted theory. An agent always bases its decisions on the accepted theory.

4. COHERENCE-DRIVEN ROBOT

We describe our approach with a coherence-driven robotic agent on a simple grid environment taking actions with changing environment and having an objective to maximise points earned. At each cell the robot can chose between a *plug* action to restore its energy or a *move* action to earn points. The environment is kept dynamic by varying the density of plugs. The robot has an *energy_sensor* (e_s) to sense the current energy level, a *plug_sensor* (p_s) to sense whether the current cell is plug-able, and a *density_sensor* (d_s) to sense the current density of plugs.

The robot has certain domain knowledge which helps to get its desire satisfied encoded in belief, desire and intention logic. For example, $(B(move \rightarrow points), 1)$ is a belief that a move will fetch a point with a confidence 1. Some of the theory elements of the robot are as given below:

$desire(points, 1.0)$
$belief(move \rightarrow points, 1.0)$
$belief(d_s, X), belief(es, Y) \rightarrow belief(energy, (1 - X * Y)/2))$
$belief(energy \rightarrow move, 1.0)$
$belief(d_s, X), belief(e_s, Y) \rightarrow belief(plug, (1 - X * Y)/2))$
$belief(plug \rightarrow energy, 1.0)$
$intent(move, A) \not\leftrightarrow intent(plug, B))$

Coherence graphs are constructed corresponding to the belief, desire and intention elements in the theory. Further, two bridge rules are used to combine the constructed coherence graphs. Bridge rule $b_1 = \frac{C_B:(B(p \rightarrow q),\alpha), C_D:(Dq,\beta)}{C_D:(Dp,\min(\alpha,\beta))}$ generates a new desire p given the desire of q and a belief that p facilitates q with minimum of the degrees. $b_2 = \frac{C_B:(Bp,\alpha), C_D:(Dp,\beta)}{C_I:(Ip,\min(\alpha,\beta))}$ generates a corresponding intention given a desire and a belief that the desire is achievable (realistic agent). Applying bridge rules repetitively, coherence graph of the robot as in Figure 1 is constructed.

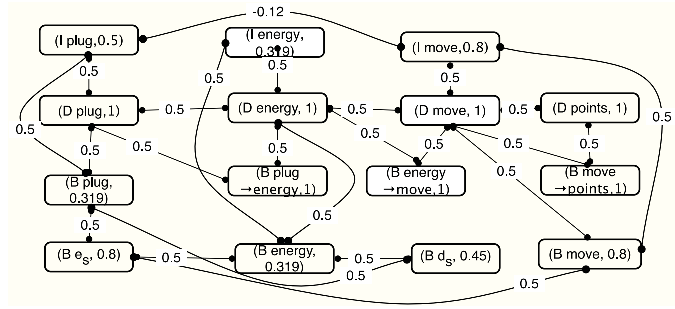

Figure 1: Coherence graph of robot $e_s = 0.8, d_s = 0.5, p_s = 1$

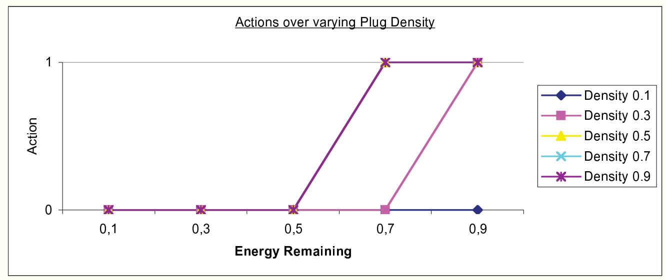

Figure 2: The actions over different plug density levels

The actions of the robot for different plug densities are as in Figure 2. Each series indicates the actions of the robot for a fixed density and for increasing charge left in the robot. As we can notice, if the plug density is too low (0.1), the robot tend to charge (0) whenever it encounters a plug no matter what the remaining charge. Where as it tend to consider the action of move (1) at higher plug densities for similar values of remaining charge which matches human intuition.

5. DISCUSSION AND FUTUREWORK

In this paper, we have introduced action selection based on coherence maximisation which takes a dynamic view of agent cognitions, can detect and resolve conflicts among cognitions, can perform uncertainty reasoning and can reason at a global level while also fully integrated into the BDI representation. One of the immediate future work is to evaluate our approach more thoroughly by comparing with other approaches. We also plan to incorporate the representation of plans and study how plans can be included in the coherence maximising process.

6. REFERENCES

[1] S. Joseph, C. Sierra, M. Schorlemmer, and P. Dellunde. Deductive coherence and norm adoption. *Logic Jnl IGPL*, 2009.
[2] A. S. Rao and M. P. Georgeff. Bdi agents: From theory to practice. In *ICMAS–95, First International Conference on Multi-Agent Systems: Proceedings*, pages 312–319. MIT Press, 1995.
[3] P. Thagard. *Coherence in Thought and Action*. MIT Press, 2002.