g-BDI: A Graded Intensional Agent Model for Practical Reasoning

Ana Casali[1], Lluís Godo[2], and Carles Sierra[2]

[1] Dept. of Computer Science, Universidad Nacional de Rosario (UNR)
Centro Intl. Franco-Argentino de Ciencias de la Información y de Sistemas (CIFASIS)
Av Pellegrini 250, 2000 Rosario, Argentine
acasali@fceia.unr.edu.ar

[2] Institut d'Investigació en Intel·ligència Artificial (IIIA) - CSIC
Campus Universitat Autònoma de Barcelona s/n
08193 Bellaterra (Catalunya), Spain
{godo,sierra}@iiia.csic.es

Abstract. In intentional agents, actions are derived from the mental attitudes and their relationships. In particular, preferences (positive desires) and restrictions (negative desires) are important proactive attitudes which guide agents to intentions and eventually to actions. In this paper we overview recent developments about a multi-context based agent architecture g-BDI to represent and reasoning about gradual notions of desires and intentions, including sound and complete logical formalizations. We also show that the framework is expressive enough to describe how desires, together with other information, can lead agents to intentions and finally to actions. As a case-study, we will also describe the design and implementation of recommender system on tourism as well as the results of some experiments concerning the flexibility and performance of the g-BDI model.

1 Introduction

In the recent past, an increasing number of theories and architectures have been proposed to provide multiagent systems a formal support for their reasoning and decision making models, among them the so-called BDI architectures [16,9,15]. We consider that making the BDI architecture more flexible will allow for designing and developing intensional agents potentially capable to have a better performance in uncertain and dynamic environments. Along this research line we have developed a general model for *graded BDI agents* (g-BDI agents for short), specifying an architecture able to deal with the environment uncertainty (via graded beliefs) and with graded mental proactive attitudes (via desires and intentions). In the g-BDI model, belief degrees represent the extent to which the agent believes formulas hold true. Degrees of positive or negative desires allow the agent to set different levels of preference or rejection respectively. Intention degrees also give a preference measure but, in this case, modelling the

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cost/benefit trade off of achieving an agent's goal. Then, agents having different kinds of behaviour can be modelled on the basis of the representation and interaction of their graded beliefs, desires and intentions.

The formalization of the g-BDI agent model is based on multi-context systems (MCS) [10], and in order to represent and reason about the beliefs, desires and intentions, we followed a many-valued modal approach, following the approach in [11,12,13], where uncertainty reasoning is dealt with by defining suitable modal-like extensions of suitable many-valued logics. The logical framework of this model has been presented in [4,6] and it will be summarized in Section 2, while in Section 3 we present a small example of how the model works. Finally, in Section 4 we describe a prototype of a tourism recommender system which has been developed as a proof concept, where the g-BDI model has been used to design a Travel Assistant agent, which recommends tourist packages and destinations according to the user's preferences and constraints. The implementation details system have been described in [5,8] and experimentation and validation of the system is reported in [7]. We end up with some conclusions n Section 5.

2 Graded BDI Agent Model

The specification of the g-BDI agent model is based on multi-context systems (MCS) and is an extension of the work of Parsons et al. [15] about multi-context BDI agents. Multi-context systems were introduced by Giunchiglia and Serafini [10] to allow different formal (logical) components to be defined and interrelated. The MCS specification contains two basic components: units (or contexts) and bridge rules, which channel the propagation of consequences among unit theories. Thus, a MCS is defined as a group of interconnected units $\left\langle \{C_i\}_{i\in I}, \Delta_{br} \right\rangle$. Each context C_i is specified by a 3-tuple $C_i = \langle L_i, A_i, \Delta_i \rangle$ where L_i, A_i and Δ_i are its language, axioms, and inference rules respectively. Δ_{br} can be understood as rules of inference with premises and conclusions in different contexts, for instance a bridge rule like

$$\frac{C_1 : \psi, C_2 : \varphi}{C_3 : \theta}$$

specifies that if formula ψ is deduced in context C_1 and formula φ is deduced in context C_2 then formula θ is added to context C_3. When a theory $T_i \subseteq L_i$ is associated with each unit, the specification of a particular MCS is complete.

The deduction mechanism of a multi-context system $\left\langle \{C_i\}_{i\in I}, \Delta_{br} \right\rangle$ is therefore based on two kinds of inference rules, internal rules Δ_i, and bridge rules Δ_{br}, which allow to embed formulae into a context whenever the conditions of the bridge rule are satisfied.

In the basic specification of the g-BDI agent model as a MCS we have two kinds of contexts: three *mental* contexts, to represent beliefs (BC), desires (DC) and intentions (IC), as well as two *functional* contexts, for planning (PC) and communication (CC). The overall behavior of the system will depend of the logical representation of each intentional notion in their corresponding contexts and the particular set of bridge rules Δ_{br} used. Thus, a g-BDI agent model will

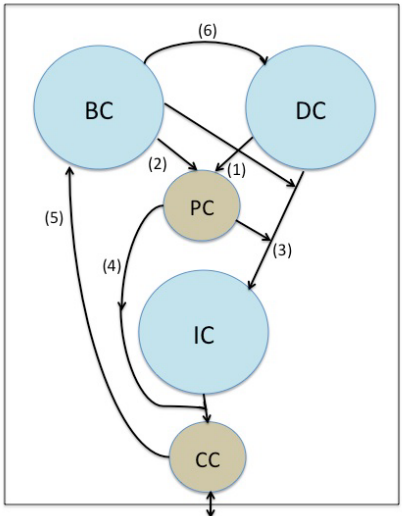

Fig. 1. Multi-context model of a graded BDI agent

be defined as a MCS of the form $A_g = (\{BC, DC, IC, PC, CC\}, \Delta_{br})$. Figure 1 illustrates such a g-BDI agent model with the different five contexts and six bridge rules relating them.

Next, we synthesize the purpose and formalization of each component (i.e. contexts and bridge rules) in the agent model. For full details the reader is referred to [3].

2.1 Belief Context (BC)

The aim of this context is to model the agent's uncertain beliefs about the environment. Since the agent needs to reason about her possible actions and the environment transformations they cause and their associated cost, this knowledge must be part of any situated agent's belief set. To represent knowledge related to action execution, we use Dynamic Propositional logic (PDL) as the base propositional logic (PDL has been proposed to model agent's actions e.g. in [14].) To account for the uncertainty or belief on the result of actions, either a probability-based approach or possibilistic-based approach (based on necessity degrees) can be adopted in the Belief Context BC. To do so, a many-valued modal-like logic (BC_{prob} or BC_{nec} respectively) is defined over a propositional dynamic language $\mathcal{L}_{PDL}$ to reason about the probability or necessity on dynamic logic formulas.

For instance, let us consider a Belief context BC_{prob} where belief degrees are to be modeled as probabilities. Then, for each classical formula φ, we consider a modal formula $B\varphi$ which is interpreted as "φ is probable". This modal formula $B\varphi$ is then a *fuzzy* formula which may be more or less true, depending on the probability of φ. In particular, we can take as truth-value of $B\varphi$ the probability degree of φ. This is the guiding idea exploited in the probabilistic logic BC_{prob}, which is formally defined as a modal-like extension of Rational Pavelka logic (RPL) [12], an expansion of $[0,1]$-valued Łukasiewicz logic with a truth-constant $\overline{r}$ for every rational $r \in [0,1]$, following the approach proposed in [13,12]. We use this logic to reason about the $B\varphi$'s formulas since the probability axioms are easily expressible using Łukasiewicz logic connectives.

The modal language (B-formulas) of the logic BC_{prob} is built from propositional variables of the form $B\varphi$ for each $\varphi \in \mathcal{L}_{PDL}$. Compound formulae are defined in the usual way in the Rational Pavelka logic (RPL) using the Łukasiewicz connectives $\rightarrow_L$ and $\neg_L$, and truth-constants $\overline{r}$, for each rational $r \in [0,1]$ (note that nesting of the operator B is not allowed). For instance, if an agent has formula $\overline{0.6} \rightarrow_L B[\alpha]\varphi$ in its BC context, it means that he believes that the probability of having a goal φ true after perfoming action α is at least 0.6.

The semantics for this language is given by probabilistic Kripke structures of the following form: $M_{BC} = \langle W, \{R_\alpha : \alpha \in \Pi\}, e, \mu\rangle$ where $\langle W, \{R_\alpha : \alpha \in \Pi\}, e\rangle$ is regular Kripke model of PDL and $\mu : F \rightarrow [0,1]$ is a probabilistic measure on a Boolean algebra $F \subseteq 2^W$ such that for each crisp φ, the set $\{w \mid e(\varphi, w) = 1\}$ is μ-measurable. The e evaluation is extended as usual to PDL-formulae and it is extended to B-modal formulas by means of the folowing probabilistic interpretation of atomic belief formulas,

– $e(B\varphi, w) = \mu(\{w' \in W \mid e(\varphi, w') = 1\})$

and by means of Łukasiewicz logic truth-functions for compound modal formulas.

The axioms and rules for BC_{prob} are built in layers according to the nature of the language $\mathcal{L}_{BC}$ and the particular uncertainty model chosen, here probability. Namely, the set of axioms consists of: (i) axioms of propositional Dynamic logic for PDL-formulas; (ii) axiom of RPL for B-formulas, and (iii) the following probabilistic axioms for B-formulas:

(BC1) $B(\varphi \rightarrow \psi) \rightarrow_L (B\varphi \rightarrow_L B\psi)$
(BC2) $B(\varphi \vee \psi) \leftrightarrow_L B\varphi \oplus (B\psi \ominus B(\varphi \wedge \psi))$
(BC3) $\neg_L B(\bot)$
(BC4) $B\varphi$, for each theorem φ of PDL

where $\Phi \oplus \Psi$ is a shorthand for $\neg_L \Phi \rightarrow_L \Psi$ and $\Psi \ominus \Phi$ is a shorthand for $\neg_L(\Phi \rightarrow_L \Psi)$.[1] Deduction rules for BC are Modus Ponens (both for $\rightarrow$ of PDL and for $\rightarrow_L$ of RPL) and Necessitation for the modality B.

In [6] it is proved that the logic BC_{prob} is sound and Pavelka-style complete with respect to the above probabilistic semantics.

2.2 Desire Context (DC)

Desires represent the *ideal* agent's preferences regardless of the agent's current perception of the environment and regardless of the cost involved in actually

[1] Note that in Łukasiewicz logic $(x \Rightarrow_L 0) \Rightarrow_L y = \min(1, x+y)$ and $(x \Rightarrow_L y) \Rightarrow_L 0 = max(0, x-y)$.

achieving them. Positive desires represent what the agent would like to be the case. Negative desires correspond to what the agent rejects or does not want to occur. In this setting, one can also express indifference in a natural way just by expressing that has neither a positive nor a negative preference over an object. Furthermore, positive and negative desires can be graded to represent different levels of preference or rejection, respectively.

In the g-BDI agent model, following the approach on bipolarity representation of preferences in [1,2], we model in the DC context positive and negative information in the framework of possibilistic logic. In a similarly way as we do in the *BC* context, to represent and reason about the agent bipolar preferences in the *DC* context a modal many-valued approach is used to deal with the (positive and negative) desire degrees and a corresponding layered structure of axioms is set. As for combining one kind of desires (positive or negative) usually the conjunction of independent positive (resp. negative) preferences should produce a higher positive (resp. negative) preference. The degree of a disjunction of positive (resp. negative) preferences is computed as the minimum of the preference degrees, following the intuition that if the disjunction is satisfied at least the minimum of the satisfaction (rejection) levels is guaranteed. This corresponds to the use of the so-called *guaranteed possibility measures* to model the strength of the preferences [1]. In this way, a basic logic framework for the Desire context (DC schema) to capture these combination properties for positive and negative desires is independently defined.

The language $\mathcal{L}_{DC}$ in the DC context is defined over a classical propositional language $\mathcal{L}$ (built from a countable set of propositional variables *Var* with connectives $\wedge$, $\rightarrow$ and $\neg$) expanded with two (fuzzy) modal-like operators D^+ and D^-. $D^+\varphi$ reads as "φ is positively desired" and its truth degree represents the agent's level of satisfaction would φ become true. $D^-\varphi$ reads as "φ is negatively desired" (or "φ is rejected") and its truth degree represents the agent's level of disgust on φ becoming true. Notice that, as in BC, we do not allow nesting of the D^+ and D^- operators. As in the BC_{prob} logic, we use Rational Pavelka logic as the fuzzy logic to reason about the $D^+\varphi$ and $D^-\varphi$'s formulas.

The intended DC models are Kripke structures $M = \langle W, e, \pi^+, \pi^- \rangle$ where W and e are defined as in the BC semantics and π^+ and π^- are preference distributions over worlds, which are used to give semantics to positive and negative desires:

- $\pi^+ : W \rightarrow [0,1]$ is a distribution of positive preferences over the possible worlds. In this context $\pi^+(w) < \pi^+(w')$ means that w' is more preferred than w.
- $\pi^- : W \rightarrow [0,1]$ is a distribution of negative preferences over the possible worlds: $\pi^-(w) < \pi^-(w')$ means that w' is more rejected than w.

The truth evaluation for non-modal formulae $e : \mathcal{L} \times W \rightarrow \{0,1\}$ is defined in the usual (classical) way, and it is extended to atomic modal formulae $D^-\varphi$ and $D^+\varphi$ by:

- $e(D^+\varphi, w) = \inf\{\pi^+(w') \mid e(\varphi, w') = 1\}$
- $e(D^-\varphi, w) = \inf\{\pi^-(w') \mid e(\varphi, w') = 1\}$

The basic set of axioms axioms and inference rules aim capturing these combination properties, considering positive or negative desires independently, are: axioms of classical logic for non-modal formulae, axioms of Rational Pavelka logic for modal formulas, the following preference handling axioms

(DC0$^+$) $D^+(\varphi \vee \psi) \equiv_L D^+\varphi \wedge_L D^+\psi$
(DC0$^-$) $D^-(\varphi \vee \psi) \equiv_L D^-\varphi \wedge_L D^-\psi$

and modus ponens for $\rightarrow$ and for $\rightarrow_L$, together with rules of introduction of D^+ and D^- for implications:

(ID$^+$) from $\varphi \rightarrow \psi$ derive $D^+\psi \rightarrow_L D^+\varphi$
(ID$^-$) from $\varphi \rightarrow \psi$ derive $D^-\psi \rightarrow_L D^-\varphi$.

Soundness and completeness results have been also proved for this basic logic for graded, independent positive and negative desires. It is also possible to extend this framework to deal with different forms of interaction between positive and negative desires by adding some suitable axiom schemes. In [6], we have considered three additional schemes:

(DC1$^+$) $D^+\varphi \wedge_L D^+(\neg\varphi) \rightarrow_L \bar{0}$
(DC1$^-$) $D^-\varphi \wedge_L D^-(\neg\varphi) \rightarrow_L \bar{0}$
(DC2) $(D^+\varphi \otimes D^-\varphi) \rightarrow_L \bar{0}$
(DC3) $(D^+\varphi \wedge_L D^-\varphi) \rightarrow_L \bar{0}$

Intuitively, axioms (DC1$^+$) and (DC1$^-$) capture the constraint that an agent cannot have simultaneously a positive (negative) degree for a goal φ and for its contrary $\neg\varphi$. On the other hand, axiom (DC2) captures a constraint stipulating that the positive and negative degree for a same goal cannot sum more than 1, while axiom (DC3) is stronger and forbids having a positive and a negative desire for a same goal.

2.3 Intention Context (IC)

This unit is used to represent the agent's intentions. Together with the desires, they represent the agent's preferences. However, we consider that intentions cannot depend just on the benefit of reaching a goal φ, but also on the world's state and the cost of transforming it into one where the formula φ is true. By allowing degrees in intentions we represent a measure of the cost/benefit relation involved in the agent's actions towards the goal.

We represent in this context two kinds of graded intentions, intention of a formula φ considering the execution of a particularly plan α, noted $I_\alpha\varphi$, and the final intention to φ, noted $I\varphi$, which takes into account the best path to reach φ. As in the other contexts, if the degree of $I\varphi$ is δ, it may be considered that the truth degree of the expression "φ is intended" is δ. The intention to make φ true must be the consequence of finding a feasible plan α, that permits to achieve a state of the world where φ holds. Indeed, a suitable bridge rule (described in Subsection 2.5 as bridge rule (3)) infers these degrees of intention towards a goal φ for each plan α that allows to achieve the goal.

The agent intentions will be represented in the IC context by a theory $\mathcal{T}_\mathcal{I}$ over Rational Pavelka logic RPL. The language used is built in a similar way as done in the BC and DC contexts. We start from a classical propositional language $\mathcal{L}$ with a finite set of actions or plans Π^0 at the agent disposal to achieve her desires. Then, for each $\alpha \in \Pi^0$ we introduce a modal operator I_α such that the truth-degree of a formula $I_\alpha\varphi$ will represent the strength the agent intends φ by means of the execution of the particular action α.[2] We also introduce another modal operator I with the idea that $I\varphi$ will represent that the agent intends φ by means of the best plan in Π^0. These atomic modal formulas are then combined using Łukasiewicz connectives and rational truth-constants. Then, for instance, if the agent IC theory $\mathcal{T}_\mathcal{I}$ contains the formula $I_\alpha\varphi \rightarrow_L I_\beta\varphi$ then the agent will try φ by executing the plan β before than executing plan α.

Models for IC are Kripke structures $M = \langle W, e, \{\pi_\alpha\}_{\alpha\in\Pi^0}\rangle$ where W is a set of worlds and $\pi_\alpha : W \times W \rightarrow [0, 1]$ is the utility distribution corresponding to action α: $\pi_\alpha(w, w')$ is the utility of applying α to transform world w into world w'.[3] Then e is extended to Boolean formulae as usual and to atomic modal formulae by

- $e(w, I_\alpha\varphi) = \inf\{\pi_\alpha(w, w') \mid w' \in W, e(w', \varphi) = 1\}$
- $e(w, I\varphi) = \max\{e(w, I_\alpha\varphi) \mid \alpha \in \Pi^0\}$

and to compound modal formulae using the truth functions of Rational Łukasiewicz logic.

The set of axioms for the IC logic consists of: axioms of classical logic for the non-modal formulas, axioms of Rational Pavelka logic for the modal formulas and the following specific axioms for the I_α and I modalities:

(IC0) $I_\alpha(\varphi \vee \psi) \equiv_L I_\alpha\varphi \wedge_L I_\alpha\psi$
(IC1) $I\varphi \equiv_L \bigvee_{\alpha\in\Pi^0} I_\alpha\varphi$

The rules are modus ponens for $\rightarrow$ and for $\rightarrow_L$ and introduction of I_α for implications: from $\varphi \rightarrow \psi$ derive $I_\alpha\psi \rightarrow_L I_\alpha\varphi$ for each $\alpha \in \Pi$.

Again, suitable soundness and completeness results can be proven for such a logic.

2.4 Planner and Communication Contexts (CC and PC)

The Planner Context (PC) has to look for feasible plans, these plans are generated from actions that are believed to fulfill a given positive desire and avoiding negative desires as post-conditions. These feasible plans are computed within this unit using an appropriate planner that takes into account beliefs and desires injected by bridge rules from the BC and DC units respectively.

[2] The IC context is not concerned about the question of whether a given desire can be reached by the execution of a particular action, this is left for the Planner Context, see next subsection.

[3] Indeed, it can be seen as a kind of refinement of the R_α relations of the action dynamic logic semantics considered in the BC context.

The Communication unit (CC) makes it possible to encapsulate the agent's internal structure by having a unique and well-defined interface with the environment. The theory inside this context will take care of the sending and receiving of messages to and from other agents in the multiagent society where our graded BDI agent lives.

Due to their functional aspect, we will not go into further details of these two units.

2.5 Bridge Rules (BRs)

A collection of basic bridge rules is considered to establish the necessary interrelations between context theories. We describe them next:

1. There are bridge rules from DC to PC that, from the positive and negative desires (pro-active attitudes), generate predicate instances in the PC unit that are used by the planner program to build the feasible plans:
$$\frac{DC : (D^{+}\varphi, d)}{PC : \lceil (D^{+}\varphi, d) \rceil} \text{ and } \frac{DC : (D^{-}\psi, n)}{PC : \lceil (D^{-}\psi, n) \rceil} \tag{1}$$
2. The agent knowledge about the world state and about actions that change the world, is introduced from the belief context into the Planner as first order formulas:
$$\frac{BC : B\varphi}{PC : \lceil B\varphi \rceil} \tag{2}$$
3. Regarding intentions, there is a bridge rule that infers the degree of $I_\alpha\varphi$ for each feasible plan α that allows to achieve φ. The intention degree is thought as a trade-off among the benefit of reaching a desire, the cost of the plan and the belief degree in the full achievement of φ after performing α. The following bridge rule computes this value from the degree of $D^{+}\varphi$ (d), the degree of belief $B[\alpha]\varphi$ (r), the cost of the plan α (c):
$$\frac{DC : (D^{+}\varphi, d), BC : (B[\alpha]\varphi, r), PC : fplan(\varphi, \alpha, P, A, c)}{IC : (I_\alpha\varphi, f(d, r, c))} \tag{3}$$
Different functions f allow to model different agent behaviors. For instance, if we consider an *equilibrated agent*, where all the factors involved are equally taken into account, the function might be defined as the average among these factors. In other cases, a weighted average may be used where the different weights w_i are set according to the agent expected behavior:
$$f(d, r, c) = (w_d d + w_r r + w_c (1 - c)) \,/\, (w_d + w_r + w_c)$$
For example, for a *greedy agent*, w_c may be set greater than the other weights: w_d and w_r.
4. The information supplied by the above bridge rule to the IC unit allows this unit to derive, for each desire φ, a formula $(I\varphi, i)$ where i is the maximum degree of all the $(I_\alpha\varphi, i_\alpha)$ formulae, where α is a feasible plan for φ. The

plan α_b that allows to get the maximum intention degree i_{max} considering all the agent desires, will be set by the PC unit as the *best plan* (see the definitional axiom (IC1) for I in Subsection 2.3). Finally, we also need rules to establish the agent interaction with the environment, meaning that if the agent intends φ at degree i_{max}, the maximum degree of all the intentions, then the agent will choose to execute the plan α_b —*bestplan*— that will allow him to reach the most intended goal φ:

$$\frac{IC : (I_{\alpha_b}\varphi, i_{max}), PC : bestplan(\varphi, \alpha_b, P, A, c)}{CC : C(does(\alpha_b))} \tag{4}$$

5. Through the communication unit the agent perceives all the changes in the environment that are introduced by the following bridge rule in the belief context:

$$\frac{CC : \beta}{BC : B\beta} \tag{5}$$

6. *Bridge rules to generate desires in a dynamic way.* In the desire context DC different schemas to represent and reason about desires were presented but how desires are derived was not discussed. In a dynamic environment the agent desires will change, depending on her beliefs and also on the set of current desires. Notably, Rahwan and Amgoud in their argumentation-based approach to practical reasoning [17] provide an argumentation-based framework for generating consistent desires, among other tasks, see also [18]. The basic elements of this argumentation framework are the desire-generation rules. We introduce in our g-BDI model a multi-context and many-valued version of these rules. As the desire and belief formulae in the premise are coming from different contexts, we define the following bridge rules for desire generation:

$$\frac{BC : (B\varphi_1 \wedge ... \wedge B\varphi_n, b), DC : (D^+\psi_1 \wedge ... \wedge D^+\psi_m, c)}{DC : (D^+\psi, d)} \tag{6}$$

   Namely, if the agent has the beliefs $B\varphi_1, ..., B\varphi_n$ in degree greater or equal then a threshold b and positively desires $D^+\psi_1, ..., D^+\psi_m$ in degree at least c, she also desires ψ in degree at least d.

With the description of this set of bridge rules (BR) we have finished a short description of all components of the g-BDI agent model.

3 A Small Example

Here we present a simple example as to show how the proposed agent model works.

Peter, who lives in Rosario, wants to planify his activities for the next week. He activates a personal assistant agent based on our *g-BDI model* to find an adequate travel plan (transportation + accommodation). He would be very happy attending to a conference on his speciality scheduled to take place in Buenos Aires (φ_1) and he would be rather happy visiting a friend living near this city (φ_2). But he would indeed prefer much more to be able to do both things. Besides, he doesn't like to travel during the night (ψ). This assistant has Peter's positive and negative desires represented by the following formulae in the theory T_{DC} of the *agent*'s Desire context:

$$T_{DC} = \big\{(D^+\varphi_1, 0.8), (D^+\varphi_2, 0.6), (D^+(\varphi_1 \wedge \varphi_2), 0.9), (D^-\psi, 0.7)\big\}$$

This means that the agent has rather high positive desires on achieving φ_1 and φ_2 but he even has a higher desire to achieve both (0.9). At the same time, the agent he rather rejects ψ, represents by a rather negative desire on ψ (0.7).

The agent also has knowledge about the conference schedule, his friend's agenda and transportation information, that is represented in the theory T_{BC} of the Belief context BC. Moreover, from this information and the set of positive and negative desires in T_{DC}, the planner context (PC) looks for *feasible* travel plans that are believed to satisfy φ_1 and/or φ_2 by their execution, but avoiding ψ as post-condition. Assume both α and β are found as feasible plans, whose normalized costs are $c_\alpha = 0.6$ and $c_\beta = 0.5$ respectively.

On the other hand, assume the Belief context (BC) is able to estimate the following beliefs (modelled as probabilities) about the achievement of the different goals by the feasible plans α and β, represented by the following formulae in the theory T_{BC}:

$$\begin{aligned} T_{BC} \supseteq \{&(B[\alpha]\varphi_1, 0.7),\ (B[\alpha]\varphi_2, 0.6),\ (B[\alpha](\varphi_1 \wedge \varphi_2), 0.42),\\ &B[\beta]\varphi_1, 0.5),\ (B[\beta]\varphi_2, 0.6),\ (B[\beta](\varphi_1 \wedge \varphi_2), 0.3)\} \end{aligned}$$

Then, using Bridge rule (3) and choosing the function f as

$$f(d, r, c) = r \cdot (1 - c + d)/2,$$

which computes an expected utility (taking the value $(1 - c + d)/2$ as the global utility of reaching a goal with desire degree d and cost c, and 0 otherwise), the agent computes the different intention degrees towards the goals by considering the different feasible plans (i.e. α or β). In this example, the intention degrees for the goal with the highest desire degree, i.e. $\varphi_1 \wedge \varphi_2$, are:

$$(I_\alpha(\varphi_1 \wedge \varphi_2), 0.273) \text{ and } (I_\beta(\varphi_1 \wedge \varphi_2), 0.210)$$

From these results, the *assistant agent* choses to recommend Peter the plan α that would allow him to attend the conference and to visit his friend ($\varphi_1 \wedge \varphi_2$).

4 A Case Study: An Application of a Tourism Recommender System

In this section,as a matter of application of the previously introduced main components of the g-BDI agent model, we succinctly describe the general architecture of a Tourism Recommender system that has been developed (see [8,5] for more details). The goal of the system is to recommend the best tourist packages on Argentinian destinations according to the user's preferences and restrictions. The packages are provided by different tourist operators. This system has been designed using a multiagent architecture and we particularly use the g-BDI model to specify one of its agents, the Travel Assistant Agent (T-Agent). The purpose of this prototype implementation was to show that the g-BDI agent model is useful to develop concrete agents on a real domain.

Inspired in the different components of a tourism chain, in the analysis phase we have identified the following roles: the Provider role (tourist package providers), the Travel Assistant role and Service roles (hotel chains, airlines, etc.). However, in this case study we don't deal with the service roles, we only mention them as necessary collaborators of the Provider role. Other functional roles have been identified as well, like for instance the Interface role, to manage the user interface, and the repository Maintenance role (R-Maintenance), to update and code into the system format the packages sent by the provider roles. In this simplified version of Recommender System, we define two agent's types: the Provider agent and the Travel Assistant Agent. We assign the interface role, the repository maintenance role and the travel assistant role to the Travel Assistant Agent (*T-Agent*).

The internal architecture of the Provider agents (*P-Agent*) is not considered in our implementation and for our purposes they are considered only as tourist packages suppliers. The multi-agent architecture of the prototype version of the tourism recommender system, composed by a *T-Agent* and two *P-Agents*, together with the main source of information they interact with (the destination ontology and the package repository) is illustrated in Figure 2. This multiagent system is easily scalable to include other providers.

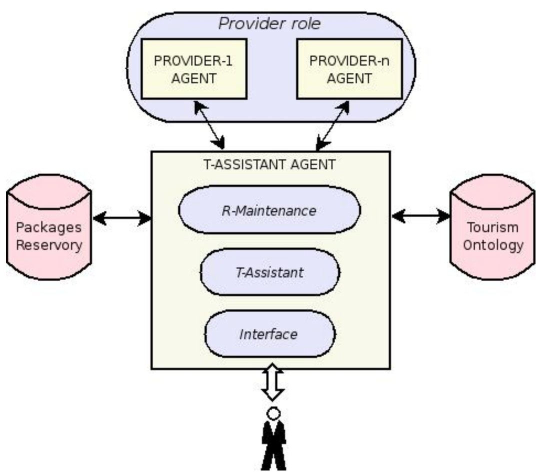

Fig. 2. Multiagent architecture of the Tourism Recommender System

The implementation of the Recommender system was developed using SWI-Prolog, a multi-threaded version of prolog which is a suitable language both to deal with logical deduction and allowing an independent execution of the different contexts (i.e. in different threads). Moreover, each *P-Agent* runs in a different thread, so in this way being independent from each other and from the *T-Agent*. When the *T-Agent* requests for information, the *P-Agents* send to *T-Agent* all the current packages they can offer. The communication between agents is by message exchange.

Next, we briefly describe how the contexts have been implemented in order to obtain the desired behaviour of the *T-agent* (for a detailed description see [8]).

Communication Context (CC): The CC is the agent's interface and is in charge of interacting with the tourism operators (*P-Agents*) and with the tourist that is looking for recommendation. The *T-Agent*, before beginning its recommendation task, updates its information about current packages (carrying out its reservory maintenance role). It behaves as a wrapper translating the incoming packages into the *T-Agent* format and sends them to the Planner context. The user's interface has been developed as a Web service application and it is responsible for:

- *Acquiring user's preferences:* they are explicitly obtained from the user by filling in a form. The tourist can set her preferences (positive desires) and restrictions (negative desires) and assign them a natural number from 1 to 10 to represent the level of preference (resp. restriction) for the selected item. Preferences are given about the following issues: geographic zone, natural resources, infrastructure, accommodation, transport or activities. The constraints are related to the maximum cost she is able to afford, the days available for traveling and the maximum total distance she is willing to travel. Once the user finishes his selection, the CC sends all the acquired information to the Desire context DC.

- *Showing the resulting recommendation:* as a result of the *T-Agent* deliberation process, the CC receives from the Intention context a ranking of feasible packages that satisfies some or all of the tourist preferences. Then, he can visualize the information about them (i.e. the description of the transport, destination, accommodation, activities) opening suitable files.

- *Receiving Tourist's feedback:* After analyzing the ranking of the recommended packages, the user can express through the CC interface her opinion about the recommendation. Namely, the user can select one of the following three possible evaluations:

1. *Correct*: When the user is satisfied with the ranking obtained.
2. *Different order*: When the recommended packages are fine for the user, but they are ranked in a different order than the user's own order. In such a case, the user is able to introduce the three best packages in the right order.
3. *Incorrect*: The user is not satisfied with the given recommendation. Then, the interface enables him to introduce a (textual) comment with his opinion.

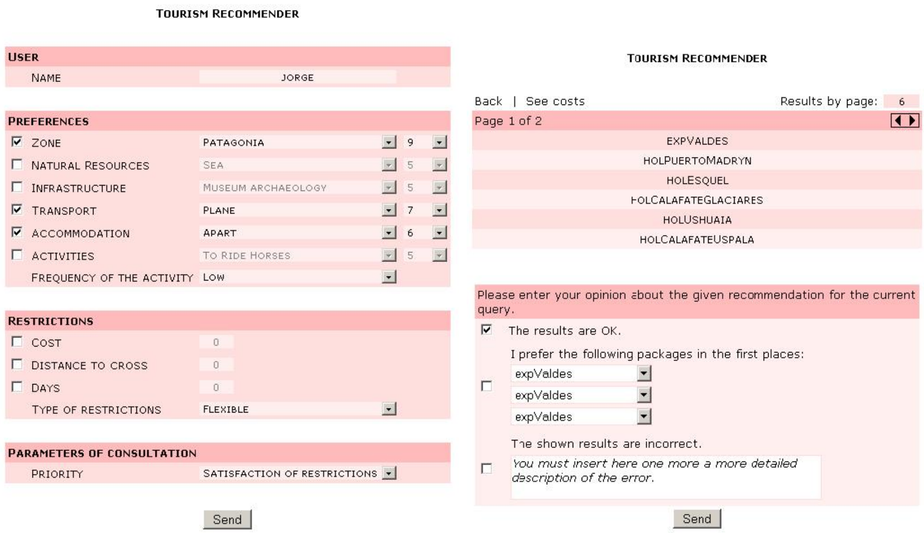

Fig. 3. Two screenshots of the user interface. Left: acquisition of user's preferences. Right: package recommendation and user feedback.

All the information resulting from the user data entry is stored to evaluate the system behaviour.

An example of a tourist's preferences specification and the system recommendation using this interface is shown in Figure 3.

Desire Context (DC): As the *T-Agent* is a *personal agent*, its overall desire is to maximize the satisfaction of the tourist's preferences. Thus, in this context the different tourist's graded preferences and restrictions are respectively represented as positive and negative desires. For instance, the preferences of a tourist that would like to go to a mountain place and to travel by plane but not more than 2000 kms could be represented by the following theory:

$$\mathcal{T}_{DC} = \{(D^{+}resources\_mountain, 0.9), (D^{+}transport\_air, 0.7),$$
$$(D^{+}(resources\_mountain \wedge transport\_air), 0.92), (D^{-}(distance \geq 2000), 0.5)\}$$

The *T-Agent* uses the desires as pro-active elements, and are passed by a bridge rule to the Planner context that looks for feasible packages.

Belief Context (BC): In this context the *T-Agent* represents all the necessary knowledge about tourism and the Argentinian domain: tourist packages (each package is represented as a list containing an identifier, a tour provider, the package cost and a travel-stay sequence), information about destinations (represented by a destination ontology) and rules to infer how much preferences can be satisfied (to some degree) by the feasible tourist packages. This context also contains knowledge about *similarity relations* between concepts to extend the possibility of satisfying a tourist with similar preferences than the actually selected ones. Besides, the BC is in charge of estimating the extent (the belief) $B([\alpha_P]\varphi)$ to which a desire (preference) φ will be achieved when selecting a given package α_P.

Planner Context (PC): The Planner Conext (PC) is fundamental for the *T-Agent* implementation. The PC unit is assumed to contain a set of available plans, coded as instances of the predicate *planner* with *paq* formulae (see below). The Planner context is responsible for looking among them for *feasible packages*. By *feasible package* we mean a package that fulfills, to some degree, one of the positive desires (elementary or combined) and avoids, as post-condition, the satisfaction of the agent's negative desires above to a given threshold. The set of feasible plans is determined within this context using an appropriate searching method that takes into account information injected by bridge rules from the BC and DC units, including positive and negative desires, information about packages (including their cost), the agent's beliefs about package destinations and the estimation of the agent's desires fulfillment by the different plan executions.

After the PC has identified the set of feasible packages, they are passed to the Intention context, which is in charge of ranking of these packages according to the user's preferences.

Intention Context (IC): In order to rank the feasible packages to be offered to the user, the Intention context IC of the *T-Agent* is in charge of estimating the intention degree for each feasible package as a trade off between the benefit (expected satisfaction) and the cost of reaching the user's desires through that package. Thus, first, this context estimates the expected satisfaction $E(D, \alpha)$ of a tourist's desire D assuming she selects a package α. Second, using a suitable bridge rule, it computes the intention degree (the truth degree of the formula $I_\alpha D$) towards the desire D by executing a tourist package α using a function that combines the expected satisfaction $E(D, \alpha)$ and the normalized package cost CN. In the following Subsections we give some insights of how this estimations are implemented in the *T-Agent.*

A first experimentation of this prototype has been carried out with promising results (see [7] for a preliminary report). Considering 52 queries, 73% of the user's opinions were satisfactory (namely 40.4% with *correct order* and 32.7% with *different order* as user feedbacks). Furthermore, we have performed some experimentations using this recommender agent with the aim of proving different properties of the g-BDI model of agents. On the one hand, we have performed a sensitivity analysis to show how the g-BDI agent model can be tuned to have different behaviors by modifying some of its component elements. On the other hand, we have also done some experiments in order to compare the performance of recommender agents using the g-BDI model with agents without graded attitudes.

5 Conclusions

In this paper we have overviewed the main characteristics of a general graded BDI agent model. In this model, the agent graded attitudes have an explicit and suitable representation. Belief degrees represent the extent to which the agent believes a formula to be true. Degrees of positive or negative desires allow the agent to set different levels of preference or rejection respectively. Intention degrees also give a preference measure but, in this case, modelling the cost/benefit trade off of achieving an agent's goal. Then, agents having different kinds of behaviour can be modelled on the basis of the representation and interaction of their graded beliefs, desires and intentions. In this respect, the role of preference representation is fundamental in this agent model as they are the agent proactive attitudes which lead agent to intentions and then, to actions.

As proof of concept, a prototype of multiagent Tourism Recommender system has been developed, where the g-BDI architecture has been used for modelling the T-Agent, showing in this way that the model is useful to develop concrete agents in real domains. We remark that the graded model of information representation and reasoning in the g-BDI agent has several advantages for this implementation. For instance, this model enables an expressive representation of the domain knowledge (agent beliefs), the user's preferences (desires) and the resulting intentions. Also, it makes it possible to compute in a graded way the expected satisfaction of the different tourist's preferences by the execution of several packages, so providing rankings of recommendations. Indeed, some validation and experimentation results reported in [7] show that (i) g-BDI agents are useful to build recommender systems in a real domains such as tourism, (ii) they provide satisfactory results, and (iii) the distinctive feature of recommender systems modelled using g-BDI agents, which is using graded mental attitudes, allows them to provide better results than those obtained by non-graded BDI models.

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