BDI Agents with Fuzzy Perception for Simulating Decision Making in Environments with Imperfect Information

Giovani P. Farias, Graçaliz P. Dimuro and Antônio C. Rocha Costa
PPGMC - C3, Universidade Federal do Rio Grande
96201-900 Rio Grande, RS, Brazil, Email: {giovanifarias, gracaliz, ac.rocha.costa}@gmail.com

Abstract—**This work introduces a model of fuzzy perception for BDI agents, to support the simulation of decision making processes in environments with imperfect information. An application to a fuzzy prey-predator environment was developed, as an example, where the process of deciding which prey a predator should attack is based on its fuzzy perception of the strength of the prey, and on the comparison of the preys' strengths with its own strength. Different simulations were realized for the comparative evaluation of different types of predator agents, in contexts with and without competition between predators. The quantitative analysis of the simulations shows that the fuzzy predator agent presents the best scores. However, the important result is that the fuzzy predator seems to behave more adequately in the environment, in the sense that it presents an apparently more natural, coherent and realistic behavior.**

I. Introduction

Fuzzy sets and Fuzzy Logic (FL) [1] may be viewed as an attempt to formalize/mechanize two kinds of human capabilities. The first one is the capability to reason and make rational decisions in an environment of *imperfect information* (i.e, of imprecision, uncertainty, incompleteness of information, conflicting information, partiality of truth and partiality of possibility). And second, the capability to perform a wide variety of physical and mental tasks without any measurements and any computations [2].

Zadeh [3] pointed out the *Incompatibility Principle*, which states that "complexity and precision are incompatible properties", arguing that the conventional numerical-based approaches are inadequate to model human-like complex processes. Therefore, "the closer one looks at a real-world problem, the fuzzier becomes its solution".

In the context of Social Simulation (SS), Grüne-Yanoff [4] and Rossiter et al. [5] remarked that one often has to deal with "fuzzy" social concepts, which are difficult to formalize and observe in the real-world system. For that reason, FL has been used in SS for representing vagueness, uncertainty and subjectiveness in everyday life.

Among the agent models commonly used in agent-based simulation of decision processes in complex environments, there are the ones of an intentional nature, whose behaviors can be explained by attributing certain mental attitudes to the agents, such as knowledge, belief, desire, intention, obligation, commitment (see, e.g., [6], [7]).

A well-known intentional model is the BDI (Beliefs, Desires and Intentions) architecture, introduced by Rao and Georgeff [8]. This model is based on the representation of the agent's *beliefs* about the states of the world and a set of *desires*, which identify those states that the agent has as goals. By a process of deliberation, the agent formulates one or more *intentions* (the states which the agent is committed to bringing about). The agent then builds a plan to achieve those intentions (through some form of means-ends reasoning), and executes it. After that, the agent uses its perception about the environment (which may include itself) in order to have its beliefs updated.

Although Rao and Georgeff explicitly acknowledge that an agent's model of the world is incomplete, the BDI model does not take into account the influence of the imperfect information (in the sense discussed above) acquired from the world in beliefs, desires and intensions. In particular, it does not consider that the agent could have a "fuzzy" perception of the world. Then, in this paper, we experiment with a BDI agent with *fuzzy perception* operating in a task environment with imperfect information, namely, a fuzzy prey-predator system.

Prey-Predator systems are an important theme in the area of Population Dynamics, their modeling having achieved a classical status through the formulation of the so-called Lotka-Volterra equations [9]. The particular type of systems that we simulate was inspired by the Fuzzy Prey-Predator Model introduced by Peixoto et al. [10].

The paper is organized as follows. Section II discusses related work. Section III presents some concepts on the fuzzy inference system used in this work. The environment with imperfect information inspired by the Fuzzy Prey-Predator Model is introduced in Sect. IV, including our approach for the fuzzy perception module to be included in the BDI architecture of the predator agent. The results on simulations are discussed in Sect. V. Section VI is the Conclusion.

II. Related Work

In the context of social simulation, FL has been playing an important role, and it is possible to find many interesting works using FL to deal with different problems that can not be solved with classical simulation models and tools. In this section, we briefly present some of those works, according to the different issues covered by them.

Hassan et al. [11] observed that simple agent models, as those normally used with exiting tools, are neither sufficient nor adequate to deal with the uncertainty and subjectiveness that have to be considered in the analysis of *values* (e.g., *trust*) in human societies. In their agent-based social modeling and simulation, FL was used to naturally specify attributes of the agents representing individuals, the evolution of the agent minds, the inheritance, the relationship and similarity between individuals, etc. In the same direction, in [12], fuzzy filters were used for modeling *trust* in social modeling using multiagent systems.

In Ghasem-Aghaee and Ören [13], human *personality* facets and traits (according to the Big Five and OCEAN models) were specified as conditional rules in fuzzy agents, in order to perform human behavior simulation. With related objectives, Dimuro et al. [14] introduced an approach based on FL for the evaluation of the social exchange values generated in the simulation of social exchanges between *personality*-based agents, with the analysis of the fuzzy equilibrium equation.

Sabeur and Denis [15] presented an application of FL in the simulation of human behavior and social networks, representing *behavioral* elements, such as stress, motivation or fatigue, and *sociological* aspects. Hassan et al. [16] use a fuzzy system to model friendship dynamics with an agent-based model that could manage social *relationships*, together with demographics and evolutionary crossover.

Fort and Pérez [17] used FL to model the adaptive behaviour of the agents playing the Iterated Prisoner's Dilemma, governed by Pavlovian strategies, to analyze the evolution of *co-operation*. Sabater et al. [18] proposed a fuzzy representation of evaluations for the system Repage, which adopts a cognitive theory of *reputation*.

Concerning *fuzzy perception* in robots, Cuesta and Ollero [19] used it to improve robot's navigation, and Mobahi and Ansari [20] applied fuzzy perception to improve the credibility in robot's emotions.

Notice that the agent architectures proposed so far mostly deal with two-valued information. Casali et al. [21], however, incorporated a formal model to represent and reason under uncertainty, introducing a general model for *graded BDI agents*, and an architecture, based on multi-context systems, able to model these graded mental attitudes. In [22], the model was used to specify an architecture for a travel assistant agent that helps a tourist to choose holiday packages, and in [23] it was applied to build a recommender system for tourism.

Hybrid models can be found in the literature, introducing some kind of fuzziness to *BDI* architecture. Long and Esterline [24] introduced a BDI agent, which uses fuzzy inference engines, fuzzy controllers and classifiers, for the modeling of co-operative societies of artificial agents, outlining some social conditions necessary for agents to form joint intentions and actions. Lokuge and D. Alahakoon [25] introduced a BDI agent coupled with a neural network and an adaptive neuro fuzzy inference system for application in container terminal operations, allowing the improvement the decision making process in such a complex, dynamic environment. A BDI agent with a fuzzy neural network was also used by Hai-bo et al. [26] for application in autonomous underwater vehicles. Shen et al. [27] have explored a hybrid BDI model based on deliberative and fuzzy reasoning, and in [28] the model was improved within the context of wireless sensor networks.

However, neither the nice formalization by Casali et al. nor the other analyzed works have considered the influence of fuzzy perception on the operation of a BDI agent and its decision making.

III. On Fuzzy Inference Systems

Fuzzy set theory [1], [2], [3] is based on the idea that several elements in human thinking are not exact data, but can be approximated as classes of objects in which the transition from membership to nonmembership is gradual rather than abrupt, represented by membership grades in the interval $[0;1]$. Since human reasoning sometimes does not follow the two-valued or multivalued logic, FL is a logic with fuzzy truths, fuzzy connectives, and fuzzy rules of inference.

Fuzzy inference systems are non-linear models that aim to describe the input-output relationship of a real system using a family of linguistic **If-then** constructions and the inference mechanisms of FL. Among the several methods available for fuzzy inference, we adopt in this work the *Kang-Takagi-Sugeno* (KTS) method [29], where each fuzzy rule represents a local model of the real system under consideration[1]. The k_{th} rule of a KTS system with input vector $X = (x_1, \dots, x_N)$ and output z presents the general form:

$$\begin{array}{ll} \textbf{If} & (x_1 \textbf{ is } A_{1,k}) \textbf{ and } \dots \textbf{and } (x_N \textbf{ is } A_{N,k}) \\ \textbf{then} & z = f_k(X), \end{array} \tag{1}$$

where the linguistic terms $A_{n,k}$ $(n = 1, \dots, N)$ in the rule antecedents represent fuzzy sets with membership functions $\mu_{n,k}$, which are used to partition the domains of the input variables into overlapping regions. The functions f_k in the rule consequents are usually first-order polynomials of the form:

$$f_k(x_1, \dots, x_N) = b_{0,k} + b_{1,k}x_1 + \dots, b_{N,k}x_N. \tag{2}$$

For a given input $X = (x_1, \dots, x_N)$, the degree of fulfilment of the k_{th} rule evaluates the compatibility of the input X with the rule antecedent and determines the contribution of the rule's response $z = f_k(x_1, \dots, x_N)$ to the overall model's output. The degree of firing of the k_{th} rule is expressed as

$$w_k(x_1, \dots, x_N) = T_1(\mu_{A_1,k}(x_1), \dots, \mu_{A_N,k}(x_N)), \tag{3}$$

where T_1 is a t-norm (triangular norm). In this work, T_1 is the *Minimum* t-norm (called Gödel t-norm), and then Eq. 3 becomes :

$$w_k(x_1, \dots, x_N) = \min\{\mu_{A_1,k}(x_1), \dots, \mu_{A_N,k}(x_N)\}. \tag{4}$$

The overall output of a normalized first-order TSK fuzzy model with K rules is given by

$$z = \frac{\sum_{k=1}^{K} T_2(w_k(x_1, \dots, x_N), f_k(x_1, x_2, \dots, x_N))}{\sum_{k=1}^{K} w_k(x_1, \dots, x_N)}, \tag{5}$$

[1]The adoption of the KTS method is due to its better performance in some applications, since it avoids the defuzzification step. See [29] for details.

where T_2 is also a t-norm. In this work, T_2 is the *Product* t-norm, so that Eq. 5 results in:

$$z = \frac{\sum_{k=1}^{K} w_k(x_1, \ldots, x_N) \cdot f_k(x_1, x_2, \ldots, x_N)}{\sum_{k=1}^{K} w_k(x_1, \ldots, x_N)}. \quad (6)$$

IV. A Fuzzy Prey-Predator Environment

In [10], Peixoto et al. proposed a fuzzy rule-based system to elaborate a predator-prey model to study the interaction between aphids (preys) and ladybugs (predators) in citriculture. Due to the lack of available information about the phenomenon, instead of using the usual differential equations that characterize the classic deterministic models, they introduced a fuzzy approach for analyzing the problem.

In this paper, we informally build on the fuzzy prey-predator approach for an agent-based simulation in order to analyze the ability of a predator with fuzzy perception in surviving in an environment of imperfect information.[2]

In this environment, the age and the weight of a prey (and of a fuzzy predator itself) are vague information for the fuzzy predator. However, such information is crucial for a predator to evaluate the strength level of a certain prey in comparison with its own strength level, and, therefore, to estimate the probability of the success of its attack to such prey, which is given by:

$$Prob = 50 + \frac{RAP - RPP}{200}, \quad (7)$$

where RAP and RPP are the predator's and the prey's strength levels, respectively.

We assume that (i) predators and preys are initially randomly distributed in a grid; (ii) the food is always available for the different preys, and (iii) a predator loses weight for being looking around for preys and much more for each unsuccessful attack (on the contrary, it gains weight if its attack is successful). Then, the predator survival during the evolution of the time depends on its decision about attacking or not any prey it finds during its life. This decision is based on the imperfect information that the agent can perceive through its fuzzy perception mechanism, which uses a fuzzy inference system to determine the prey's strength level and its own.

The predator is a BDI agent with beliefs[3] on the following parameters: age, weight and strength level. The age and weight the agent can perceive through its perception mechanism. The strength level can be estimated considering perceived ages and weights. The abilities of the predator are: random movement looking for preys, perception of preys's age and weight, estimation of prey's strength level in comparison with its own strength level at the current time, and decision on attacks to preys, which considers if the probability of success satisfies $Prob > 0.25$ (Eq. 7). The constraints of its life are:

[2]Notice that we did not study population dynamics, as it was done in [10], although this can be considered in future work.

[3]In this paper, we do not refer to the agent's desires or intentions, only to its beliefs, since this is the component of the BDI model that is connected to the fuzzy perception mechanism.

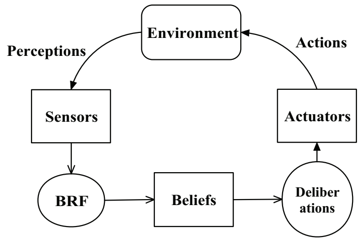

Fig. 1. Part of the BDI model with a fuzzy perception module.

(i) at each movement it loses a fixed amount of weight (*weight loss rate*), and has its age incremented by a fixed value (*aging rate*); (ii) at each successful attack, it gains a fixed amount of weight (*attack reward*); otherwise, it loses a fixed amount of weight (*attack punishment*); (iii) there is a minimum weight that a predator can support; if it achieves a weight less than the minimum then it dies by *weakness*; (iv) there is a maximum age that a predator can achieve; after that it dies by ageing.

A. Characterizing the Fuzzy Predator (FP) Agent

The Fuzzy Predator (FP) has a perception mechanism directly connected to the BRF (Belief Revision Function) of its BDI architecture, partially depicted in Fig. 1. This means that the fuzzy perception mechanism receives as input data the prey's age and weight, as well as the predator's own age and weight, all of which are perceived through the predator's non precise sensors. Then, using the KTS inference system (Sect. III), the predator infers the prey's strength level, and also its own strength level, updating its beliefs with the inferred information, in order to let this information be used in the decision process.

The linguistic variables `age`, `weight` and `strength level` are modeled as fuzzy sets with trapezoidal membership functions (Fig. 2). The analysis of those linguistic variables allowed the construction of a knowledge base composed by the linguistic rules presented in part in Table I. Table II shows part of the rule base for the KTS inference system of the perception model of the FP agent, each one with 2 inputs $(\texttt{age}, \texttt{weight}) \in \mathbb{R}^2$ and the output $z \in \mathbb{R}$, where *"young"*, *"adult"*, *"old"*, *"very light"*, *"light"*, *"average"*, *"heavy"* e *"very heavy"* represent fuzzy subsets of $\mathbb{R}$.

Example 1: In order to see how the inference system of the fuzzy perception mechanism operates, let us consider the following crisp input data: $\texttt{age} = 16$ and $\texttt{weight} = 84$. Those values are fuzzified, considering the membership grades in relation to the fuzzy subsets that define those linguistic variables, given in Fig. 2. Then, the age value $age = 16$ is considered "young" with grade $\mu_{young}(16) = 0,4$ and "adult" with grade $\mu_{adult}(16) = 0,6$. The weight value $weight = 84$ is evaluated as "heavy" with grade $\mu_{heavy}(84) = 0,6$ and "very heavy" with grade $\mu_{very-heavy}(84) = 0,4$.

For each combination of those sets achieved by the input data, some of the rules of the knowledge base are activated. In this case, four rules are fired, namely, the rules R_4, R_5, R_9 and R_{10} of the Tables I and II. Using Eq. 4, it is possible to

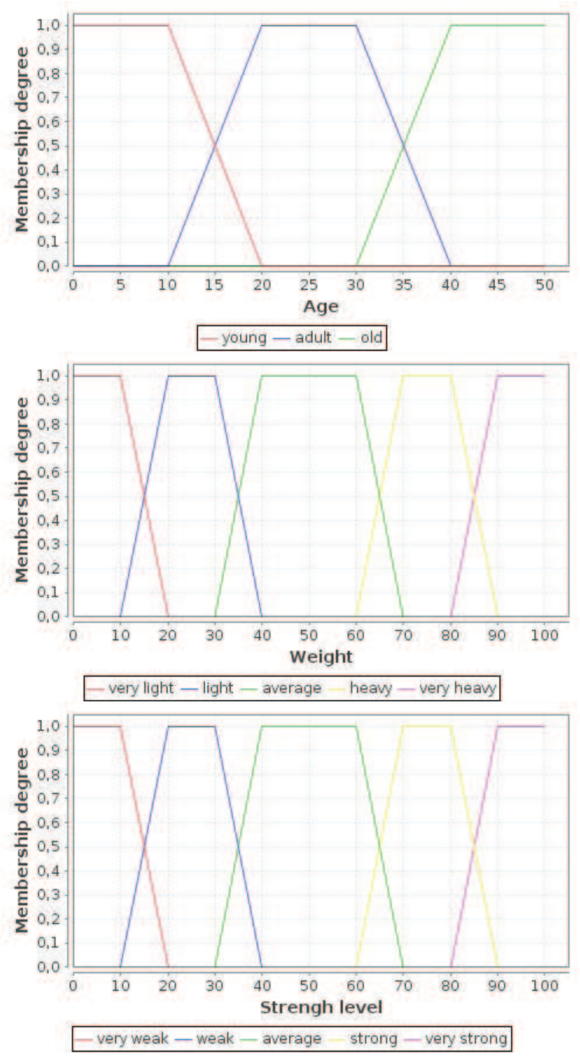

Fig. 2. Membership function for the considered linguistic variables.

find the degrees of firing of each one of those rules, as, e.g., $w_4 = \min\{\mu_{young}(16), \mu_{heavy}(84)\} = 0,4$. Then, one has that $w_5 = 0,4$, $w_9 = 0,6$ and $w_{10} = 0,4$. Using Eq. 6, we obtain the overall output of the process, where f_4, f_5, f_9 and f_{10} are calculated using Table II:

$$z = \frac{w_4 f_4(16,84) + w_5 f_5(16,84) + w_9 f_9(16,84) + w_{10} f_{10}(16,84)}{w_4 + w_5 + w_9 + w_{10}} = 74,$$

which represents the predator's strength level.

B. The Crisp Predator (CP)

For the comparative analysis of simulations, we implemented a Crisp Predator (CP), which is a BDI agent that does not consider that the information about itself and the one perceived from the environment are vague or incomplete. Its perception mechanism is inspired on the perception mechanism of the fuzzy predator, but, instead of using fuzzy subsets for the modeling of the input linguistic variables, we use classical sets with the usual characteristic functions into the set $\{0,1\}$. For each set of input date, only one rule of the knowledge base is activated. The characteristic functions of the sets related to the linguistic variable `age` are:

TABLE I
LINGUISTIC RULE BASE.

If	`age`	**and**	`weight`	**then**	`strength level`
R_1	young		very light		very weak
R_2	young		light		very weak
R_3	young		average		weak
R_4	young		heavy		average
R_5	young		very heavy		average
R_6	adult		very light		average
R_7	adult		light		average
R_8	adult		average		strong
R_9	adult		heavy		very strong
R_{10}	adult		very heavy		very strong
R_{11}	old		very light		very weak
R_{12}	old		light		very weak
R_{13}	old		average		weak
R_{15}	old		very heavy		average

$$\mu_{young}(x) = \begin{cases} 1 & \text{if } x \leq 15; \\ 0 & \text{otherwise} \end{cases} \quad \mu_{adult}(x) = \begin{cases} 1 & \text{if } 15 < x < 35; \\ 0 & \text{otherwise} \end{cases}$$

$$\mu_{old}(x) = \begin{cases} 1 & \text{if } x \geq 35; \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

The characteristic functions of the sets related to the linguistic variable `weight` are:

$$\mu_{very-light}(x) = \begin{cases} 1 & \text{if } x \leq 15; \\ 0 & \text{otherwise} \end{cases} \quad \mu_{light}(x) = \begin{cases} 1 & \text{if } 15 < x \leq 35; \\ 0 & \text{otherwise} \end{cases}$$

$$\mu_{average}(x) = \begin{cases} 1 & \text{if } 35 < x \leq 65; \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

$$\mu_{heavy}(x) = \begin{cases} 1 & \text{if} 65 < x \leq 85 \\ 0 & \text{otherwise} \end{cases} \quad \mu_{very-heavy}(x) = \begin{cases} 1 & \text{if } x > 85 \\ 0 & \text{otherwise} \end{cases}$$

Example 2: Considering the same input data (`age`, `weight`) of Ex. 1 and the characteristic functions given in Equations 8 and 9, one has that `weight` $= 84$ and `age` $= 16$ are definitely evaluated as "heavy" ($\mu_{heavy}(84) = 1$) and "adult" ($\mu_{adult}(16) = 1$), respectively. In this case, only the rule R_9 of the rule base of Tables I and II is activated. Obviously, the firing degree of this rule is $w_9 = 1$. The general output, given by Eq. 6, results in the value of the straight level:

$$z = \frac{w_9 f_9(16,84)}{w_9} = \frac{1 \cdot 88}{1} = 88$$

To enrich the possible comparisons, we have implemented a Greedy Predator (GP), which always attacks the preys it encounters, without considering any reasoning on strength levels and the probability of success of its attacks to preys.

V. Analysis Of the Simulation Results

The simulations were realized to obtain a general view of the behaviors of the different predators[4] in two kinds of the Fuzzy Prey-Predator Environment: competitive (Sect- V-A) and non-competitive environments (Sect. V-B). The implementation was done in the Jason platform [30].

[4]Since we are not analyzing population behavior, in the simulations we only consider either 2 or 3 predators, in order to be able to compare directly their surviving abilities.

TABLE II
RULE BASE FOR THE KTS INFERENCE SYSTEM.

If `age` **and** `weight` **then** `strength level` = f_k(`age`, `weight`)			
R_1	young	very light	$f_1(x,y) = \dfrac{x+y}{2}$
R_2	young	light	$f_2(x,y) = \dfrac{x + (\frac{y}{2})}{2}$
R_3	young	average	$f_3(x,y) = \dfrac{(x+y) - 10}{2}$
R_4	young	heavy	$f_4(x,y) = (x-1) + \dfrac{y}{2}$
R_5	young	very heavy	$f_5(x,y) = x + \dfrac{y}{2}$
R_6	adult	very light	$f_6(x,y) = \dfrac{x+y}{2} + 25$
R_7	adult	light	$f_7(x,y) = \dfrac{x+y}{2} + 30$
R_8	adult	average	$f_8(x,y) = \dfrac{x + \frac{y}{2} + 100}{2}$
R_9	adult	heavy	$f_9(x,y) = \dfrac{x+y}{4} + 63$
R_{10}	adult	very heavy	$f_{10}(x,y) = \dfrac{\frac{x}{2} + y}{2} + 40$
R_{11}	old	very light	$f_{11}(x,y) = \dfrac{(50-x)+y}{2}$
R_{12}	old	light	$f_{12}(x,y) = \dfrac{(50-x) + \frac{y}{2}}{2}$
R_{13}	old	average	$f_{13}(x,y) = \dfrac{(50-x)+(y-10)}{2}$
R_{15}	old	very heavy	$f_{15}(x,y) = (50-x) + \dfrac{y}{2}$

The results were obtained from a total of 100 simulation runs. In each run, the time grows in discrete units (1 time unit = one predator movement). In the beginning of each run, the predators present the following initial parameters: `age` $=$ 1 and $weight = 50$. Those parameters change at each time instant according to the following fixed rates[5]: the *weight loss rate* (-0,1 kg for each movement/time), the *aging rate* (-0.05 year for each movement/time), the *attach reward* (+2 kg for each successful attack), and the *attack punishment* (-1 kg for each non successful attack). The simulation run ends when all the predators have died, either for weakness (weight less than 1 kg) or for ageing (age equal to 50 years).

A. The Competitive Environment

The competitive environment consists of 2 kinds of predators (FP e CP) and different 250 preys. At each successful predator attack, the corresponding defeated prey dies. Considering that there is no prey reproduction, the prey population tends to decrease, increasing the probability of the predator not finding a prey as it moves in the environment, which may cause increasing weight losses. In this sense, both predators compete for the preys remaining in the environment.

[5]Variations of the initial parameters and rates are not considered here, since they affect only the agent's deliberations, not its perceptions.

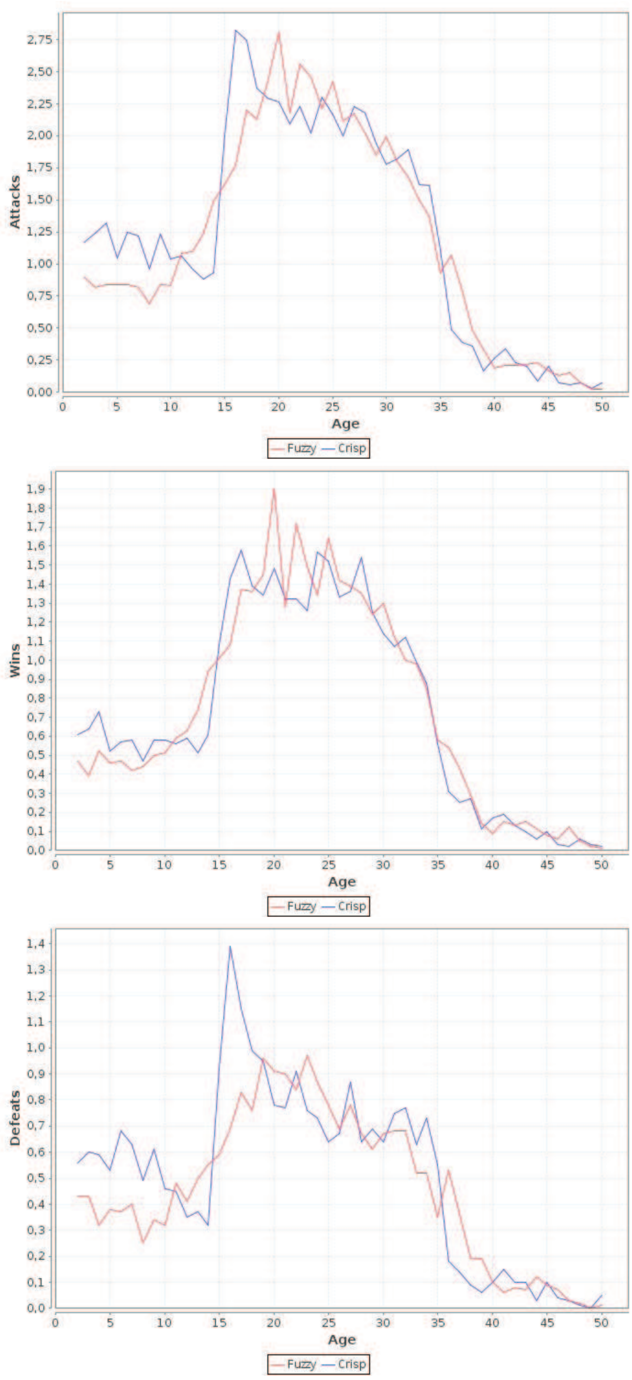

Fig. 3. The average of attacks (top), victories (middle) and defeats (bottom) at an age i, with $1 \leq i \leq 50$, in a competitive environment.

Figure 3 (top) shows the average number of predators' attacks at each year. Observe that the number of the CP's attacks surges around the age of 15. This is so because, before 15, the agent thinks that it is young (with too low strength level), but, suddenly, as it achieves 15 years old, it concludes that it is already an adult (with too high strength level). The increase in the number of the FP's attacks is more gradual, showing more coherence in its decisions. On the other hand, one might have expected that the high number of attacks would have lasted until around the age of 35, since it is only after this age that the CP considers itself old. However, due the prey population decreasing, the number of the attacks of both predators also decreases, even before the age 35. Around the age 35, the decrease in the number of the attacks of the CP is much more abrupt than the smooth decreasing of the number of the attacks of the FP, as it passes from young to adult/old.

Figure 3 (middle) presents the average of predators' victories at each year. There is a significant increase in the number of victories when the CP is around 15, which is an expected result, since this is the period that, as it considers itself an adult by this age, it increases a lot the number of attacks until around the age of 35, when it considers itself old, as discussed in the previous paragraph. Also, due to the decrease in the prey population, and consequently, the decrease in the number of attacks, the number of victories also decreases, even before the age 35. Again, it is possible to observe that the graph corresponding to the FP increases and decreases smoothly, as the agent becomes old, whereas the one of the CP increases abruptly around 15 and decreases around 35, also drastically.

Analogous analysis can be done concerning the average of number of the predators' defeats at each year, which is shown in Fig. 3 (bottom).

B. The Non-competitive Environment

The non-competitive environment consists of 3 kinds of predators (FP, CP and GP), and 250 different preys. For each prey that dies in consequence of a predator attack, another prey with similar characteristics appears in the environment, at a random position. This means that the predators always have the same chance to find a prey to attack.

Figure 4 (top) shows the average number of predators' attacks at each year. For the same reasons discussed in Sect. V-A, the number of the CP's attacks surges around the age of 15. However, since the prey population is constant along the time, the high number of attacks of the CP lasts until around the age of 35, and then it follows drastically. The behavior of the FP is much more natural and coherent, since it presents a gradual increase in the number of attacks as it becomes an adult, and a also a smooth decrease as it becomes old. The high number of attacks of the GP during its life was as expected. During adulthood the numbers of attacks of all predators are similar.

Figure 4 (middle) presents the average number of predators' victories at each year. There is an abrupt increase in the number of victories when the CP is around 15, due to the high increase in the number of its attacks by this age. However, since the prey population does not decrease, the number of victories stays high until around the age 35. After that, it decreases radically. Again, it is possible to observe that the graph corresponding to the FP increases and decreases smoothly, as the agent becomes old. The higher number of victories of the GP is due to its attack strategy. During adulthood, the numbers of victories of the three kinds of predators are similar. The highest numbers of victories, for Crisp and Fuzzy predators, appear between the ages of 20 and 33. Analogous analysis can be done concerning the average of number of predators' defeats at each year (Fig. 4 (bottom)).

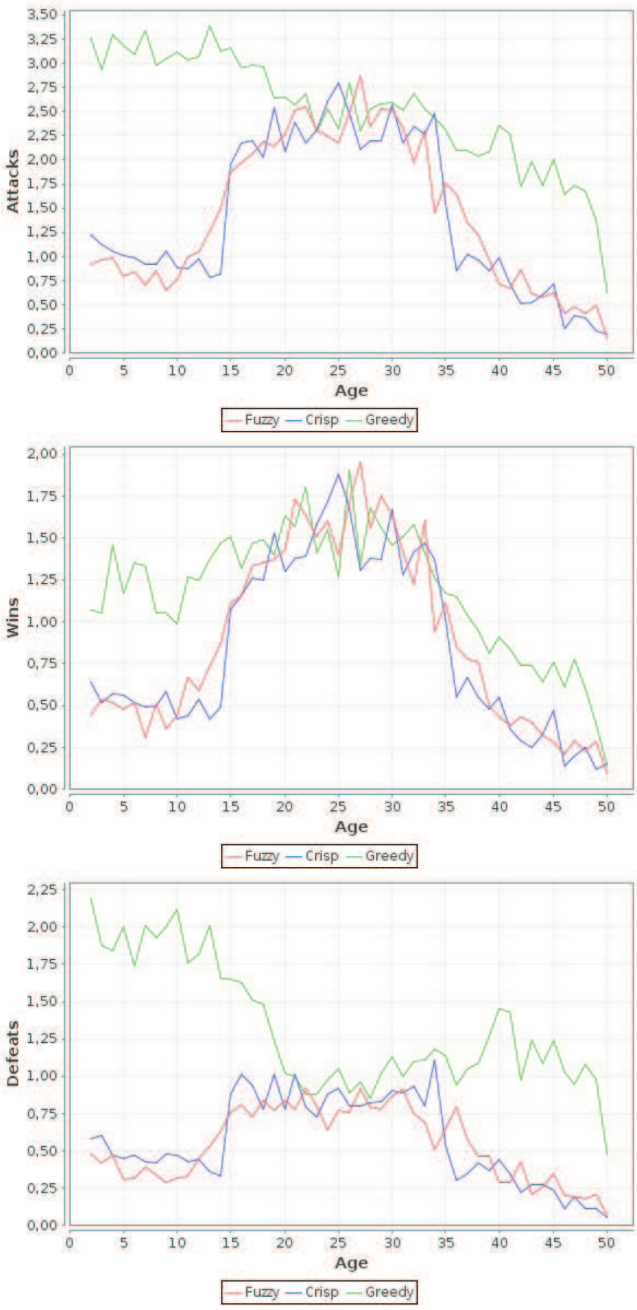

Fig. 4. The average of attacks (top), victories (middle) and defeats (bottom) at an age i, with $1 \leq i \leq 50$, in a non-competitive environment.

Figure 5 (top) shows the average number of accumulated attacks during the predators' lives, until they reach a certain age i, with $1 \leq i \leq 50$. As expected, the GP had an average number of accumulated attacks much higher than the other two predators, which had a similar attack behavior.

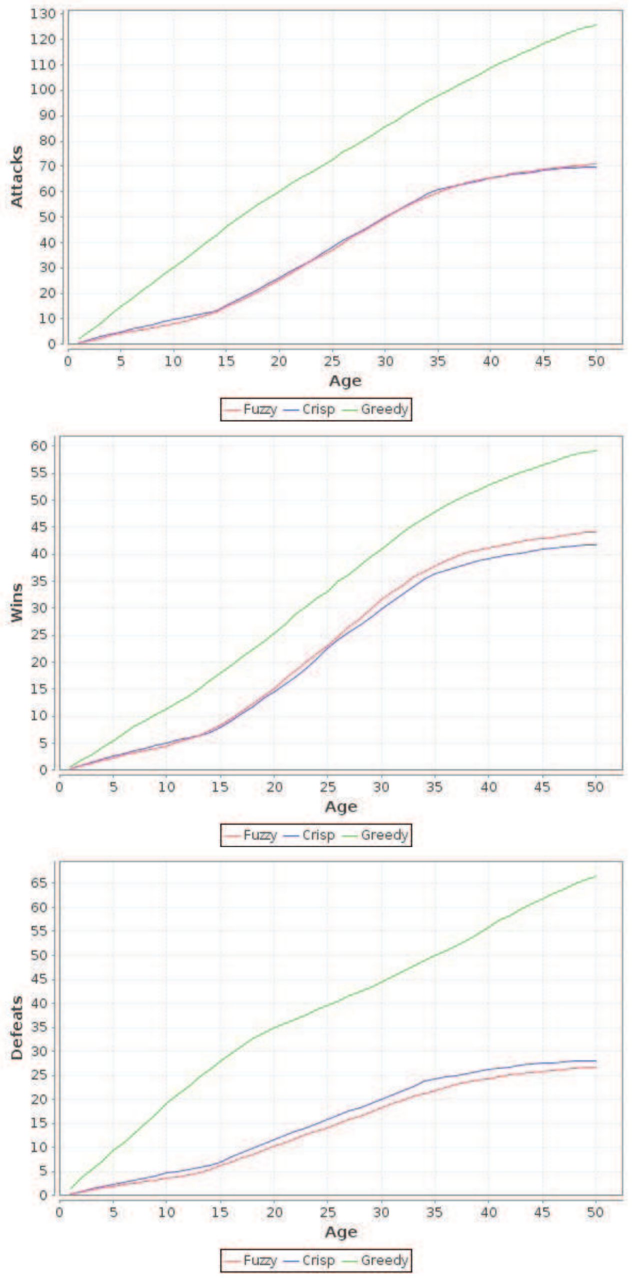

Fig. 5. Average accumulated number of attacks (top), victories (middle) and defeats (bottom) during the predator life until the age i, with $1 \leq i \leq 50$.

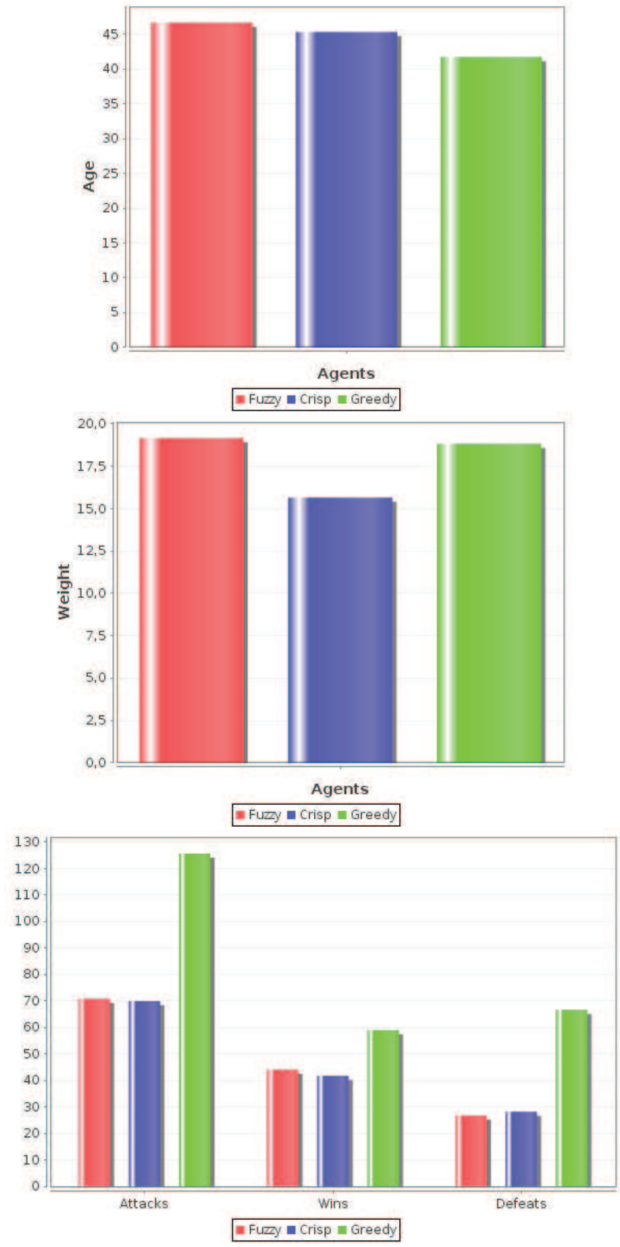

Fig. 6. Average lifetime (top), average weight at the end of the life (middle) and average of number of attacks/victories/defeats (bottom) of predators.

Figure 5 (middle) presents the average number of accumulated victories during the predators' lives, until they reach an specific age. As expected, the GP had an average number of accumulated victories much higher than the other two predators. However, this number for the FP is higher than that of the CP, as they become older.

Analogous analysis can be done concerning the average number of accumulated defeats during the predators' lives, until they reach an specific age, shown in Fig. 5 (bottom). Figure 6 (top) shows the average lifetime of the predators. As expected, the Greedy and Fuzzy predators present the lowest and the highest average lifetimes, respectively.

Figure 6 (middle) presents the average weight of predators at the end of their lives. The average weight of the FP at the end of its life is the highest one.

Figure 6 (bottom) shows the average number of attacks, victories and defeats of predators during its whole life. The GP is the one that presents the highest averages in all categories, and it is the one that has the average number of defeats higher than that of victories. Its average numbers of attacks and victories are higher than the ones of the CP, whereas the average number of defeats is lower than that of the CP.

We conclude that the simulation of the fuzzy perception of the FP allowed for a more faithful simulation of naturally expected smoothness of the development of predation ability of predators in a Fuzzy Prey-Predator environment.

VI. Conclusion

This paper introduces a model of fuzzy perception for BDI agents in task environments with imperfect information, which was inspired by an analysis of a particular Fuzzy Prey-Predator model. The aim was to analyze the influence of fuzzy perception on the ability of BDI agents to simulate decision making processes in fuzzy environments. For that, we have defined a perception mechanism directly connected to the BDI agent's BRF. The perception mechanism uses a KTS inference system, which is application dependant.

The simulations allowed us to obtain a general view of the behaviors of the different predators (CP, FP, GP) in two kinds of the Fuzzy-Predator Environment: a competitive environment and a non-competitive environment.

Although the difference between the results obtained by the Fuzzy and the Crisp predator agents were not so significant in the quantitative analysis that we have performed, it seems that the Fuzzy predator agent showed a more adequate simulated behavior in the environment with imperfect information, presenting a more natural, coherent and realistic behavior than the other agents.

Finally, two issues on the obtained results are important to point out. Firstly, the BDI agent with fuzzy perception seems to be a good model to be used in agent-based simulations in environments with imperfect information. Secondly, a fuzzy perception module can be a good alternative solution in the design of a BDI agent that can not perceive the information of the environment with accuracy.

Future work will consider a fuzzy perception mechanism for a BDI agent that is more application independent. For that, we are considering the use of the Mamdani inference method [1] in the level of the agent plans, so that the fuzzification of the input data will be directly reflected in the agent's set of beliefs, then extending to account for fuzzy beliefs.

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