Fuzzy Rules for Events Perception and Emotions in an Agent Architecture

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Abstract

In complex simulations, multi-agents systems allow to model virtual humans with an explicit cognitive process representation. However, this cognitive process is hard to model and is therefore generally simplified in an application-dependant way. In order to improve the realism of individual and collective behavior of these agents, we propose to integrate the perception of events and the computation of agents emotions in a fuzzy framework. The modeling of the perception and its effect on emotions through fuzzy rules enables the agents to consider properly the virtual environment.

We show how different kinds of fuzzy rules can help in the calculus of emotions. Computation of emotions is based on the evaluation of events' occurrence. Once the events are perceived by the agents, our method uses the desirability of these events to compute emotions relevant to crisis situations. We illustrate this model with a traffic simulation example.

Keywords: Fuzzy Rules, Events, Desirability, Emotions, Multi-agent Systems, Virtual Reality

1. Introduction

In complex simulations, multi-agents systems allow to model virtual humans with an explicit cognitive process representation. However, this cognitive process is hard to model and is therefore generally simplified in an application-dependant way. In virtual reality and social simulations, the humans implicated in the simulated situation are virtual autonomous humans [1] represented in a virtual environment which may interact with avatars. The main difficulty is to obtain credible behaviors that take into account personality, emotion and physiology.

The agent cycle is classically considered as a perception / decision / action loop. In this article, we focus on the first part of the process, *i.e.* the perception. An incorrect perception function may lead to inconsistencies in the decision, hence reducing the plausibility of the situations. Furthermore, we link the perception to the emotion modeling, because they impact each other: the percepts modify the emotional state of the agent, and the emotional state of the agent modify the way the agents perceive the situation. There are some works from psychological field about personality and emotion [2] but the adaptation of these models to an agent architecture is not straightforward because of a lack of formal specification [3].

A virtual human is a cognitive agent situated in a simulated environment. There are different possibilities in order to obtain an intelligent behavior: imitate cognitive functioning [4], or manipulate a set of observed behaviors [5]. The first approach is difficult because of the complexity of the process itself, for which there is no consensus in the community. The second approach ignores the decision process, and is therefore not explanatory. Our approach is to build a hybrid architecture that simulates high-level motivational interdependencies in behavior choice.

Our approach is based on cognitive intentional agents because computations of emotions is only relevant for cognitive agents. If an agent does not have a cognitive process, it cannot have emotions. Furthermore, the computation of emotions is based on the agent's goals. A major feature of the model is to be able to trace back how the actions in the simulation create desirable or undesirable situations. The modeling of the perception and its effect on emotions through fuzzy rules enables the agents to consider properly the virtual environment via the desirability of the perceived situations.

The article is organized as follows. Section 2 motivates the use of fuzzy rule systems to include emotions in the perception process of the agents. In section 3, we present what kind of architecture can be used with our perception modules and we give an overview of the three modules. Then, in section 4, we describe how to evaluate the events' occurrence. We show how to compute desirability in section 5 and how to compute emotions in section 6. The three modules are illustrated with a vehicle simulation throughout the model presentation. Finally we conclude and give some perspectives in section 7.

2. Motivation

In the literature, a standard definition for emotions does not exist. According to [6], there are 92 different definitions of emotion in the literature. Here, we use the definition of emotion as conscious states [7]. In emotions modeling, several works have been proposed: Gratch [8] proposes the most accomplished current model for the representation of agents' emotions. However, its formalism is complex and fully dedicated to the representation of emotions. As a consequence, this model is not easily adaptable and needs a complex calibration. It is adapted to domains where a subtle individual emotion representation is needed (facial expression representation, dialog management, ...) for a limited number of agents.

DETT [1] agent architecture [9] deals with the link between personality and emotions in a straightforward way. It is based on properties defined in OCC model [10]. Especially, DETT defines *tendencies*, that is the inclination of an agent to feel and to update its emotions in time. However, there are two limits to this approach: DETT is not explanatory (there is a direct link between emotion and action, but no high-level decision), and it models only two emotions (fear and bravery) in relation with two personality aspects (cowardice and temper).

Silverman proposes a complete architecture [3] that considers agent emotions, physiology and personality. The functional separation of modules is static, in order to experiment unitary tests. This approach is complementary of ours. On one hand, we evaluate emotion, personality and physiology in a well-known architecture (BDI) instead of an *ad hoc* one. On the other hand, we explore "classical" procedure in agent's decision and fuzzy rules in agent's perceptions and emotions.

In cognitive modeling, BDI architecture [11, 12] is often used for its intuitive representation of agent reasoning. The reasoning is decomposed in modules for a clear structure. However, in the original model, emotions, personality and physiology are not taken in account in the decision process. From this observation, Jiang and al. developed the eBDI architecture [13] that introduced emotion in a BDI architecture. However, the authors do not explain how they compute the emotions of the agents.

Human beings often need to deal with imprecise concepts. Based on this observation, Lotfi A. Zadeh developed fuzzy set theory that generalizes classical set theory to allow the notion of partial membership [14].To model the impact of emotions in the cognitive process of the agents within this framework, fuzzy sets represent the desirability of a particular event for the agents, as in [16]. The use of fuzzy logic allows to work with quantitative and qualitative descriptions in an expressive language.

To represent the mappings between emotion and events, other formalisms can be used, such as the interval-based approach used in the OZ project [15]. We decide to use fuzzy logic in order to allow the agents to achieve smooth transitions in the resultant behavior with a relatively small set of rules.

We base our approach on the model FLAME using fuzzy logic in order to represent emotions [16]. In the FLAME model, fuzzy rules represent the relation between events and desirability. However, in FLAME, the desirability computation only uses the impact of an event on a goal and the importance of this goal for the agent, which is applied to the behavior of a pet.

In our model, we intend to represent human behavior in complex situations. For this reason, we use fuzzy rules in order to determine if an event is perceived or not. When the occurrence of an event is validated by the agent's perception, we use a mechanism similar to FLAME mechanism to compute the desirability of a particular event.

In fuzzy rules, according to the typology proposed by Dubois [17] there are two main kinds of rules: conjunctive [18] and implicative [19] rules. In our representation we decide to use two kinds of fuzzy rules in function of the kind of knowledge we are dealing with. We will show that conjunctive rules fit the event's evaluation and implicative rules the desirability computation.

3. Perception and Emotion for Cognitive Agents

We intend to propose modules for intentional cognitive agents. Our modules are made to be adapted to any sort of cognitive agent with an explicit intention modeling. The modules evaluate the occurrence of events and compute the emotional state of the agent. This computation uses the agent intentions in order to compute the desirability of each event.

The proposed modules are (i) an event evaluation based on the perceptions of agents, (ii) a events' desirability evaluation based on event evaluation and goals of considered agent, and (iii) an emotion update based on the computed desirability, the occurrence of the event and the OCC model [10]. Figure 1 shows an overview of our modules in an agent architecture.

Fuzzy rules are able to represent two kinds of information: fuzzy conjunctive rules represent observed facts and fuzzy implicative rules represent models as restriction of possible worlds. Event's evaluation is modeled by fuzzy conjunctive rules because the perception process can be assimilated to observed facts information. Event's desirability computation is based on the cognitive model (goals and rules) of each agent, it is then natural to represent them as implicative rules. The process of emotion computation is a sequence: first, the events are perceived and computed thanks to conjunctive

[1] Disposition, Emotion, Trigger, Tendency

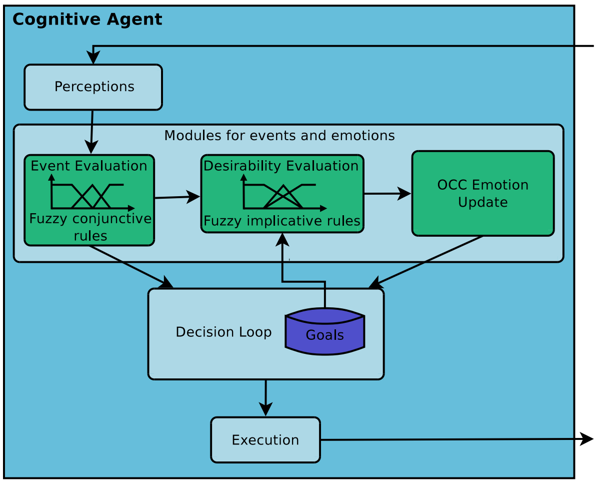

Figure 1: Modules for events and emotions in a cognitive agent architecture

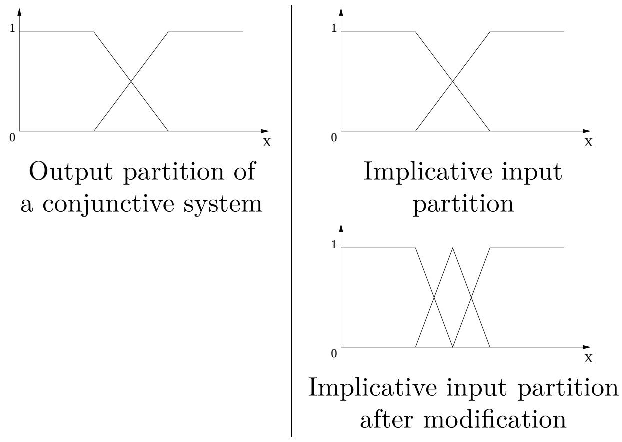

Figure 2: Re-use of output partition for input partition

rules, then the fuzzy output obtained from this system is re-used as an input of the desirability computation by implicative rules. A level of desirability is obtained for each event and allows us to compute emotions. Furthermore, the use of emotions as parameters of the fuzzy rules allows a feedback: the perception modifies the emotions, which in turn modify the perception, *etc.*

The output of a conjunctive rules system is used as the input of an implicative rule system. The input partition will then be based on the conjunctive output partition because the inferred information is relevant for this specific partition. Partition can be used directly or split if the model needs more granularity and needs more fuzzy sets to express all the rules. Figure 2 shows two ways of re-using fuzzy output partition for the input. After inference with implicative rules, a numerical desirability level is obtained by defuzzification in order to be used in the emotion's evaluation. However, it is possible to keep the fuzziness of the output if we want to use the desirability of the event in an other system of fuzzy rules for the decision process. The defuzzification is necessary just because of the computation of emotion.

The three modules will be detailed in the following sections.

Illustrative example

We illustrate our model with a microscopic traffic simulation example. Simulation has proved to be useful in a number of areas related to traffic management: understanding the traffic system, predicting the future state of a network according to past and current data, and a priori assessment of modifications of either infrastructure or in-car improvements such as Intelligent Transportation Systems.

Microscopic simulation models are generally based on the seminal work from Gipps [20]. It proposes a car-following equation, to which was later added a lane-changing algorithm [21]. Although they keep track of each vehicle, these models are not agent-based in the sense that the vehicles are not autonomous but purely reactive entities in a centralized system. A comprehensive review of car following models is found in [22].

Some works have tried to introduce real decision processes in traffic simulation, see *e.g.* [23]. Some of them use fuzzy logic. In [24], the whole behaviour model is driven by fuzzy logic rules to overcome the normativity of classic modeling. However, there is no decision process *per se*, since it is replaced by the set of fuzzy rules. Peeta *et al.* [25] propose a fuzzy logic based approach to determine the en-route time-dependent non-truck driver discomfort level. This discomfort level is then used to modify the behaviour of the car drivers. Our modeling adds several features, such as emotion computation and subjective perception.

In the following, we illustrate the steps and calculations of our model with a *driver* agent example. An agent represents a couple Vehicle/Driver and its goal is related to a trip from an origin to a destination. The agents travel on a network, and have three levels of decision: strategic (planning), tactical (acceleration, lane choice) and operational (psychomotor). In this paper, we study the perception part of the tactical level. The starting situation of our scenario is the following: A *driver* agent is travelling to its work (figure 3). Its goal is to arrive on time, but the highway is congested. It has two choices: trying to get out of the highway at the next exit, or staying in its queue. Furthermore, it has the possibility to use the emergency lane to get to the exit more speedily. We show in the next sections how fuzzy rules help to model and compute its perception and decision process.

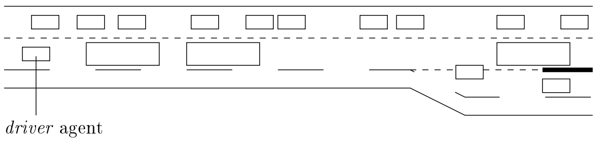

Figure 3: Traffic simulation: initial situation

4. Fuzzy Conjunctive Rules for Events Perception

To know if an event occurs, we use the percepts of the agents. Each event is deduced from several facts perceived by the agent. The output on figure 4 represents the occurrence possibility for each event.

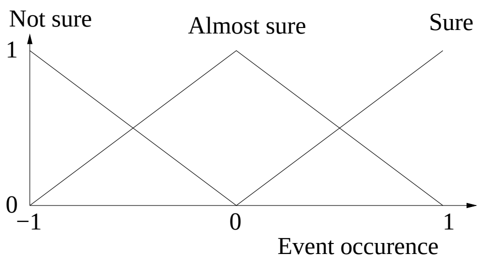

Figure 4: Fuzzy sets for event occurrence

The computation of events is based on observed facts. In this case, the data used (perception of the agent) is typically assimilated to observed examples and must therefore be represented by conjunctive rules [26].

Conjunctive rules are often expressed as:

- If X is A_1 then Z is O_1
- If X is A_2 then Z is O_2
- ...

If we consider the real meaning of these rules (conjunction of inputs with an output), we should rewrite these rules without the notion of inference *if-then* (implication):

- When X is A_1, Z is O_1 is observed
- When X is A_2, Z is O_2 is observed
- ...

With conjunctive rules, the output O' is given by:

$$O' = A' o \bigcup_{k=1}^{n} (A_k \wedge O_k) \tag{1}$$

with $\bigcup$ the union, $\wedge$ the conjunction and o the $sup - \top$ composition. The t-norm $\top$ determines the implication. $\top$ is a triangular norm [27].

For example, minimum and product constitute t-norms.

We want to use fuzzy rules to compute the desirability according to events. In this context, events are evaluated in function of the facts perceived by the agent. The percepts of the agent are indications of facts of higher level, *e.g.* in our scenario, each vehicle perceived (its type, car or truck, and its current speed) is an indication of whether the agent will be able to travel the current network section at a normal pace or not.

The evaluation of event occurrence is done by rules that take into account the importance of each fact F_i for any event E:

- When fact F_1 is $Important$ and fact F_2 is $NotImportant$ and ..., event E occurs.
- When fact F_1 is $Important$ and fact F_2 is $Important$ and ..., event E does not occur.
- ...

These rules must be seen as a mapping of events with facts. From several facts, we can deduce a particular event. Occurrence evaluation of events is evaluated by an occurrence's value between -1 and 1. At -1, the agent evaluates that the event did not occur, and at 1 that the event has occurred . Between these values the event occurrence possibility increases.

Even when the rules are shared by all the agents, the occurrence perception of an event is different for each agent, since it depends on the perceived facts of each agent; it is deduced from their field of vision and hence from their set of percepts.

Illustrative example

The instantaneous perception of a driver modifies its short-term plans, the tactical level. The perception takes into account its direct vision and mirrors. In this article, we do not separate the different types of signals it may perceive (vision and sound).

In the driver scenario, the rule to compute the "travel time delayed" event, which means that the agent will not pass its current section without being delayed, is based on three criteria:

- Mean speed of the vehicles. Under 70% of the target speed of the vehicle[2], it is considered as low, and over 95% it is considered as normal.
- Number of vehicles in the perception area. It is well known that over a threshold, the speed in function of the number of vehicles drops quickly (see *e.g.* [20]). Hence, under this threshold, which depends on the number of lanes and capacity of the section, the number of vehicles is considered as low, and over it is considered as important. We have fixed the values at respectively 30 and 60.
- Percentage of trucks. Under 0.05, it is considered as low, over 0.2, it is high.

Fuzzy sets are given in figure 5 for the average speed perception, figure 6 for the number of vehicles and figures 7 for the percentage of trucks.

[2]The target speed is a driver parameter, which depends on the legal speed limit and represents the speed the agent would attain if there were no other vehicle on the road.

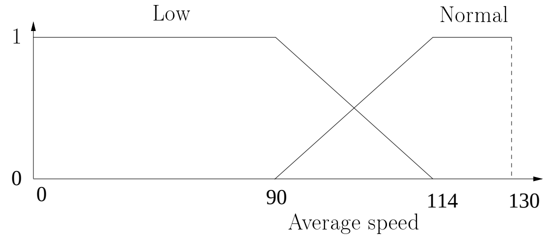

Figure 5: Fuzzy sets for average speed, with 120km/h being the target speed.

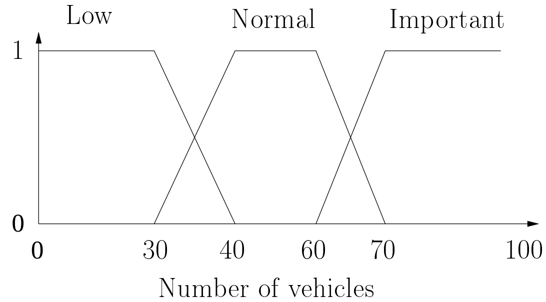

Figure 6: Fuzzy sets for the number of vehicles.

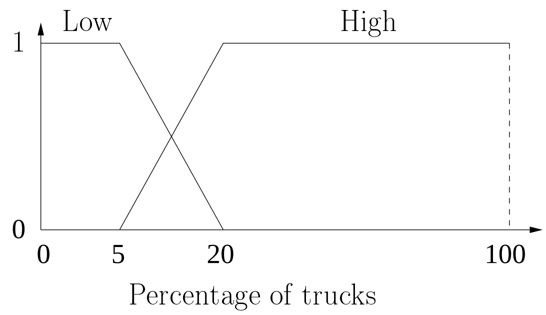

Figure 7: Fuzzy sets for trucks percentage.

For the event "travel time delayed", we use the rule set described in table 1. Some explanations can be given on these fuzzy rules. Each of the three parameters considered independently does not lead to a high travel time. The parameter "number of vehicles" is objective, but the average speed and the percentage of trucks may be impacted by the first: an agent situated in a dense vehicle flow tends to perceive a lower average speed; and trucks act as distracters. Furthermore, if the vehicles travel slowly, they may not easily be overtaken, hence creating bottlenecks.

	When Average speed	and Number of vehicle	and Truck percentage	Then Occurrence of event is
1	normal			not sure
2	low	normal		quite sure
3	low	important	low	quite sure
4	low	important	high	sure
5	low	low	low	not sure
6	low	low	high	quite sure

Table 1: Fuzzy rules for occurrence computation

Some explications can be given on these 6 rules. The most important parameter is the average speed. If the average speed is normal, the event does not occur. If the average speed is low, we consider the number of vehicles and then the truck percentage. The more important the number of vehicle, and the higher the truck percentage, the more likely the event "travel time delayed".

5. Fuzzy Implicative Rules for Desirability

If an event occurs according to the output inferred by fuzzy rules, we compute for each agent the desirability of the event considering the impact of this event and the importance of the goal(s) linked with this event.

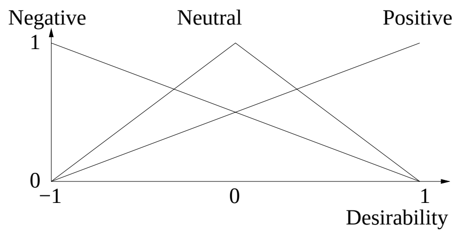

Figure 8: Fuzzy sets for event's desirability

We use fuzzy implicative rules to compute the desirability of events. As we represent the cognitive process of each agent, we choose to use implicative rules because cognitive knowledge can be compared to a formal model, since formal models are restrictions of possible worlds. Indeed, cognitive knowledge is not a mapping between input and output, it links directly the personal knowledge of each agent to the environment. Each knowledge must then be seen as a restriction of possible worlds. The use of fuzzy implicative rules is more appropriate considering the output partition of figure 8 as shown in [28].

Fuzzy implicative rules in one dimension can be expressed as:

- If X is A_1 then Z is O_1
- If X is A_2 then Z is O_2
- ...

With implicative rules, the output O' is given by:

$$O' = A' o \bigcap_{k=1}^{n} (A_k \rightarrow O_k) \qquad (2)$$

Conjunction and implication operators cannot be chosen independently.

In the presence of an approximate fact A' and the implication $A \rightarrow O$, we are able to calculate O' defined by:

$$\mu_{O'}(v) = \sup_{u \in U} \mu_{A'}(u) \top (\mu_A(u) \rightarrow \mu_O(w)) \qquad (3)$$

where $\mu_A(x)$ is the membership function of fuzzy set A. A membership function defines on each point of the universe the membership value of u to the fuzzy set A. The compositional rule of inference $(sup - \top)$ is often denoted as o.

As explained before, we use fuzzy rules to compute the desirability according to events through a formal model. As in FLAME model [16], we base the desirability of event on their impacts on agent's goals and on the goal's importance for the considered agent. However, we use fuzzy implicative rules because we intend to model the cognitive models of agents. Hence, the form of the fuzzy rules is:

If $Event\_Occurence(E)$ is A_1,

and $Impact(G_1, E)$ is B_1, and $Impact(G_2, E)$ is B_2, and ...,

and $Importance(G_1)$ is C_1, and $Importance(G_2)$ is C_2, and ...,

then $Desirability(E)$ is O

where the G_l are the goals, A_i, B_j, C_k and O fuzzy sets.

Illustrative example

Once an event is evaluated, we use the rules of table 2. If the event is not sure and if the event has no impact on the event, it is considered neutral for the desirability of this event. If the event is sure it has a direct influence on the Desirability. If the event is quite sure, it depends on the importance of the event.

	If Event Occurence	and Impact (Event)	and Importance (Event)	Then Desirability (Event) is
1	Not Sure			Neutral
2		No Impact		Neutral
3	Quite Sure	Negative	Important	Negative
4	Quite Sure	Negative	Not Important	Neutral
5	Quite Sure	Positive	Important	Positive
6	Quite Sure	Positive	Not Important	Neutral
7	Sure	Negative		Negative
8	Sure	Positive		Positive

Table 2: Fuzzy rules for desirability evaluation

For instance, in our scenario, the event "travel time delayed" impacts the goal "be on schedule". Hence, the following rule is relevant:

If $Event\_Occurence(traveltimedelayed) is sure$

and $Impact(beonschedule, traveltimedelayed)$ is $Negative$

and $Importance(beonschedule)$ is $Important$

Then $Desirability(traveltimedelayed)$ is $Negative$.

If the agent has other goals (*e.g.* "drive cautiously"), but these goals are not impacted by the event, then the rule will be:

If $Impact(drivecautiously, traveltimedelayed)$ is $NoImpact$,

then $Desirability(traveltimedelayed)$ is $Neutral$

Based on that kind of rules, the desirability of each event can be computed. Once the level of desirability is given for each event, we compute a global desirability for each goal linked to these events.

6. Emotions computation

OCC model [10] is our base for the computation of emotion. We use the desirability of event to compute emotions. In OCC's model, emotions are based on the notion of desirable or undesirable event as described in table 3. Two notions are important to compute emotions: the desirability of an event and its occurrence. Desirable events lead to joy, hope, satisfaction or disappointment. Undesirable ones lead to distress, fear, fear-confirmation or relief. The emotion depends of the occurrence (or non-occurrence) of desirable (or undesirable) events.

Emotion	Rule
Joy	Occurrence of a desirable event
Distress	Occurrence of an undesirable event
Hope	Waiting for a desirable event
Fear	Waiting for an undesirable event
Satisfaction	In hope state: desirable event occurs
Fear-confirmation	In fear state: undesirable event occurs
Disappointment	In hope state: desirable event does not occur
Relief	In fear state: undesirable event does not occur

Table 3: Emotion according OCC model

Table 4 summarizes the practical computation of 8 basic emotions. The likelihood is based on the probability of each event to happen and can be different for each agent according to its personality. In our simulation, we decide to compute likelihood for each agent. The more an event happens, the more likely it is to happen again. At the beginning of the simulation, the likelihood of an event is 0 and the more this event occurs and is perceived by an agent, the more this likelihood increases. The maximal likelihood is 1.

Emotion	Formula for calculation
Joy	If $Des(e) > 0$ then $E_{joy} = Des(e)$
Distress	If $Des(e) < 0$ then $E_{distress} = \lvert Des(e) \rvert$
Hope	If $Des(e) > 0$ then $E_{hope} = Des(e) * likelihood(e)$
Fear	If $Des(e) < 0$ then $E_{fear} = \lvert Des(e) * likelihood(e) \rvert$
Satisfaction	If E_{hope} & $occurs(e)$ then $E_{satisfaction} = E_{hope}$
Fear-confirmation	If E_{fear} & $occurs(e)$ then $E_{fear-confirmation} = E_{fear}$
Disappointment	If E_{hope} & $not\_occurs(e)$ then $E_{disappointment} = E_{hope}$
Relief	If E_{fear} & $not\_occurs(e)$ then $E_{relief} = E_{fear}$

Table 4: Calculation of emotions

Illustrative example

In the *driver* scenario, let us assume that the agent has perceived the event "travel time delayed" as sure. Since its main goal is to be on schedule, and considering the impact the event has on this goal, the desirability of the event is negative. Hence, the emotions of the agent are:

- Distress = desirability ("travel time delayed")
- Fear = desirability ("travel time delayed") * likelihood("travel time delayed")

Although the management of stress is not in the scope of this article, we can give some explanation on its calculation. Stress is the nervous tension and a consequence of general adaptation. It is influenced [3] by temporal pressure, tiredness, positive or negative events and actions success / failure. Hence, in our example, the stress of the agent is increased if undesirable events occur.

We have seen that the agent can change the lane on which it drives. Since the situation is also congested on the left lane, its two options are (i) staying in queue and (ii) use the emergency lane to exit the highway. The agent feels distress and fear not to be on schedule, and the alternative plan (ii) is the only way not to be late. Hence, the agent chooses to use the emergency lane.

However, after choosing an intention, the agent updates one more time its emotions. Here, the desirability of using the emergency lane is high, since it has a positive impact on the goal "be on schedule". However, when the agent updates its emotions, two emotions are added: hope, which is valued as desirability ("emergency lane use"), and shame. Shame happens for an action done by the agent which is disapproved by standards. Depending on its personality characteristics, the agent will either reconsider its action choice (case of a normative agent), or keep it.

7. Conclusion

The simulation of human behavior, in particular in complex driving situations, needs to consider emotions in order to obtain plausible behavior. The interest of cognitive models with fuzzy computations is that the behaviors and chains of actions are explainable.

For these reasons, we proposed three modules. Our model presents a perception module, a desirability module and an emotion module based on two kind of fuzzy rules in order to model two different kinds of information. The main originality of this work is to evaluate the occurrence of events through an example-based modeling via conjunctive rules, and the desirability of these events through model-based modeling via implicative rules. Then, based on these calculations and the OCC model, we are able to compute emotions in a FLAME-like fashion. This allows a more flexible way of modeling each step of the perception and decision process.

This work can be improved in several directions:

- Cognitive abilities differences. In the actual version of our work, each agent has the same set of rules. In order to obtain more diversity in the simulated behaviors, it would be interesting to consider different sets of rules according to the particular agent's characteristics (age, personality, . . .).
- Perceptions. Event's perception is based on fuzzy rules. We need to build several sets of rules in order to perceive many events of driving situations (accidents, breakdowns, police, . . .) or of more general situations.
- Emotions and desirability. It will be interesting to consider more complex emotions (reproach/trust, . . .) that need to take into account the actions of others agents/vehicles. We want to study conflict in emotions in the case of triggering contrary emotions.
  In a complex scene many events can happen in the same time. Then it is important to make choices about each event according to their importance for the agents. For example, some events can be ignored if they are not really important considering the agent's intentions. Furthermore, the agents generally have a limited cognitive load.

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