IADIS International Journal on Computer Science and Information Systems
Vol. 4, No. 3, pp. 66-81
ISSN: 1646-3692

CONCEPTION OF MULTI AGENT SYSTEM INTEGRATING NATURALISTIC DECISION ROLES: APPLICATION TO MARITIME TRAFFIC

Thierry Le Pors. *Naval academy, Naval Academy Research Institute, Lanvéoc Poulmic, BP 600, 29 240 Brest armées, France. phone: + 33 (0)2 98 23 40 21. Fax: + 33 (0)2 98 23 38 57.*
University of South Brittany – CRPCC/LESTIC – Centre de recherche, rue de Saint-Maudé. 56321 Lorient Cedex, France.
lepors@ecole-navale.fr

Thomas Devogele. *Naval academy, Naval Academy Research Institute, Lanvéoc Poulmic, BP 600, 29 240 Brest armées, France. phone: + 33 (0)2 98 23 40 21. Fax: + 33 (0)2 98 23 38 57.*
thomas.devogele@ecole-navale.fr

Christine Chauvin. *University of South Brittany – CRPCC/LESTIC – Centre de recherche, rue de Saint-Maudé. 56321 Lorient Cedex, France. phone : (33) 0297874521. Fax : (33) 0297874500.*
christine.chauvin@univ-ubs.fr

ABSTRACT

This paper focuses on simulating naturalistic decision making of experts in complex situations. The cognitive model described here is integrated into a multi-agent system. It integrates theories of Natural Decision Making with the purpose of producing realistic simulated decision. This model uses fuzzy representations for the identification of different elements of a situation, and pattern matching between the current situation and a set of typical known situations. We propose a conception methodology to build Decision Roles Based on Patterns (DRBP). Then, to validate this model, we choose to apply it to maritime traffic. Maritime traffic simulation requires elaborated cognitive features: the collision regulations require interpretation and rely to a certain extent on anticipation of the actions of the other ship.

KEYWORDS

Agent – Naturalistic Decision Process – Roles – Maritime traffic

1. INTRODUCTION

Computer simulations of human decision based on regulations are common in traffic and social simulations (Doniec et al 2006, Best & Lebiere 2006, Fournier et al 2003). Different possibilities where studied to model them, like case based reasoning and learning through existent data, ascribed as the connectionist approach to cognition. Problems with these simulations appear when dealing with domain experts: in a situation, an expert does use specific mental representations of situations and have a good understanding of the rules. Experts anticipate the others' actions and they produce variant decisions, based on their expertise of a situation. The purpose of this article is to build a realistic simulation of maritime traffic and to reproduce efficient decisions into training simulators.

In TRANS (Fournier et al 2003), a multi-agent simulation of maritime traffic, decisions are based onto spatiotemporal rules. Rules are defined among roles, organised into groups and spatial groups. In Agent-Group-Roles (AGR) systems, individual behaviours are defined among the roles of an agent. Each role played by the agent is a part of its global behaviour. Those used for decision making can be identified the way agents are: cognitive or reactive. For the purpose of this article, we will talk of two kinds: decision roles based on rules (DRBR) and decision roles based on patterns (DRBP). TRANS decision is based on rules, that is to say decision on measurements. DRBP use experts' knowledge to produce a decision. In Naturalistic Decision Making (NDM), experts use mental representation of situations and try to associate them to known situations to produce a decision, the way case-based reasoning does (Aamodt & Plaza, 1994), that is to say decision on mental representation. Mental representations do not use direct measurements, but representations of measurements: semantic values (Zadeh, 1999). We believe that DRBP will have a better realism, in terms of decision, considering we can build a base of patterns related to experts' knowledge, and considering the data they choose to explain their decisions. Therefore our objective is here to propose agents with more cognitive features to take into account collision avoidance, as experts do, in TRANS.

Maritime traffic is an open and heterogeneous system in which many different objects interact. Collision avoidance in this environment requires a high expertise of the different situations and the different types of ships that can be encountered. It requires also anticipation of the actions of the other ship.

Of course, collision regulations (International Maritime Organization 1972) allow the watch officers to identify which ship has to manoeuvre. For example, in a crossing situation, the rule 15 settles that the ship coming from starboard has to avoid the ship coming from port. This works as priority rules for cars except that no boundaries are specified (it is an open environment). Furthermore, actions are also described for the ship coming from port: if the other ship does not move early, this ship must avoid the other one. Respect of the rules happens, in reality, about 4 times out of 5: this demonstrates that other parameters are taken into account for the decision.

Therefore, building a model of maritime traffic requires analyzing experts' behaviours and translating it in informal rules. We choose to base our work on (Chauvin & Lardjane 2008) studies on collision avoidance between merchant vessels and car ferries in the Dover Straits in Europe: 400 merchant vessels pass through this region each day and this East-West traffic is crossed by the North-South traffic of 70 car ferries linking the Continent to England. Our simulator, CogTRANS, applied to maritime traffic, was built by extracting data from two inputs: observations of collision avoidance between merchant ships and car ferries from radar on ground, and then comparing these data to verbalizations of watch officers during these collision avoidance situations. Data collected consist of 62 collision avoidance situations.

This article focuses on the implementation of a naturalistic decision making system in roles in a maritime context. First of all, we present a brief state of the art of multi-agent and decision making systems. Then, section 3 presents a generic conception methodology for DRBP models. The CogTRANS simulation on collision avoidance is then detailed in section 4. The last section shows results of simulations on a case study. Some prospects are debated in conclusion.

2. STATE OF THE ART

The decision making process of an agent is composed of a simple loop perception-decision-action. The different steps of this loop may still be more complex, using learning or complex memory systems if trying to model human decision making process. Furthermore, studies in psychology and cognitive sciences propose models of human decision making that have successfully been implemented in agent systems. Natural Decision Making (NDM) has been used in different computational models of decision making (R-Cast Agents (Fan, 2006), BDI (Norling et al. 2000)), due to its modularity and its good interconnection with agent decision making loop.

NDM framework describes how people make decisions and perform cognitive functions in complex situations. The two following models are integrated into NDM theory. Klein (1997) proposes the Recognition Primed Decision (RPD) model to explain how people make quick and effective decisions in complex situations. This one is composed of three steps: matching a situation to a known one, following the course of action and, if no situation matches to the current situation, mentally simulate a course of action. In cognitive demanding situations, experts' decision consists of a simple pattern matching. Endsley's model of Situational Awareness (SA) was mostly used on research on aircraft pilots (Endsley 1997): situational awareness describes how people construct a mental representation of a situation and how it is used to make decisions. Identifying a situation is composed of three levels: 1/direct perception of relevant elements of a situation; 2/comprehension of the different elements perceived; 3/projection in the future.

Norling et al (2000) identify 3 approaches for realizing RPD agents. The first one is considering agents are experts and know every situation: this approach is very close to case-based reasoning. They suppose a case correspond to only a situation and should provoke a single reaction. The other two approaches consider into reinforcement learning for known plans and context learning, thus implicate more known situations by an agent. A common mistake in case based reasoning is considering the system better and better as it learns new cases, offering better decisions to the situations it encounters. So we choose to use the first approach presented by Norling et al (2000), but instead of building a complete base of cases, we choose to use patterns taken from watch officers' verbalizations.

Cognitive architectures like Soar (Newell 1990) and ACT-R (Anderson 1996) are used to model human cognitive processes. ACT-R has already been applied to NDM paradigm (Byrne & Kirlik 2005), and also to model cognitive agents in multi-agent simulations (Best & Lebiere 2006). These architectures study human cognition in a microscopic view. ACT-R is a modular architecture where each module reproduces a process of human cognition. Models using ACT-R are very accurate, but have a certain cost in CPU performance if simulating many agents. In the framework of experts' reasoning, these processes can be simplified to allow a simulation of a huge number of agents. Our model is inspired by ACT-R decision making system and integrates RPD and SA paradigms; it uses a pattern matching system close to ACT-R system.

Finally, we choose to make the DRBP model using qualitative data for mental representation. Car ferry watch officers share the same conceptualization for the situations they encounter, but a "semantic value" may be different from an individual to another (10 Nm may be "very far" for one, and "far" for the other). To emulate those differences, we applied fuzzy sets in the decision process to represent those values.

3. THE DRBP MODEL: A CONCEPTION METHODOLOGY USING EXPERT KNOWLEDGE

Here is presented the BRBP model, a generic decision model. It has been implemented in CogTRANS, a simulation platform of maritime traffic, based on TRANS (Fournier et al, 2003). This section presents first how is built such a decision model; next section will focus on its implementation in CogTRANS for the simulation of maritime traffic.

Figure 1 shows a simplified diagram of the DRBP and how it is linked to the simulation: this role gets data from simulation and produces an action that will be translated in quantitative data by another role.

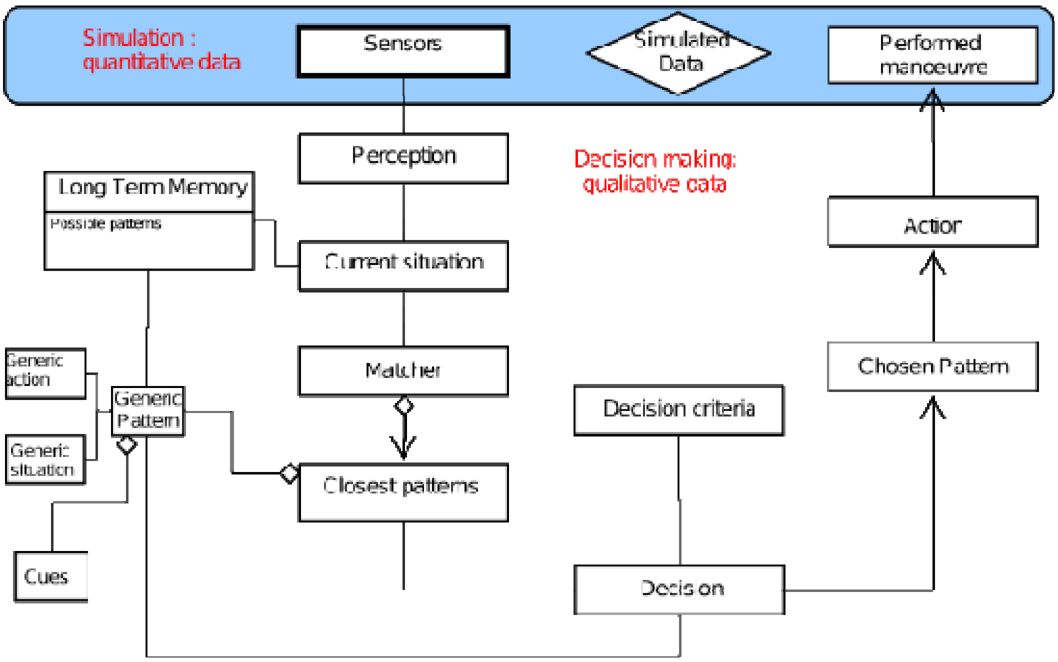


Figure 1. cognitive role of collision avoidance.

This decision model is based on four principal steps:

- Perception of the environment: a mental representation (composed of semantic values) is built matching data from the simulation using fuzzy sets. A mental representation of a situation is defined by several cues. Each cue is also represented with a semantic value, used in the second step.
- Matching the current situation to a set of known situations: those situations are matched using semantic distances between the different semantic values.
- Decision on criteria: this step is used to represent different agent profile, and different decisions, using a same set of known situation patterns.
- Action: the decision of action is traduced in an action in quantitative data.

The data structures used in DRBP are presented in our conception methodology. Figure 2 presents the different steps needed to build this decision model of the DRBP. Two kinds of data are needed for this model: data collected among experts, through meetings and compilation of their verbalizations, and statistical data about their expertise domain. This diagram is composed of four parts. First part, as said before, is the data recovery represented in yellow. The three others parts are built modules and represented in blue in the diagram. Those are composed of mental structures creation, procedural knowledge creation and decision modules creation.

Mental representations of the experts are deduced through the verbalizations they give when they perform actions related to their expertise or during meetings after the situation. Studying those verbalizations allows underlining common verbalizations used in given situations. The different elements used in our model to the conception of the role are: critical cues (which element of its environment makes he/she choose an action?), possible action decisions (what can be done in the given situation?), and then the decision criteria (which sub-goal is reached with a given decision?). This section presents the methodology of implementation of a NDM role in three steps: building expert knowledge, then their procedural memory and the different sub-modules used in DRBP (perception, matching, decision on criteria and action).

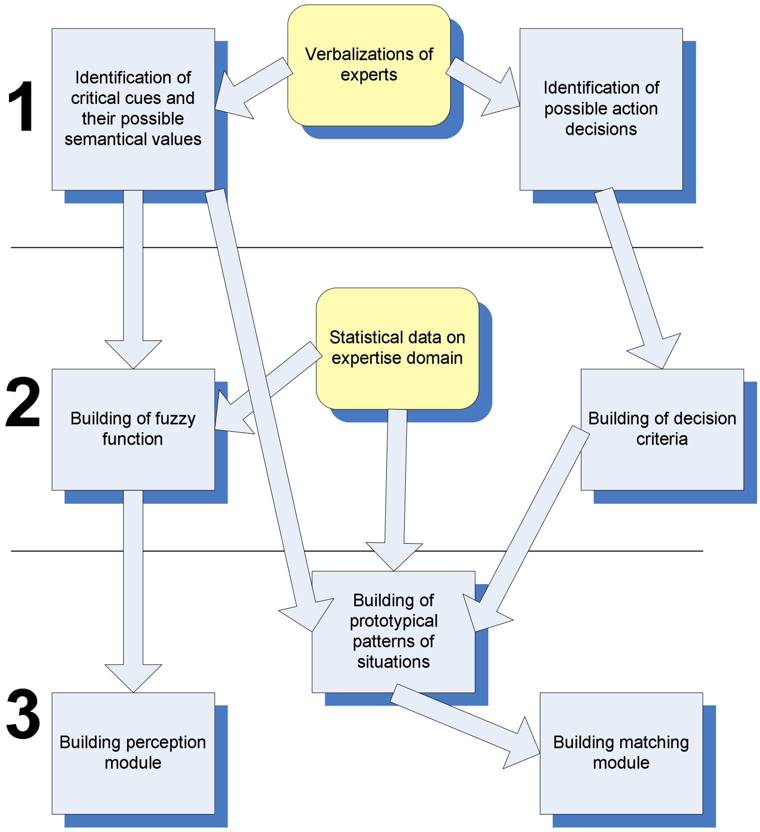


Figure 2. the DRBP conception methodology.

3.1 Identification of Representations used by Experts

As shown on the diagram, the different critical cues used by experts that must be reproduced in simulation must be identified first. Those cues are elements used by experts to identify a given situation. In DRBP model, linguistics variables are used to describe a critical cue each possible value of a linguistic variable is called a semantic value. Experts often only precise those semantic values: linguistics variables are defined afterwards through meeting. As each role created represents a goal, each role is associated to a set of n variables as shown on figure 3.

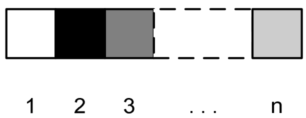


Figure 3. List of n critical cues.

Each critical cue is associated to a linguistic variable, each variable is associated to a string matching the verbalization of the expert, and each string is associated to a value between 0 and 1. Different elements in a situation may be represented by a single critical cue used by an expert. A critical cue may be of two kinds: a true/false (or unknown) value or a scalable cue. True and false values are associated to 1 and 0 and scalable properties are distributed on the [0;1] interval (represented by the grey scale on figure 3).

Then action decisions are built on the same way and are associated on semantic values. The DRBP returns an action decision linked to its goal. One or more roles are built to transform this action decision in an action. It should be noticed that situations where experts thinks that no action should be performed, should to be implemented in this model. Depending on the field of expertise, “No action” can be identified as a real action. Or it can be in fact hiding another action (“I am waiting for him to move first”).

The cues and their semantic values presented here will be used to build the different situation patterns shown in next section.

3.2 Building Internal Tools of the DRBP.

Decision criteria are a not related to Naturalistic Decision Making: they are a tool used to build different agent profiles using the same set of known situation patterns. Though, they should be obtained the same way cues are: through experts’ verbalizations, it can be understood as a sub goal of the decision (respecting the rules, making a secure action, doing it fast, and so on).

Those criteria add sense to a given situation: two decisions may have the same cues and the same action decision but can be considered in a different way using the meaning of the criteria. The same decision can be made for two different reasons.

As semantic distance are, decision criteria are normalized, but on the [-1,1] interval. This represents the fact that some criteria may have a positive or a negative impact on the choice of a decision.

Then we are able to build patterns of situation: those are composed of a list of n semantic values (each one related to a linguistic variable) linked to an action decision (from a list of m action decisions) and criteria values. Figure 4 presents the list of semantic values (the grey scale represent different values from 0 to 1) and a list of action decisions. Only one action decision is selected (represented on the figure: only one box is blackened).

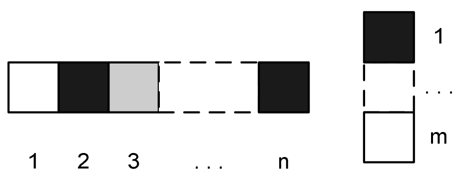


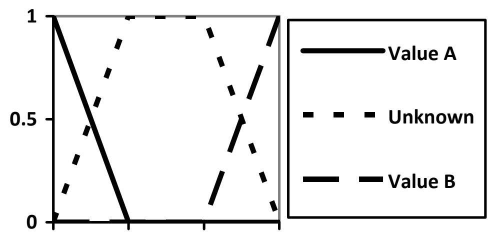
Figure 4. A list of semantic values is linked to only one action decision.

Finally, fuzzy sets (Zadeh, 1965) must be built. Each set represents a linguistic variable and is used to translate quantitative information from the simulation (distances, speeds, sizes) in semantic values. Those allow building a mental representation of the current situation.

Those fuzzy sets are adapted from (Yager, 2007): the different critical values identified, in statistical studies, as the different limits of the semantic values are used to build the significant points of their associated fuzzy sets. Then for each point of the X-axis, sum of the Y-axis equals 1.

Two methods may be used to build those fuzzy sets:

- Experts do not define all the values of an interval ("less than 1.5 meters is small", "more than 1.9 is tall"): these values are completed by unknown values, inspired from (Shafer, 1976), as shown on the left diagram in figure 5.
- Experts define the whole possible values in an interval: each possible quantitative value making sense. Unknown values may still be used in semantic values limits to represent the difficulty for the expert to understand a situation with limit values (as shown on figure 5, right).



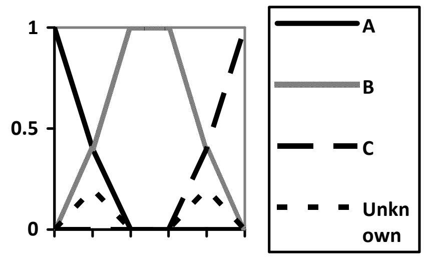


Figure 5. Use of the unknown value in fuzzy sets.

Though the unknown value allows the system to take into account incomplete situations, and imprecision of the semantic values

It should also be noticed that the choice to distinguish semantic values from the fuzzy sets used for perception is based on the characteristics of the critical cues: critical cues may be composed of different quantitative information, so more than one fuzzy set may be related to a single cue.

We now need to build the different modules of the DRBP model.

3.3 Building the DRBP Sub Modules

First, the pattern base must be built: it is a collection of all known prototypical situations. Problems when building this pattern base may occur when compiling data. This step is necessary to remove redundant data and to be sure that the pattern base is coherent.

Removal of redundant patterns is done by compiling decision criteria for identical situations (same semantic values for the cues, and same action decision). Second step is a compilation of action decisions for patterns with same semantic values and same decision criteria (as shown on figure 6). Patterns must be compiled only if experts consider there only one situation. It is important not to lose meaning in the pattern base; some choices probabilities may be altered doing so.

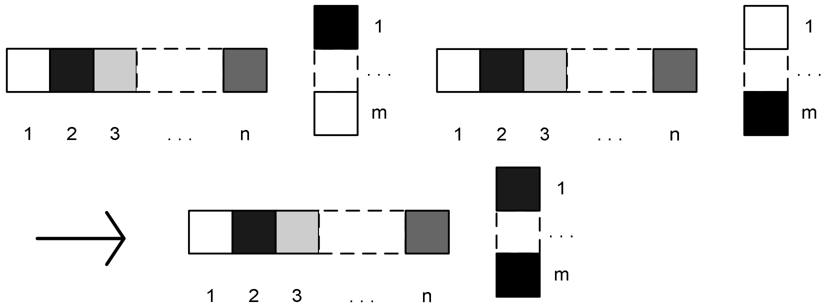


Figure 6. Compilation of redundant patterns.

Then, the perception module uses the different fuzzy sets to build the mental representation. This module should traduce how different pieces of information are sent to the agent and how efficient are their perceptions: the accuracy of the different sensors of the agent must be integrated here (eyes and radar should have different precision to determine the position of an object and its kind). This module is associated to a *sensor* parameter specifying which kind of data is possible to identify, and a perception function giving its accuracy for this kind of data and modifying it if there is any interference from the environment (visibility, weather and so on). When the mental representation of the current situation is built, it is sent to the pattern-matcher.

This pattern-matching module compares semantic values of the mental representation of the current situation and those contained in the different patterns of prototypical situations to determine which the closest patterns of the current situation are (as shown on figure 7). Typically it consists of a sum of each semantic distance for each linguistic variable. If a threshold is not reached, the pattern is selected as a close pattern.

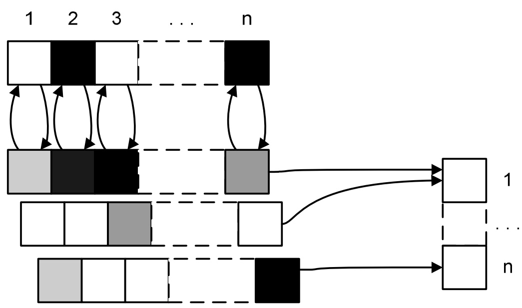


Figure 7. The pattern matching consists of a computation of semantic distances.

Other rules may be applied in this module to represent experts' specific knowledge of their expertise domain: specific rules on combination of semantic values may alter the threshold to be reached. This represents the fact that some specific combination of cues might be identified by experts as a situation to be avoided or favored (Herbig, 2009).

The algorithm of pattern-matching and the threshold may change, depending of the field of expertise to be simulated. Some of these fields must consider only situations where each cues are matched, in other ones, a decision might be made ignoring one or more decisions.

Finally, the closest patterns are sent to the decision module. This module must be parameterized with a decision algorithm (single criterion decision, multi-criteria decision, weighing with semantic distance or not, random choice, best semantic distance choice). Depending of the requirements of the simulation, the different criteria used for the decision must be identified and each pattern must be weighed for each criterion.

The decision selected is then sent to the action module, this one translate the decision in parameters which are sent to an external role. This new role is linked to the agent physical part and traduces the parameters as an action in simulation. Next section presents an implementation of this model into TRANS.

4. MODELLING COLLISION AVOIDANCE

(Fournier et al, 2003), developed at naval academy, allows ships to interact following strict rules deducted from collision regulations. The decision making process is based also on geographical information: an antagonist ship in a zone around the ship, and in a collision route, will provoke a reaction. The interest of this model consists in its AGR model (Ferber and Gutknecht, 1998). This model is an organisational model of agents, indicating which agent belongs to which group and what their roles (following route, fishing…) are inside these groups. An agent may then play multiple roles depending on the groups it belongs. In TRANS, agents belong to geographical, fleet or type of ship groups. TRANS proposes a good organisational model of agents and a precise model of the maritime context. Collision avoidance can be simulated but it lacks realism. Our objective is to integrate NDM in collision avoidance role to propose agents with more cognitive features. Each type of ship shares the same collision avoidance roles. For TRANS, anti collision relies on a strict interpretation of the regulations. In CogTRANS, we chose to transform this DRBR a DRBP. Maritime experts' decision making is based on several patterns to define collision avoidance manoeuvre (Chauvin and Lardjane 2008). These patterns define the memory of the expert. Each pattern associates a generic manoeuvre (its semantic value) to a generic situation. Four generic manoeuvres can be performed by a ship: turn port, turn starboard, slow down and do nothing (as a lack of action of a ship has a meaning in the regulations). Then a situation is defined by several cues. Each cue is also represented with a semantic value. These cues and their values are based on verbalizations of watch officers. For example, they need to identify the type of ship they encounter: then the semantic value will be a symbol (small merchant vessel, big merchant vessel); for a distance it is a qualitative value as *close*, (less than 1 Nautical mile, i.e. 1852 meters), or *very far* (more than 5 Nm).

Along this article we will present different aspects of the model through the same example: a crossing situation between a give-way small merchant vessel and a stand-on car ferry. The car ferry goes at 19 knots and the merchant vessel at 14 knots. If none of them move, the car ferry will pass 0.3 Nm ahead the merchant vessel (considered being not sufficient for experts); figure 8 illustrates this example: two ships (the circles) are in a collision avoidance situation (the black lines represent their past trajectories.

Figure 8. Visualization of a collision avoidance situation in CogTRANS

Here are presented the different steps of the DRBP module and how they were adapted for the CogTRANS platform.

Sensors (radar, calculators linked to radars, or simply human vision) collect quantitative data from simulation. For example Time and Distance to the Closest Point of Approach (CPA) are calculated through positions and speeds, as the tools onboard ships calculate them.

The **perception module** regularly checks sensor data. It integrates data with the three levels of situational awareness. These allow constructing the current situation. This current situation is composed of the same cues as generic situations. As shown in last section, fuzzy sets (Zadeh, 1965) allow taking into account uncertainty of different kinds. Here, data from sensors are quite precise due to the different systems onboard ships. We use it to represent vagueness of the semantic values. We apply this theory to cues recognition, each cue being considered as a distinct attribute of a situation. Each cue has multiple semantic values plus one: the unknown. We use this value to define intermediate values that have no meaning for the pilot (if 12 knots is slow and 20 knots is fast, unknown value will have a peak at 16 knots).

Figure 9 is an example of fuzzy data applied to the cue *type of ship*. As the ships encountered by the car ferry may be large or small merchant ships, and as they act differently depending of the type of ship, we need to represent this cue. Types of ships are identified by their speed: a small merchant vessel is usually slow whereas big merchant vessels are fast.

Cues used for the simulations are:

- zone of ship presence: 1: zone of emergency (very close, less than 0.8 Nm), 2: stand-on ship action zone (close, around 1.5 Nm), 3: give-way ship action zone (around 3 Nm), 4: perception zone (more than 4 Nm)
- crossing position: crossing far astern (more than 0.7 Nm), crossing astern (around 0.4 Nm), collision (less than 0.2 Nm), crossing ahead (around 0.6 Nm), crossing far ahead (more than 1 Nm)
- type of ship: small merchant vessel (12 knots and less), big merchant vessel or car ferry (more than 18 knots)
- kind of situation: face to face, crossing, taking over

- Preference: give-way ship (me: if taking over and faster, if bearing between 22.5° and 157.5°), stand-on ship (me: if taking over and slower, if bearing between 202.5° and 337.5)

Other optional cues can be introduced in this model (speed differential, flag of the ship).

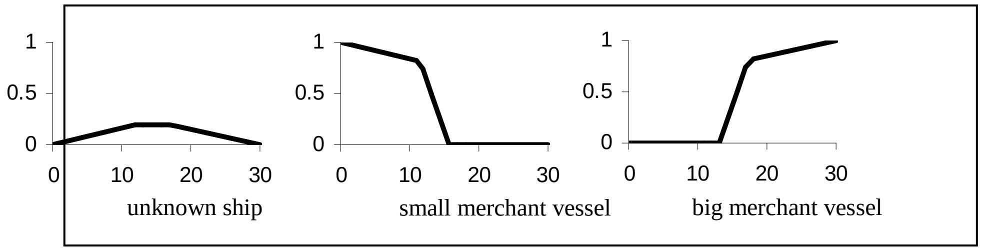


Figure 9. Example of belief functions associated to a type of ship. X-axis: speed in knots. Y-axis: probability of identification.

For our example, the merchant vessel as a good chance of being identified as a small merchant ship, but may be identified as an unknown ship. The crossing position has a good chance of being identified as “crossing ahead” and about 20% probability being identified as a collision situation.

The next step, **pattern matching,** consists of a comparison of cues of the current situation to the cues of each known pattern, associating each pair to a symbolic distance. The distances between cues are here given by a simple computation of single semantic distances between each semantic value of the current situation and its corresponding value in the different patterns. This module returns a list of closest patterns to the decision module, using a simple pattern matching algorithm: patterns with best weight W_j are selected for decision. nbC is the number of cues with a given value in a pattern. S_j is the cue of the current cue pattern and P_j the cue belonging to the pattern to be matched.

$$W_j = \frac{\sum_{j=0}^{j<nbC} \left| S_j - P_j \right|}{nbC}$$

Table 1 presents some patterns that may be matched with the example situation present before: as our example is a clear crossing situation, the cues that may be misunderstood are the position in CPA and the type of ship. Grey cells in this table represent semantic values included in the corresponding pattern. For example, line one represent a situation pattern for any kind of ship, at perception distance, my ship is the give-way ship, I’m passing ahead. I associate this pattern to the action “no manoeuvre”.

In our example, the pattern base is evaluated and may recognize, for example, the patterns 1, 2 and 5 may be recognized by the matcher (i.e. small merchant vessel, passing close ahead), depending of the current situation identified. So the different possible actions are manoeuvring port in case of identification of a crossing ahead situation and starboard in case of a collision situation.

Decision module is specifically designed to obtain different behaviours with a same set of close patterns. For maritime traffic, we build our patterns based on the observation on one type of ship. Criteria used by this module are here to allow different profiles of agents. Each agent should introduce its own criteria (respect of the regulations, security of the action and time saving, for maritime traffic). It should be noted that patterns are associated to criteria using fuzzy sets. Having identified a few patterns, the decision module will choose preferably those responding to the criteria, in the agent profile, using a simple weighting algorithm (wheel of fortune).

Table 1. Pattern base of an agent Car Ferry (illustration of the example situation)

Patte rn	Type of ship		Situat ion	Zone of ship presence				priority		Position in CPA			Action			
N°	Small	Big	Cross	1	2	3	4	G W	S A	Ahead	Astern	Col	No	Port	Starbd	Slow
1																
2																
3																
4																
5																
6																

In our example, we weighted criteria on the range [0-1]. Actions in zone 4 are not recommended or forbidden by the collision regulations: we give them a value of 0.5. Starboard manoeuvres get a weight of 1 for the security criterion and port manoeuvres get a weight of 1 for the time saving criterion. Depending of their profiles (respectful, cautious, in a hurry), weights are multiplied by a factor (2 for example): then in case of an agent in a hurry, it has more than half chances to make the port manoeuvre, choosing the pattern number 2.

When a manoeuvre is chosen by an agent, the **Action module** associates a new speed and a new bearing for the ship. The *avoidance manoeuvre* role is activated and gains priority upon the *following route* role. When the other ship is avoided, this role is de-activated and the ship can play its other roles (following route, fishing…).

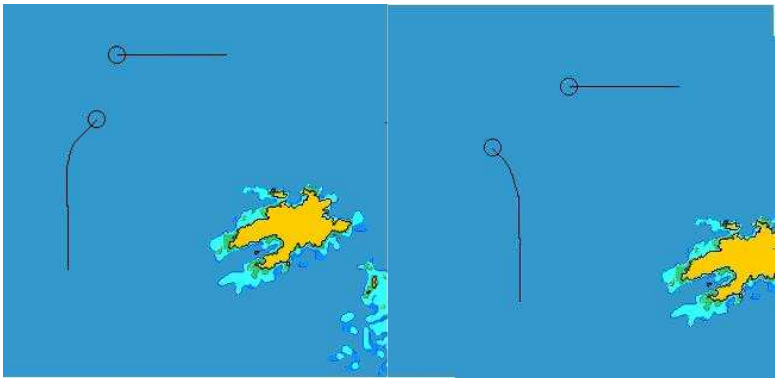


Figure 10. Collision avoidance with pattern 5 (left fig.) and 2 (right fig.)

In our example, if our ship chose pattern 2, the bearing of the ship will be modified in a large way (between 10° and 15°) for the action to be visible from the other ship, as shown on figure 10. The action module contains this “base of actions”.

5. CASE STUDY AND RESULTS

To validate our decision making role, we decide to apply it to a specific case of collision avoidance in maritime traffic, based on the collected data. We choose to simulate crossing situations between car ferries and any other type of merchant ships.

We observe that belief functions cause the simulation to be less deterministic: the pattern corresponding to the current situation is not always chosen.

Table 2. Data on collision avoidance, real and simulated. Matching column represents the correspondence between real and the equivalent simulated situation: i.e. 46% of left maneuvers in a real situation are reproduced in an equivalent simulated situation, (with same parameters of distances, angles and speed).

	Real data	Simulated data	Predicted actions
Stand-on avoids	11(18%)	9(15%)	6 of 11(55%)
Give-way avoids	51(82%)	53(85%)	48 of 51(94%)
Right manoeuvres	49(79%)	54(87%)	47 of 49(96%)
Left manoeuvres	13(21%)	8(13%)	6 of 13(46%)

The memory of the watch officer on board the car ferry is composed of about 20 patterns of typical situations for crossing situations. These are of two kinds: patterns reproducing strictly the regulations and patterns reproducing variant actions and anticipations. These last patterns use stereotypes about the actions of the small merchant ships ("they don't follow the rules", "they will keep their course and speed"…).

Simulations were performed using "respect of the regulations" profile for the agents and reproduced in simulation the 62 known cases. Table 2 presents our results in terms of prediction: as different solutions are sometimes possible, it is difficult to obtain a predictive simulation. However, our simulations reproduced starboard manoeuvres with a rate of 94% and predict which ship to move first with a rate of 87%. Problems appear for left manoeuvres as only about half of them are predicted. Even if the errors of manoeuvring ships are transferred in an error of manoeuvre, it seems there is a lack of data. In fact, an analysis of the unpredicted left manoeuvres shows for most of them an adaptation of the decision to other parameters of the traffic: geography (navigation lanes) and zones of global traffic ("trains" of ships, causing problems to cross them). The last problem comes from prediction of the ship avoiding: this manoeuvre is still difficult to predict as if the give-way ship does not act early, each ship as a good chance to choose to avoid the other (considering distances taken into account by the collision regulations).

The simulation seems to give satisfactory results but deserve to be completed with these identified parameters. Some other parameters were identified and may deserve a study too (position of the other ship on the navigation lane, nationality of the ship, special lightings on the ship).

6. CONCLUSION

The choice of using DRBP to model experts' decision making seems relevant as it gives satisfactory results in simulations. CogTRANS was tested with more than a hundred agents in a simulation on a personal computer: this is more than sufficient to simulate zones of high traffic density. We integrated this NDM model in an agent-group-role architecture, using fuzzy sets to represent vagueness of mental representation, pattern matching based on cues, decision on different criteria and traducing this data in quantitative data.

We will focus, in further works, on improving this simulation of traffic. Much needs to be done about the different types of ships and the different situations to be encountered. Simulating traffic close to the coast side and ports is also one of our objectives: we need to know how the watch officers build mental representations of complex structures such as the coast, navigation lanes and traffic zones, and how they consider it for collision avoidance: how does it interfere with their other decisions ? Our last results seem to underline the importance of this geographical data. Further works is planned to modify our NDM role based on patterns to take into account such data. A future trail is to study level 3 of Situation Awareness, to integrate in CogTRANS maybe using different roles, each one producing a decision about a different level of granularity of the situation (one for collision avoidance, another watching evolution of global traffic, and a last one taking into account fixed elements of the environment).

DRBP allows the agents to interact taking into account regulations but also informal rules and it allows flexible reactions from the agents. CogTRANS is then more predictive than the previous TRANS model (using DRBR), due the application of informal rules. Furthermore, DRBP add more realism in the simulation as the different actions (and mistakes) of the agent are clearly identifiable ("the agent identified a simple crossing situation", "the agent chose to act now because it misidentified the ship as a small cargo"…) which can be useful for training simulators.

We should now try to validate the choice of the DRBP model on other kind of simulations and other fields of expertise.

REFERENCES

Aamodt A, Plaza E.(1994) AICom - Artificial Intelligence Communications, IOS Press, Vol. 7: 1, pp. 39-59.

Amalberti, R, Deblon, F (1992): Cognitive Modelling of Fighter Aircraft Process Control: A Step Towards an Intelligent On-Board Assistance System. *In International Journal of Man-Machine Studies*, 36 (5) pp. 639-671

Anderson J (1996) ACT: A simple theory of complex cognition. American Psychologist, 51, pp. 355-365

Best B J, Lebiere, C. (2006). Cognitive agents interacting in real and virtual worlds. In proceedings of Cognition and Multi-Agent Interaction: From Cognitive Modeling to Social Simulation, Sun R. (ed.), Cambridge University Press; New York, NY, 186-218.

Byrne M D., Kirlik A. (2005). Using computational cognitive modeling to diagnose possible sources of aviation error. In proceedings of International Journal of Aviation Psychology, 15, 135-155.

Chauvin C., Lardjane S. (2008) Decision-making and strategies in an interaction situation: collision avoidance at sea. Transportation Research, part F, 11 (4), 259-269.

Doniec A., Mandiau R., Piechowiak S., Espié S. (2008). A behavioral multi-agent model for road traffic simulation. *Engineering Applications of Artificial Intelligence*, 21, 1443-1454.

Endsley M. R. (1997). The role of situation awareness in naturalistic decision making. In Zsambok, C. E. & G. Klein (eds.), Naturalistic decision making pp. 269-283

Fan X, Sun B, Sun S, McNeese M, Yen J (2006), RPD-Enabled Agents Teaming with Humans for Multi-Context Decision Making, In proceeding of AAMAS 34-41

Ferber J (1999) Multi-Agent Systems. An Introduction to Distributed Artificial Intelligence. Addison Wesley, London.

Ferber J, Gutknecht O. (1998). A meta-model for the analysis and design of organizations in mutli-agents systems. In Demazeau Y, editor, ICMAS'98, Paris, 128-135

Fournier S, Devogele T, Claramunt C, (2003) A role-based multi-agent model for concurrent navigation systems. In proceeding of 6^{th} AGILE Conf. on GIS, Gould, M. et al., pp. 623-632

Goralski R, Gold C (2008) Marine GIS : Progress in 3D Visualization for Dynamic GIS In Proceedings of 13^{th} Spatial Data Handling, Ruas A, Gold C. (eds) Springer, LNGC, 401-416

Herbig, B., and Glöckner, A. (2009) Experts and Decision Making: First Steps towards a Unifying Theory of Decision Making in Novices, Intermediates and Experts. MPI Collective Goods Preprint, No. 2009/2.

International Maritime Organization (1972) Convention on the International Regulations for Preventing Collisions at Sea

Klein, G. (1997) The recognition-primed decision (RPD) model: looking back, looking forward. In Naturalistic Decision Making, Zsambok C.E., G. Klein (eds.) 285-292.

Newell A (1990) Unified Theories of Cognition, Harvard University Press

Norling E, Sonenberg L, Rönnquist R (2001) Enhancing multi-agent based simulation with human-like decision making strategies, In Proceedings of the second international workshop on Multi-agent based simulation, 214-228,

Shafer, G (1976) A Mathematical Theory of Evidence, Princeton University Press

Wooldridge M J (2000), Reasoning about Rational Agents, Intelligent Robots and Autonomous Agents Series, Cambridge, MA: The MIT Press

Yager R. R. (2007) Learning from Imprecise Granular Data Using Trapezoidal Fuzzy Set Representations. SUM 2007: 244-254

Zadeh L.A. (1999) From Computing with Numbers to Computing with Words -- From Manipulation of Measurements to Manipulation of Perceptions, *IEEE Transactions on Circuits and Systems*, 45, 105-119

Zadeh, L.A. (1965). "Fuzzy sets". Information and Control 8 (3): 338-353.