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

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. 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 – Roles – Naturalistic Decision Making – Simulation – Maritime traffic

1. INTRODUCTION

Computer simulations of human decision based on regulations are common in traffic and social simulations (Doniec & al 2006, Best & Lebiere 2006). Different possibilities where studied to model them, using like case based reasoning and learning through existent data. 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 use variant decisions, based on their expertise of a situation. The purpose of this article is to build a realistic simulation of maritime traffic to reproduce efficient decisions in learning simulators.

In TRANS (Fournier & 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. Roles used for decision making can be identified the way agents are: intelligent or reactive. For the purpose of this article, we will talk of two kinds of roles: decision roles based on rules and decision roles based on patterns. TRANS decision is based on rules, that is to say decision on measurements. Roles based on patterns 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), that is to say decision on mental representation. Mental representations do not use direct measurements, but representations of measurements: words (Zadeh). We believe that roles based on pattern will have a better efficiency, considering we can build a base of patterns related to experts' knowledge and considering the same data.

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 kinds 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. In fact 100

percent of ships should avoid the other from behind. This happens about 4 times out of 5 and demonstrates that other parameters are taken into account for the decision.

Therefore, building a model of maritime traffic requires analysing experts' behaviours and translating it in informal rules. We choose to base our work on (Chauvin and Lardjane 2008) studies on collision avoidance between cargo ships 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 model: 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. The CogTRANS model is then detailed in section 3. This 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 model of Situational Awareness was mostly used on research on aircraft pilots (Endsley 1997). Situational awareness (SA) 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 & al 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. A common mistake in case based reasoning is considering the system better and better as it learn new cases and can respond better to the situations it encounters. Amalberti (ref,1992----------)studies on the psychology of pilots of fighters, reveals in fact that experts use less patterns than beginners. So we choose to use the first approach presented by Norling & al, but instead of building a complete base of cases, we choose to use patterns taken from ferry pilots' verbalizations. We choose then not to implement learning, to get a model as close as possible of experts' decision making and behaviour.

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 and uses a pattern matching system close to ACT-R system.

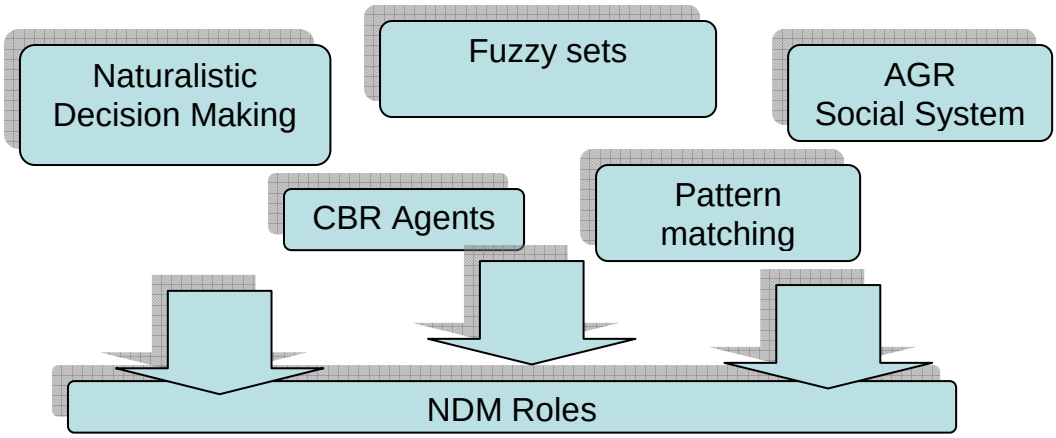


Figure 1: NDM Roles and related paradigms

Finally, we choose to use qualitative data for mental representation. Ferry pilots share the same conceptualisation 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 use fuzzy sets in the decision process to represent those values.

In CogTRANS we use what we call NDM Roles. A NDM Role is composed of two levels: a social level (the notion of role), requiring design of interactions between agents through this role and establishing exchanges with other roles; a decision level, which is independent from the social structure in which the agent evolves. Figure 1 sum up the different paradigms used for developing NDM Roles. Next part presents this specific role and its application in CogTRANS.

3. MODELLING COLLISION AVOIDANCE:

CogTRANS is based on TRANS. TRANS (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 (or none) 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, an anti collision role relies on a strict interpretation of the regulations. In CogTRANS, to improve realism, this role was changed to introduce a *more cognitive* one. Maritime experts' decision making is based on several patterns to define collision avoidance manoeuvre (Chauvin and Lardjane 2008). These patterns define the process memory. Each pattern associates a generic manoeuvre to a generic situation. For example, for a situation of collision avoidance for the give-way ship, the action associated is *turn starboard*. Then a situation is defined by several cues. Each cue is 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 Nm[1]), or *very far* (more than 5 Nm).
CogTRANS divides collision avoidance process (see figure 3) in 4 steps (perception, matching, decision and action).

Along this article we will present different aspects of the model through the same example: a crossing situation between a give-way small cargo and a stand-on ferry. The ferry goes at 19 kts and the cargo at 14 kts. If none of them move, the ferry will pass 0.3 ahead the cargo (which is considered not enough for experts); figure 2 illustrate this example.

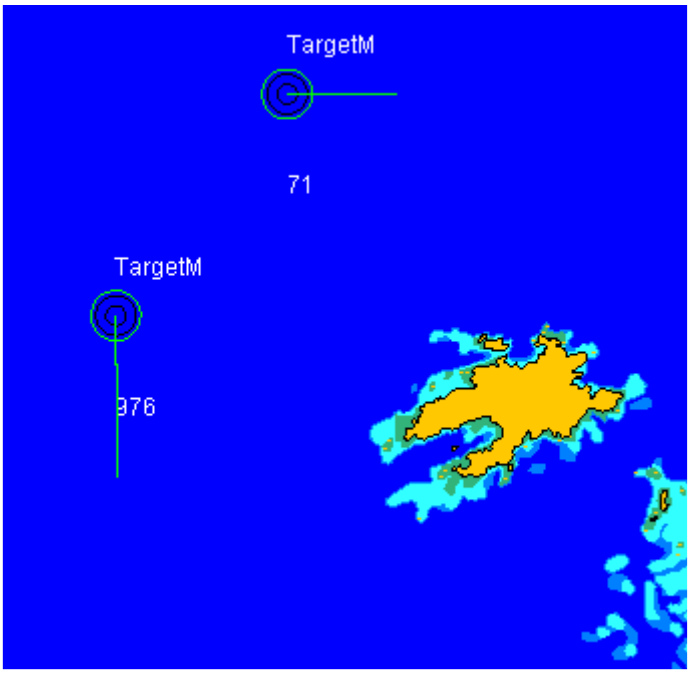


Figure 2: visualization of a collision avoidance situation in CogTRANS

Figure 4 shows the UML diagram of the NDM Role: this NDM role get data from simulation and produce an action that will be traduced in quantitative data. The internal structure of the role use representations with semantic values (qualitative values). Fuzzy sets are used along the decision process to manipulate this data. Perceptions build a mental representation through fuzzy sets, mental representation is used as crisp values for the matching and the decision is a mix of crisp and fuzzy values.

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 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 are used to construct the current situation. This current situation uses the same cues as generic situations. Fuzzy sets (ref Zadeh) 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 proof of a situation. Each cue has multiple semantic values plus one: unknown. The unknown value is inspired by

[1] nautical mile (Nm) = 1852 meters

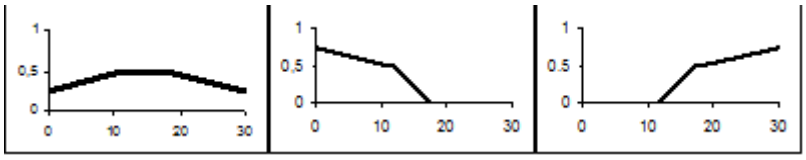
belief theory (Shafer 1976) and allows the system to take into account incomplete situations. We use this value to define intermediate values that have no meaning for the pilot (if 12 knots is slow and 20 knots is fast, unknown value will have a peak at 16 knots).

The values of the different cues were collected by meetings with pilots and watch officers. Those values are based on their verbalizations.

Figure 3 is an example of belief functions applied to the cue *kind of ship*. As the ships encountered by the car ferry may be large or small merchant ships, and as they act differently depending of this type, we need to represent this cue. Ships are identified by their speed: a small merchant vessel is usually slow whereas big merchant vessels are fast.

Used cues for the simulations presented below are:

- distance: zone of emergency (less than 1 Nm), stand-on ship action zone (between 1 Nm and 2.5 Nm), give-way ship action zone (between 2.5 and 4 Nm), perception zone (more than 4 Nm)
- crossing position: crossing far astern (more than 0.6 Nm), crossing astern (between 0.4 and 0.6), collision (0.4 astern to 0.4 ahead), crossing ahead (between 0.4 and 0.6), crossing far ahead (more than 0.6 Nm)
- kind of ship: small cargo (12 knots and less), big cargo or ferry (more than 18 knots)
- kind of situation: face to face (bearing between 337.5° and 22.5°), crossing (between 22.5° and 157.5° and between 202.5° and 337.5°), taking over (between 157.5° and 202.5°)
- 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 (speed differential, flag of the ship)



unknown ship small merchant vessel big merchant vessel

Fig. 3. Example of belief functions associated to a type of ship. X-axis: speed in knots. Y-axis: probability of identification.

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 may be given by a simple calculus or by using a set of semantic distances containing the different symbolic values possible for a cue, and how they are linked to each others. This module returns a list of closest patterns to the decision module.

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 kind of ship.

Pattern	Ship		Situation	Zone of ship presence				priority		Position in CPA			Action			
N°	Small cargo	Big cargo	Cross	1	2	3	4	GW	SA	Ahead	Astern	Col	No	Port	Starbd	Slow
1	■	■	■				■	■		■			■			
2	■	■	■				■	■		■				■		
3		■	■				■	■				■	■			
4		■	■				■	■			■		■			
5	■		■				■	■				■			■	
6	■		■				■	■			■				■	

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

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 cargo, passing close ahead).

Decision module is specifically used to obtain different behaviours with a same set of patterns. For maritime traffic, we build our patterns based on the observation on one kind 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). Depending of the criteria, the weight can be crisp (regulations are respected or not respected) or fuzzy (actions can be dangerous, very dangerous, safe…).
In our example, in case of a single criterion decision based on economy of time, the ferry should choose the pattern 2. To respect the regulations, it should choose pattern 1 (as actions are recommended for her only in zone 3).

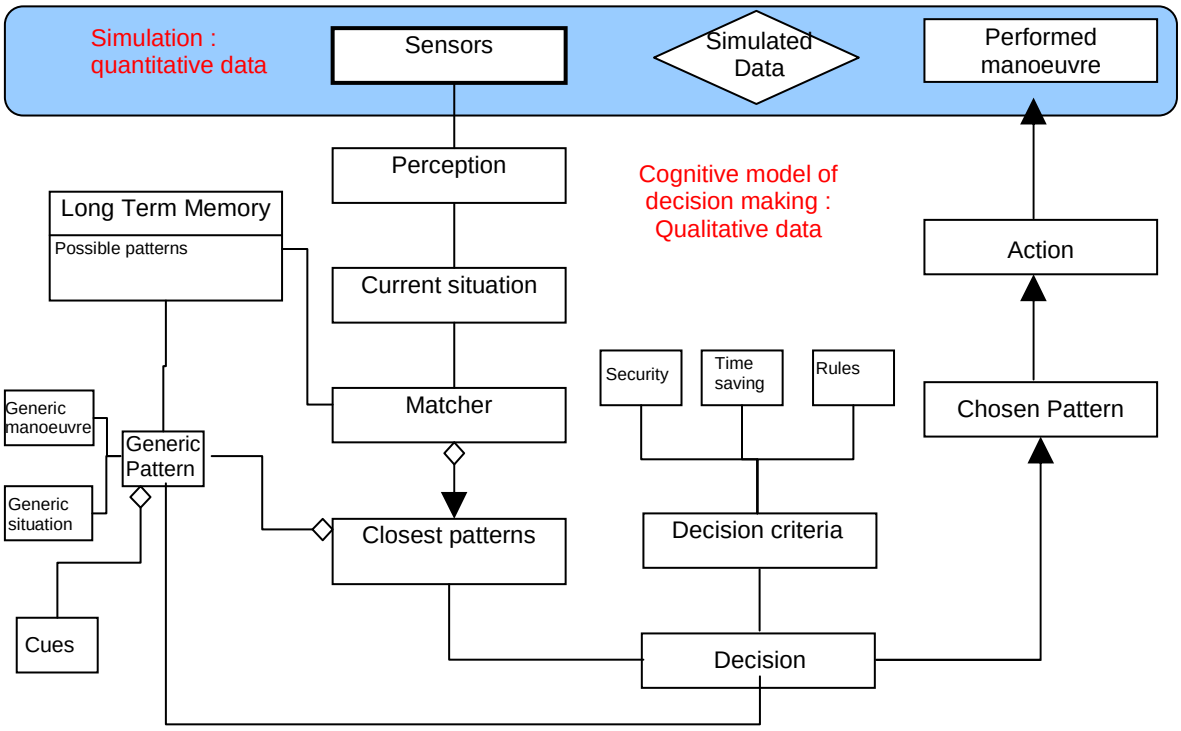


Figure 3: UML class diagram: the cognitive role of collision avoidance.

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…).
In our example, if our ship chose pattern 5, the bearing of the ship will be modified in a large way (between 10° and 15°) to compensate the tendency to come ahead and for the action to be visible from the other ship. The action module contains this “base of actions”.

4. 4 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 kind 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.

	Real data	Simulated data	Predictions
Stand-on avoids	17%	15%	94%
Give-way avoids	83%	85%	55%
Right manoeuvres	80%	87%	96%
Left manoeuvres	20%	13%	46%

Table 2: data on collision avoidance, real and simulated. Predictions column represents the correspondences between real and the corresponding simulated situation. i.e: 49% of

The memory of the watch officer on board the car ferry is composed of about 20 patterns of typical 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"…).

First results of simulations are well correlated with real data. For example, 46 % of small merchant ships in simulation choose to manoeuvre when they are the give-way ship and 51% for the same case on real observations. Although more data are needed to confirm the use of all the sets of patterns, they seem to be sufficient to reproduce this particular situation.
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 90%. 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, there seems to be 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 didn't act early, each ship as a good chance to choose to avoid the other (considering distances taken into account by the collision regulations).

The resulting 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).

Conclusion

The choice of using NDM 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 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 our next objective: we need to know how the watch officers represent themselves complex structures such as the coast, navigation lanes or traffic zones in mental representations, and how

they consider it for collision avoidance: how does it interfere with their decisions? Our last results seem to underline the importance of this geographical data. Further works is planed to modify our NDM role to take into account such data. A trail is to study level 3 of Situation Awareness, to integrate in CogTRANS maybe using different roles deciding each about different level of granularity of the situation (one for collision avoidance, another watching evolution of global traffic, and a last one taking int o account fixed elements of the environment).

Moreover, CogTRANS can be generalized to other kinds of decision making. It requires to methodologically building the four steps of the model (fuzzy perception, pattern matching, decision on criteria, action): finding the cues and their qualitative values, identifying patterns, building belief functions, finding the correct decision criteria and applying them to the patterns.

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