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Cognitive Approach to Distributed Decision Support Systems

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Abstract

Situations of distributed decision making are usually characterized by the existence of different points of view between decision makers (DMs), and by different temporal dynamics within the system, which reinforces importance of studies on information data flows between DMs, and founds usual classical DDSS approaches. We propose here not to limit the analyse of the situation (and consequently the role of the DDSS) to information flows, but to integrate cognitive modelling of each DM, and to use these latter for better analysing relevant information, in order to control it, within the flows exchanged in the system. Our approach relies on a realistic application framework concerning decision making in Maritime Patrol.

INTRODUCTION

In classical cognitive science approaches, decision making is perceived as a data processing activity (Lindsay & Norman 1980). The activity is characterized by processes composing it, information treated, flows between the different processes, and a final result. This latter is an information intended either to another cognitive activities, or to the execution of an action.

The focus in this article is distributed, or collective, decision making, i.e. situations where multiple agents have to cooperate. Our reflection relies on a realistic application framework in which a decision support system might improve global team performance.

Distributed decision making

The distributed aspects of decision refer to spatial, temporal and/or functional characteristics. The decision making may be spatially distributed in reference to the different localisations of the Decision Makers (DMs), that usually lead them to different points of view upon the surrounding environment. This separation, possibly geographic, does not prevent the cooperation between the agents that can be achieved through a network.

Temporal characteristic of the distributed decision making may be considered as “extrinsic” when referring to a dynamic and changing environment: information are only valid in a certain time frame, and the processes have to take into account these evolutions. This characteristics is also” intrinsic” when considering the converging dynamics of the collective decision, while taking into account the individual decisions of the different team mates.

The distributed aspect of the decision making may finally be considered as functional, meaning that agents may be assigned with different roles, particularly depending on their competencies. We are focusing on situations where DMs are experts of their domain. During the decision making, they mainly proceed by identification of prototypic situations (Rosch 1978). These prototypic situations are supposed to be stable structures stored in long term memory (Montgomery 1983). Observing the DM’s effective choices, it is thus possible to access to these structures by an *ad hoc* learning process.

The three dimensions of the distributed decision making are narrowly associated. The spatial distribution, which enables the obtention of different points of view, is thus linked to functional distribution which supposes that the agents perceive reliable information according to their own competencies. Let us note that, even if these pieces of

information are identical, spatial distribution might be necessary, e.g. for security reason, or simply to ensure the correct follow-up of the environment dynamic, while giving the possibility to the different agents to manage different temporal scales. The value of any data can need to be updated at any moment (breakdown, disappearance of the agent in charge of the data, rapid evolution of the data).

This situation applies to our application framework, i.e. Maritime Patrol (object at sea identification) where information of different kind (sonar, radar etc.) are necessary. Each source of information cannot separately be generally enough to proceed with the identification task and the decision making requires the intervention of varied competencies. The decision, i.e. the identification of the object, then requires cooperation of different agents who can be spatially separated (e.g. with a team on the ground, another one at sea, and a third one in a plane). Exchanges between agents are thus crucial within the process.

The previous situation is characterized by the fact that individuals have a common goal and the will to work together. We can then speak of cooperative work and of teams instead of groups. This working situation does not exclude different degrees of freedom, and a hierarchical structure can be instantiated. This latter even can be useful, e.g. when the different agents cannot succeed to a collective decision whereas not to decide is worth that a bad decision, while giving responsibility to one of the team mates, and while enabling him to “slice” the process. We thus try to approach an “anytime” process, i.e. being able to give a decision at any time.

In this article, we propose some methodological reflections, and specification elements of a distributed decision support system.

Positioning

Current distributed decision support systems (DDSS) generally focus on the global structuring of the process in different stages, and usually ignore individual processes but work directly on the aggregation or the combination of individual results (Ruta & Grabys 2000).

We propose to integrate cognitive individual models to the study of the distributed decision making in order to identify the articulations of the cooperation in terms of information exchanged by the individuals, and of the benefit to the individuals of the representations they construct of the other team mates and of the team. Our approach is resolutely anthropocentric. To maintain experts in the loop of cooperation between individuals, via artificial systems, represents a guarantee towards the complexity of the considered problems (Bisdorff 1999, Barthélemy *et al.* 2002): following Simon (1957) about the collaboration between artificial intelligence and operational research, we think that “three head are better than two” (Lenca 2002), the third one being the Human.

In this article, we are thus interested in individual representations when contributing to a collective decision. We will identify elements that a DDSS should implement to support in first place the individual processes implied in the construction of a distributed decision, and in the second place the distributed decision making itself.

A study case: decision making within a military patrol crew

Crews in charge of maritime patrol are made up with operators having various expert competencies, different points of view by the means of specialized instruments. They cooperate to achieve a common goal given by a mission they have been affected to. A hierarchy generally exists, to clearly distribute roles and responsibilities, and to avoid jamming of the process, in case of dissension.

Operators are usually four: three sensors operators (electronic support measures – ESM –, imagery – ISAR/FLIR –, acoustic analysis – SONAR –) and a leader, the tactical coordinator – TACCO –. They embark in planes like the Atlantic2 (in the case of the Casa235 plane, they are six team mates) for military and civil missions as various as surface vessel or submarine surveillance, anti-pollution fight or search and rescue at sea. Civil operations might also involve privates being at sea.

All these mission usually have a recurring task: the *track identification*. This identification consists of labelling and classification of a radar echo (called track since it is under processing), to determine its nature (submarine, surface vessel, commercial or pleasure, etc.), its membership (friend, foe or neutral), its class (frigate, etc.) (see Figure 1).

Regarding the nature of the crew and of the task, task identification is a distributed decision activity as we mentioned early. The finality of the identification is to provide a classification of the track which might be, if the mission requires it, extremely precise. Some identifications can thus provide the name of the vessel, and, consequently, all sorts of information connected, in particular via the cooperation with software agents (access to database, automated decisional agents, etc.).



Figure 1: Missions of maritime patrol

The context of these decisions is in addition often characterized by uncertainty conditions, limited time or by the fact error costs are not symmetric. In the military case, to mismatch a friend for a foe leads to what we sadly are now used to call a “friend shot”. The opposite error does not have the same cost. In the same way, in case of a search and rescue mission, not to identify a boat as being in need of emergency does not imply helps whereas people are in danger. The opposite error, once again, does not have the same costs. This leads the operators, being conscious of the consequences of their decisions, to an important level of stress. In addition, surveillance missions can be long (up to eight hours) and tiredness might become an important source of errors, particularly if a cognitive overload appears. Two famous examples in a military context sadly illustrate these kind of situations: destruction of a civil aircraft by the North-American navy (Klein 1998, chap. 6), and the strike of two civil aircrafts (Otelli 2003).

A good cooperation between human and software agents, in suitably distributing tasks between them, and in limiting situations of cognitive overload, can thus allow to better process the essential data. The tasks distribution and scheduling have particularly been studied in air traffic control, e.g. in Vanderhaegen *et al.* (1994) and in Crevits (1996). The assistance to the operators in maritime patrol might thus allow to improve the quality of decisions taken by the crew.

In this identification task, the role of a sensor operator is to propose, assisted by his own instruments and by the set of measures that he can make, a first classification, which constitutes an “individual/intermediate decision” in the team process. The role of the TACCO is to synthesize information provided by the sensors operators, to establish the global track identification, which constitute the “unified decision”.

MODELISATION

The cognitive approach in the study of individual or distributed decision making is a vast field of study, and models within are numerous, see e.g. in Lipschitz (1993). So, initially, we present two models relevant for our approach and context, and on which we rely our construction of mental representations explained in the last paragraph of this section.

The first model, called RPD – Recognition-Primed Decision – (Klein 1989, and Klein 1998, chap. 3) will help us in explaining the cognitive processes implemented by the different team mates. The second one is a model of long term memory (LTM), called MINERVA2 (Hintzman 1988), and it allows us to justify our description of the different mental representations handled by each team mate during decisional process.

Recognition-Primed Decision

Historically, this model is one of the first in the naturalistic decision making (NDM) domain. It stipulates what has become the basis of many studies, including ours: in a stressing situation, with uncertainty, time constraints or, simply, that does not require an exhaustive search for an optimal choice resulting of an explicit, analytical, rational choice (Simon 1957), expert DM decides through the recognition of the situation, of its typicality, and through associating to the identified pattern a corresponding behaviour that has been learned by experience. Let us note that situations that are studied, and particularly their dynamics, make illusory the search for an “optimal solution”.

The model presented in Figure 2 is a “diagnosis” variation of the complete RPD model, which does not describes how the course of action (COA) resulting of certain decisions can be mentally simulated before being

implemented.

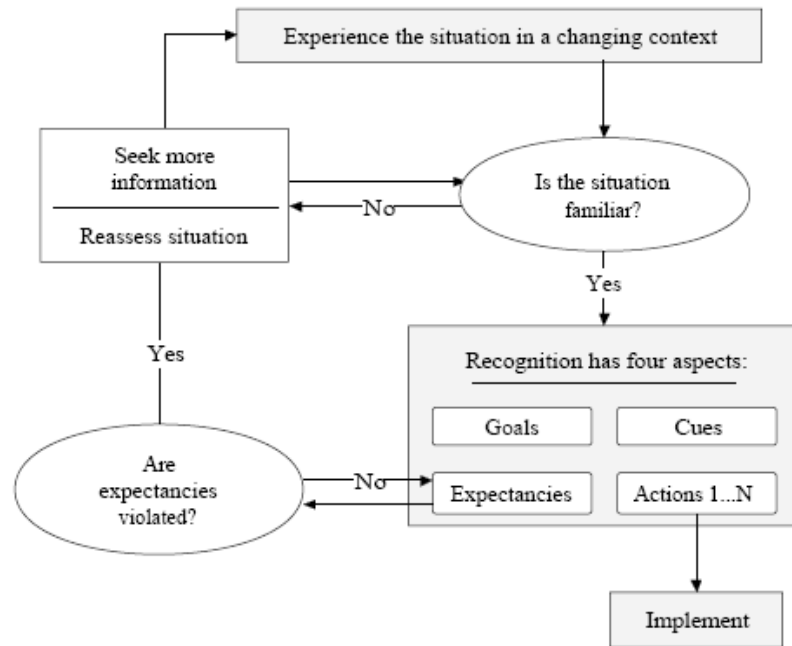


Figure 2: Recognition-Primed Decision model (“diagnosis” variation)

In the first phase of the process, the DM perceives a situation and rules about its familiarity. More precisely, this corresponds to a recovering process from LTM (Richard 2004). The DM perceives cues, and tries to construct a *satisfying* representation, thanks to a whole of events stocked in LTM (named *concepts* or *prototypes*), and activated by the context.

If the recovering process is not convincing, the DM then tries to refine its perception of the situation by a proactive search for supplementary cues, on observation dimensions he has not firstly explored. If the recovering process is convincing, he considers the situation to be familiar and recovers, in his working memory (WM), the *reference* of this (these) remembering(s). The search for dominance structures is also a typical model relying on the preceding considerations (Montgomery 1983). As these same structures can be expressed in the form of production rules, we have developed multiple approaches, essentially based on the *Moving Base Heuristic* (Barthélemy & Mullet 1994), allowing them to be learned (Lenca 1997, Le Saux 2000).

In the second phase of the process, the recovered reference is “peeled”. It thus allows to identify *critical cues* that the DM will have to follow to, according to his experiences, correctly understand the situation. Some *expectancies* are also defined: they represent awaited values on certain cues, and allow the DM to confirm or cancel his recognition of the situation. Moreover, even if the DM usually has one or more generic goals, e.g. imposed by the mission, the recovered reference allow him to define *plausible goals* adapted by the particular situation he is observing. The last point concerns the definition of a COA for the most plausible goal. This COA only represents the result of the decision if this one requires an action on the environment (pragmatic finality). Thus, in the case where decision leads to a production of information (epistemic finality), we will consider that there is no COA in the recovered reference.

Finally, if there is no violation of expectancy and that the decision has a pragmatic finality, the COA can begin. We only consider in this article decisions with epistemic finalities.

Long Term Memory Model

Decision making as described by the RPD model mainly relies on recognition and recovering from long term memory reference situations that are relevant for the decision maker. But the RPD approach does not provide many indications on the recovering processes itself. It seems thus necessary to complete this general approach with a memory model allowing to precise elementary operations involved in the reference recovering.

The MINERVA2 models within the descriptive scope of the memory system implementing a working memory and a long term memory. As a *multiple-trace model*, MINERVA2 assumes that each experienced event is represented in long term memory by its own *mnestic trace*. Thus, LTM might be seen as a (very) vast collection of traces, formed in various contexts. These contexts are moreover part of the traces, and this allows to easily isolate those too far from the situation one.

It's important to note that this model implicitly implies that the recovering process is made by *pattern-matching*.

In this case, memory is not structured according to high levels knowledge architectures (e.g. semantic network), and Hintzman locates this recovering process in the signal level of the SRK (Signal – Rules – Knowledge) hierarchy (Rasmussen 1983). This level is associated with expert behaviour, therefore the MINERVA2 model proves well adapted to the problems we are raising, and to which we want to apply the RPD model.

Recovering process is not instantaneous, but always appears in response to a (some) cue(s) from WM. We suppose that an *event* activate all traces in parallel. These latter respond together to generate a *reference* which is stored, from LTM, to WM (see Figure 3). This generation is carried out, in the model, by summing the different traces while weighing them with *activations*, calculated in order to support those whose context is similar to the situation one.

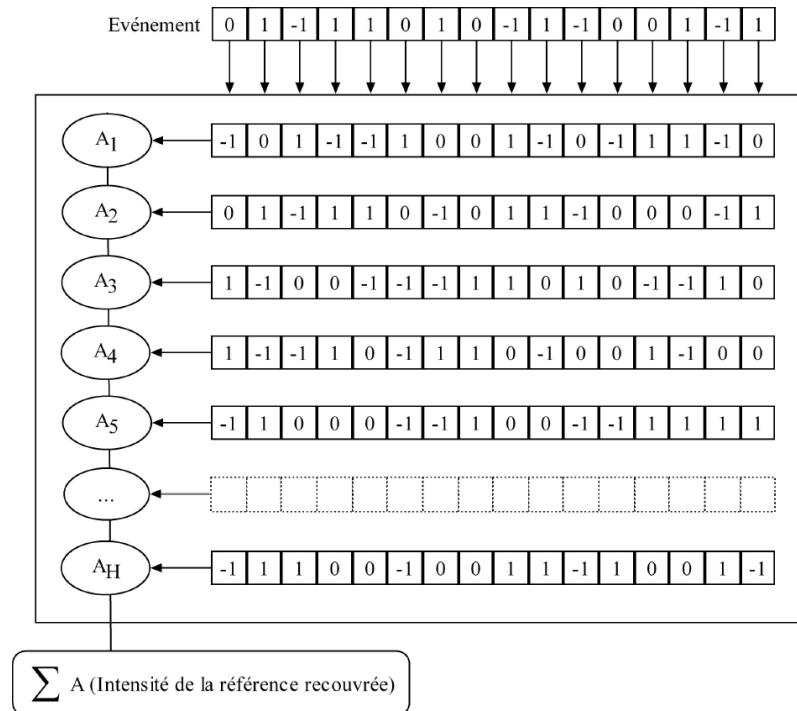


Figure 3: Traces activation following an event occurrence
(A_i represents activation degrees of each trace by the received event)

Nature of the representations

Mental representations we are describing in this article are only each DM's knowledge, at time *t*, on competencies, roles and information handled by individuals. They have to allow answers on questions about help one can bring to the others, and those he is allowed to wait for.

Representations contain no information on the kind of process implemented by the others. Each team mate knows that another one is able to make such or such processing of such or such problem dimension, but does not know, on the other hand, how these processing are implemented, mainly because the fields of expertise are different. The responsibility of these treatments falls to the concerned team mate, and to the DDSS supposed to assist the team. Thus, a formalisation of the individual processes is required for the DDSS.

It's also important to explain our position about distinction that might be introduced between *role* and *competencies* of an individual: we consider that the role assigned to an individual at a given time leads him to implement a subset of his competencies. Thus, if needed (emergency, disappearance of an agent, etc.), an individual might use competencies outside of his role. In spite of that, we suppose that roles have been judiciously chosen. In particular, this is the case in our application framework, where constitution of the team relies on the TACCO expertise, insofar that he has freedom in the choice of his team mates. In the suite, we consider this hypothesis verified.

Thus, the representation an individual has of himself contain:

- his **role**: list of the observation dimensions he *manages*, and on which he is able to give values,
- his **cues**: values on observation dimensions he directly perceives from his environment,
- his **expectancies**: expected values on some observation dimensions.

Let us note that list of possible observation dimensions on objects might be bigger than the one managed by the

individual, and thus, might imply a cooperation with a team mate whose managed dimensions would complete the scene analysis. The interest of the DDSS mainly resides in its capacity to improve this cooperation.

Thus, representation DM have of each other is simply constituted by the list of observation dimensions he manages, i.e. his role.

According to the RPD model we rely on, we stipulate that the list of dimensions is established when the situation is experienced, either from the DM experience, or after a search for information. This step is in particular necessary when activation of the recovered reference is below a given satisfaction threshold, specific to the user.

DISTRIBUTED DECISION MAKING: METHODOLOGICAL REFLECTIONS AND IMPLEMENTATION

We are mainly taking up the question: “What influences the presence of team mates does imply on the individual decision process?”. Consequently, social organization and communication within the team are two main factors to study. They might allow to explain operation differences of two teams harnessed with a same task (Hutchins 1991). We are mainly focusing here the analysis of flows between team mates.

Decision process within the maritime patrol

To decide means to find a unique solution to the objectives given by the mission, i.e. identify tracks. The solution can be obtained by the convergence of the different points of view (this makes it unique), or by the TACCO decision, in case of dissension. In the first case, the decision is unique and consensual. In the second one, it is “dictatorial”. The TACCO can obviously have an organisational role, as a negotiator or a mediator, in improving, even while requiring, a cooperative mode.

A solution is obtained by affecting values to variables allowing the identification of an object, this variables being considered at a “global” level on which team mates agree. This especially means that the interpretations of variables do not require the expertises of the equipments having been used for the measurements (the variables are global in opposition to variables specifically attached to a certain field of competencies or to a particular operator). E.g., temperature can be given by a thermometer for one DM and by an electromagnetic radiation measure for another one: at the global level, both operators will be able to cooperate (according to a certain scale of measures). We are then facing an affectation problem of values to variables, aiming at the prototypes identification (see paragraph “Long Term Memory Model”). Cooperation and information flows (global value exchanges, confirmation, etc.) must then improve recognition phase.

We can then rely on a matrix representation (see Figure 4 and Figure 5) of situations on which different models of individual decision making might apply (decision tree, bayesian network, based case reasoning, etc.).

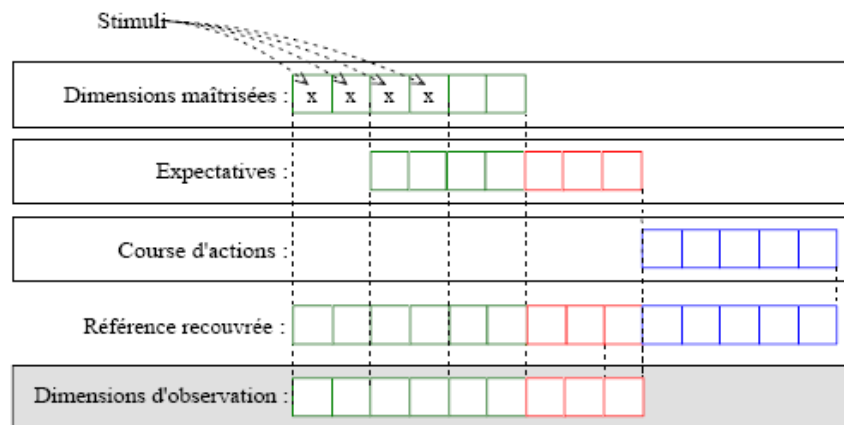


Figure 4: Information representation of agent i (crosses indicate initial cues allowing recovering from LTM)

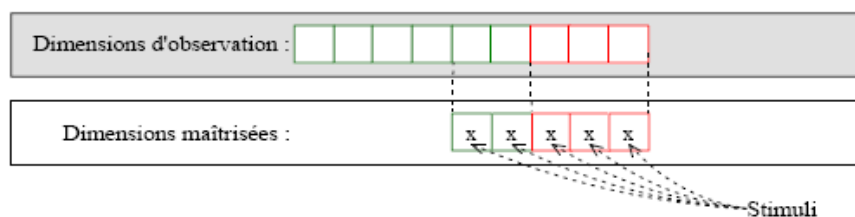


Figure 5: Information representation of agent j seen by agent i

Moreover, information flows, key points of the cooperation, and of the social organization, of the team, are easily observable with these kind of structures. They allow in particular the study of polarisation phenomena, or smoothing ones (see paragraph “Information flows control guided by collective behaviours”).

Decision process for an individual on his own

When the DM is alone, the decision process might be described this way:

- (i) Initial perception of the situation:
 - perception of initial cues;
 - context perception;
 - definition of objects under study.
- (ii) Memory recovering thanks to cues: if the recovering process is not satisfying, we go back to point (i) to search for more information (i.e. either to refine the perception of initial cues, either to select new cues), otherwise we continue.
- (iii) The recognition of the situation is satisfying. The recovered reference brings back:
 - another important observation dimensions, that might not have been taken into account .yet;
 - expectancies to verify as new data on the situation become available;
 - plausible goals.
- (iv) Expectancies tests then begin: if a violation is observed, the individual might be lead to a search for more information, or (more drastically) to start again the recovering process to get a reference better adapted (point (i)).

Decision process for an individual as a team mate

Information flows appear when there is more than one individual in charge of the decision, and when they cooperate. Let us take again the previous points to show what might be modified and added by the cooperation:

- (i) Cues perception remains an individual process. On the other hand, definition of the objects under study might require harmonization between team mates.
- (ii) Recovering processes also remain individual processes, just as the resulting notion of satisfaction. Nevertheless, during information research, one can call upon a team mate who, either has a better control over the observation control, and might thus give another finest/more reliable measure, or control another observation dimensions, and might then give complementary measures.
- (iii) Recovered references individually bring back the different preceding elements. The cooperation might then again need some harmonization, for exchanging the “plausible” goal. But this is not mandatory since a parallel work on different objects of the situation is possible.
- (iv) The considerations coming for the expectancies tests are very similar to those of the point (ii). Each team mate test the expectancies he is aware of. Nevertheless, two team mates may have some expectancies in common. If one is declared violated for one team mate, the information have to be transmitted to the other team mate who will have to take it into account.

Flows nature

With the sight of the preceding paragraph, exchanged information between team mates might simply be summarized this way:

- Exchanges of individual lists of “objects under study”;
- Exchanges of measures:
 - to confirm a personal, but not reliable, measure;
 - to obtain new measure, on a dimension not handled;
- Exchanges of the goal pursued;
- Warning about violated expectancies.

DDSS: SPECIFICATIONS

Need for individual behaviour modelling

The distributed decision support system we envisage cannot limit itself to a “surface” control of information flows: as exposed in the introduction of the article, individual decision models, even if they turn out to be heterogeneous, might allow to identify the relevant data for one DM of the team, and to understand and better use the communication impact of a variable between team mates. Conversely, only the analysis of information transmissions or missing data gives only little information for the setting of an assistance (data are missing for the novice DM, but might not be important for the expert (Shanteau 1988)).

One main function of a DDSS should therefore to integrate individual decision models that will be the basis of assistance functions to the team DMs.

Obtention of individual decision making models

If the preceding principle is commonly accepted, there remains a problem about the elicitation of the individual decision processes, and notably in dynamic or noisy environments as we mentioned above. Two approaches – at least – are possible:

- The first one consist in imposing to the machine representation a format guided by considerations of cognitive realism, but also by the capacities of this format to be adapted to consensus calculation (or any reasoning trying to aggregate the different individual decisions into one unique “collective” decision). One classic methodology consists in collecting decisional expertise to the expert DMs, and in the translation of this information into the desired format, in a fixed and definitive manner. We applied the approach in the maritime patrol framework context (Coppin & Skrzyniarz 2003, Skrzyniarz 2003), with an imposed format of decision trees for each individual decision process. This allowed to significantly improve the number of correctly identified tracks in a given time, and to globally decrease the time needed to the identification of the tactic situation.
- Exchanges of measures: the second approach relies on the non-intrusive observation of individual decisional behaviours and on the adaptation (eventually continuous) of a generic model according to information actually observed. This approach might allow avoiding the classic bias observed during expertise verbalisations (“the expert is not expert of his expertise” (Barthélemy & Mullet 1994)). This solution presents the advantage to propose an adaptable model (implementation of learning techniques), just as the implementation of a more advanced man-machine dialogue (Le Saux *et al.* 1998, Le Saux *et al.* 2002). It is rather in this direction we are turning towards, in particular because of the dynamic and changing characteristic of the environment.

The DDSS must thus integrate learning functions allowing the convergence of “satisfying” individual decision models. The definition of a “satisfying” model will be either directly bind to the predictive power of the model (comparisons of the predicted decisions with actually taken decisions by the DM), or bind to the explicit acceptance of the model by the DM if the DDSS integrates adequate means of visualisation/editing.

Information flows control...

... guided by individual interests

On the basis of individual models (following the RPD approach), it might be possible, according to the current situation, to identify a set of relevant information for each individual DM, and – but only on the basis identified individual decisional behaviours – to organize information exchanges in order to facilitate cooperation:

- Localisation of observation dimensions taking part in respective decision processes, in order to prevent or regulate “intra-dimension” conflicts between individual DMs. This function relies on study of the covering parts between sets of team mates observable dimensions (see Figure 4 and Figure 5);
- Management of requests and demands of information between DMs (also on the display and man-machine interaction fronts);
- Emphasizing and explication of consequences of a decision, or of the importance of an observed dimension by one DM of the team, regarding decision models of his team mates.

... guided by collective behaviours

The DDSS should be able to analyse and act at the group behaviour level: in this case, the DDSS will not try to improve, or eventually optimise, each individual decisional behaviour, but it will replace each observed behaviour in a group logic in order to facilitate cooperation:

- In identifying polarisation phenomena of the group (Moscovici 1996), that may lead each individual DM to adopt imitating behaviours – reinforced by facilitated access to other DMs models – and, therefore, to collectively not correctly explore the solutions space,
- In maintaining or smoothing of active minorities (Moscovici 1996) on the period of collective decision

making: in response to the preceding phenomenon, it might be necessary to encourage part of the DMs to analyse a neglected part of the solutions space. On the other hand, the maintenance of an active minority may be globally judged as negative for the collective decision,

- By the synthesis and the presentation of indicators showing the current state of the consensus or the harmonization between individual DMs.

Maritime patrol framework

In the framework of the maritime patrol, characteristics of the RPD model may be instantiated as follows:

- **Situation:** for a sensor operator, the “situation” may be reduced to one single object/track to identify. For the TACCO, the “situation” may be understood in the more common sense of “scene”, and will therefore be constituted by the tracks, each one being a whole “situation” for the sensors operators.
- **Goal:** the goal of a sensor operator consists systematically in transforming the situation he is currently treating – i.e. the track he is identifying – into a “classified track”. In other words, the goal of each operator is to move one track out of its unknown state into a classified state. This goal is transposed to the whole set of tracks for the TACCO (and complete by the eventual recognition of a “tactical plan” corresponding to the observed tactical situation).
- **Cues:** for the sensor operators, cues are the measures that are done on each track. For the TACCO, measures are completed by intermediate identifications given by the sensors operators.
- **Expectancies:** for the sensor operators, expectancies correspond to expected but not directly measured characteristics, which are induced by the track identification in progress. For the TACCO, expectancies can be similar but also, and especially, concern classification of tracks that have not yet been treated (but induced by the global comprehension of the situation). As an example, the expecting classification (expectancy) of a track localised within a set of friendly identified tracks will also be “friend”. This level of expectancies may also apply to a sensor operator who, if he works in an “intra-track” manner, may after all have context information, and thus classifications of adjacent tracks. The expectancy will then concern no longer the characteristic of the object but on his class membership.

Problems assumed by collective decision and possible role of a DDSS

Minimal expected functions of the DDSS are:

- the sharing of the studied object and of the goals: generally speaking, sensors operators are not supposed to process the tracks in the same orders. In this case, cooperation plan is systematically managed by the TACCO, and the expression of the common goal is necessarily at the global situation level. When a difficult case – or directly leading to a classification dissension – is detected, it is also possible, and necessary to lead operators in a cooperating state, i.e. to make them work on the same track;
- Exchanges and confrontations of cues/measures;
- Comparisons of single expectancies with measures of the same dimension and coming from other team mate(s).

ASSESSMENT AND PROSPECTS

The approach we have presented in this article relies on a certain number of studies on decision processes modelling that have been realised and validated in a mono-decision maker context. Otherwise, the transition to the collective dimension have already been under studies while limited to information flows between decision makers, and to a unique formalism to represent individual decision making processes. We propose here to bring together these two approaches and to validate the methodology and the decision models in a real or realistic environment. Experimentations are thus planned from technical-operational scenarios validated by domain experts, and in a framework allowing non-intrusive observations of the working decision makers, namely in the integrated laboratory THALES – ENST Bretagne, ATOL – *Aeronautics Technico Operational Laboratory*.

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