Respective Demands of Task and Function Allocation on Human-Machine Cooperation Design: a Psychological Approach

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Abstract

Cooperation between human operators and autonomous machines in dynamic (not fully controlled) situations implies a need for dynamic allocation of activities between the agents. Depending on whether tasks or functions are allocated, the demands made on human-machine cooperation design are different. Task and Subtask allocation assumes that both the human operator and the machine (or its designer) share the same decomposition of the overall task into subtasks. Function delegation is less demanding, provided that the human operator delegates functions to the machine explicitly, and within the context of a task representation transmitted by the human. This paper uses an example taken from a series of studies on human-machine cooperation in air traffic control in order to illustrates its argument.

Key Words: Human-Machine Cooperation, Dynamic Task Allocation, Dynamic Function Delegation, Design.

Introduction

Dynamic situations are frequently encountered within highly complex and risky systems such as air traffic control, *glass-cockpit* aircraft piloting, nuclear power plants, and so on. They are not fully controlled by their human operators. The reason is twofold. Firstly, the environment is not fully predictable (e.g., flight plans over a regional or national area are calculated to avoid conflicts between aircraft trajectories, but a delay of only a few minutes can create an unanticipated conflict). Secondly, not only human operators, but also autonomous machines are acting upon the same objects (e.g., in emergency situations, automatic devices are triggered without any *front-line* human operator intention). As Hollnagel and Woods (1983) have pointed out, modern Human-Machine Systems (HMS) should be considered as *Joint Cognitive Systems.*

HMS design implies the definition of activity allocation between humans and the devices they are using. Fitts' seminal work (1951) on principles for *a priori* allocation (The Human is best at... The Machine is best at...) has been widely criticized because of its restricted adaptive power (e.g., Bainbridge, 1987; Hoc, 2000; Parasuraman, 1997; and many others). For a long time, human engineering has expended some effort in defining *dynamic* allocation principles in real time (e.g., Rieger & Greenstein, 1982; Millot & Mandiau, 1995). Optimization parameters for such a dynamic allocation are diverse; for example, human workload (maintained between two boundaries in order to avoid error-prone overload on the one hand and boredom underload on the other), accessibility to data (the agent who has easy access to the necessary data will do the job), and so on. In recent literature, the real time allocation principle is referred to in various ways, but using similar concepts — dynamic task (or function) allocation (McCarthy, Fallon, & Bannon, 2000; Older, Waterson, & Clegg, 1997) or adaptive automation (Kaber, Riley, Tan, & Endsley, 2001). Although these concepts place emphasis on the adaptation of the machine to the human, the studies also integrate the adaptation of the HMS to its environment, evaluated by looking at cognitive costs (for the human), performance (overall task quality), and risk management.

In this paper, we will consider two extreme dynamic allocation modes — dynamic task allocation and function delegation — in terms of demands made on Human-Machine Cooperation (HMC) design. Activity allocation is a cooperative activity, as opposed to a private activity. The first section will delineate the framework we have defined in order to analyze cooperation. It will locate activity allocation within the other cooperative activities and introduce a crucial distinction between role, task, and function in the context of HMC. The second and third sections will present the respective demands of the two allocation principles on design, illustrating them in the air traffic control domain. In conclusion, we will develop a number of arguments in favor of function delegation in situations where the machine's ability to cooperate is restricted.

Human-Machine Cooperation

A Theoretical Framework for Cognitive Cooperation

Our approach to cooperation is more process than structure oriented. It describes cooperative activities (and their underlying representations) and must be complemented by other approaches in terms of relations and communication flows between agents. As is the case with Castelfranchi's theory (1998), ours puts at its core the notion of (negative or positive) interference (dependence or inter-dependence between different agents' goals and subgoals). We consider cooperative activities as being mainly motivated by the management of such interference, in order to facilitate individual tasks or the overall task (Hoc, 2001).

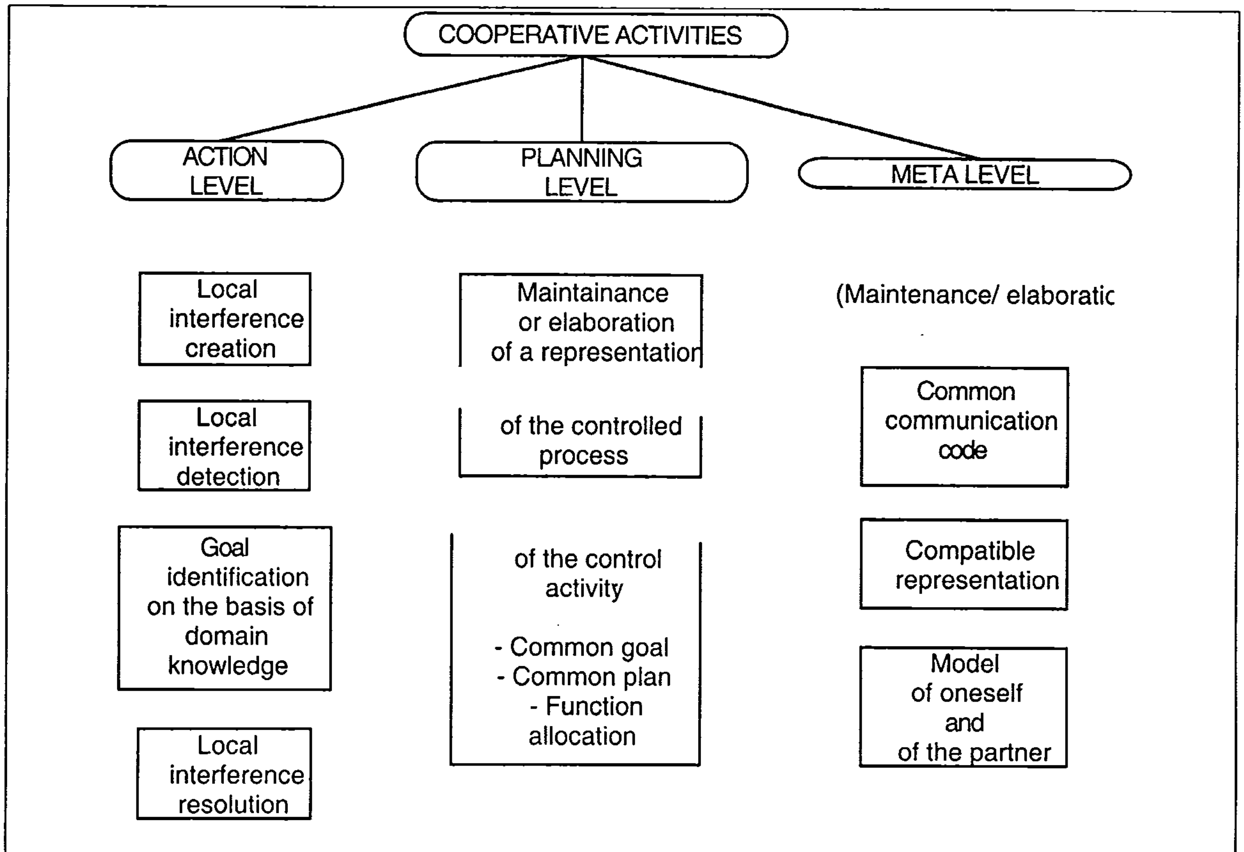

Figure 1: Cooperative activities (after Hoc, 2001).

We define three levels of cooperative activity in relation to the temporal span (or horizon) covered (Figure 1). At the action level, cooperation consists of local interference management. At the planning level, it enables the agents to maintain and/or elaborate a COFOR (COmmon Frame Of Reference), a concept similar to common ground (Clark, 1996) or a shared mental model (Cannon-Bowers, Salas, & Converse, 1993). It is concerned with the representation of the environment as well as the representation of the team's activity, and it is an internal representation as opposed to an external support (Jones & Jasek, 1997). Activity allocation belongs to the planning level. The meta-cooperation level integrates long-term constructs, including "translators" between each partner's representations or models of oneself, or of the other agents. The activities that can be found at each level enable the agent to introduce an anticipative feature into the activities situated at the previous level. For example, a model of the other agent can facilitate goal identification.

Diverse forms of interference are possible. Some of them have already been widely studied by artificial intelligence and psychology in the domain of planning (Hoc, 1988) — precondition or interaction between goals. Others are specific to cooperation (Hoc, 2001) — redundancy between agents or mutual control (of each agent over the others' activities). Redundancy is obviously a necessary condition for activity allocation. As far as HMC is concerned, mutual control is crucial since the machine is always supervised by a human operator and can therefore contribute to the correction of human errors.

The Problem of Activity Allocation between Humans and Machines

Within the HMC context, the use of concepts borrowed from human-human cooperation is justified because it has been proved that humans can transfer cooperative attitudes to machines (Nass, Fog, & Moon, 1996). However, to use concepts originated from the study of human-human cooperation, without a degree of caution, in order to approach human-machine relationships could be inappropriate. The most debatable is certainly the notion of *role* in which there are two components: the activity and the related responsibility. *Role allocation* is possible between humans, but one cannot allocate a "role" to a machine that is only able to assume a certain authority, rather than any responsibility. If an activity is allocated to a machine, there is always a 'front-line' human operator responsible for this activity. One of well-documented difficulty with automation is the complacency phenomenon that reduces human responsibility without replacing it with any 'machine' responsibility (Hoc, 2000). Certainly, in law, there is always a responsible entity, but it is always of a human nature (the human designer or the front-line human operator). Strictly speaking, there is no *role* allocation between humans and machines.

The notion of *task allocation* looks more realistic in HMC, that is to say, it is a goal that can be reached with some autonomy. The designers have no problem in performing hierarchical task analyses, decomposing overall tasks into subtasks, sub-subtasks, and so on, until they reach elementary levels. Is putting one foot in front of the other a task for a walker under ordinary conditions? When we are confronted by a human operator performing what we think of as a task, several problems can arise. An operation such as taking a step may be considered by the walker to be simply a means rather than an end. Elaborating a representation of this particular goal can jeopardize the necessary fluidity of the walk. Furthermore, when the walker stoops under a heavy burden, the high level of interaction between the two operations makes it difficult for them to be processed independently. This task decomposition is not then appropriate for the actual execution of this activity. We have defended elsewhere (Hoc, 1988) the importance of the consideration of the subject's task representation to an understanding of task execution. During its execution, a task (or sub-task) can be identified by the representation of a goal as an intention to be protected (by the performer). Dynamic task allocation between a human operator and a machine (or another human operator) is acceptable only if the designer's overall task decomposition is compatible with the task decomposition considered by the operator.

A weak form of task allocation is *function allocation*, where human's responsibility for the overall task is recognized. A particular function may be considered, sometimes as a task, sometimes as a means without any goal in itself, but just related to a superordinate goal. A function is more generic than a task because it can be utilized in the performance of different tasks. The same set of functions can be considered within different decompositions of the same (overall) task. However, dynamic function allocation is not acceptable if the human operator cannot identify the function to be allocated. Below, we will discuss *function delegation* as a particular function allocation mode where the human operator decides to allocate a function to a machine explicitly, within the framework of a task decomposition given by the human.

An Example: Air Traffic Control

In France, a research program has been developed to explore the possible benefits of adaptive automation as a solution to the yearly 7% increase in air traffic in Europe (Debernard, Cathelain, Crevits, & Poulain, 2002; Hoc & Lemoine, 1998; Vanderhaegen, Crevits, Debernard, & Millot, 1994). It has made use of diverse Automatic Conflict Resolution Devices (ACRD) to dynamically allocate some activities, either to the human controller or to the ACRD, in order to alleviate the human workload. The distinction we have just made between task and function applies clearly to this program.

Figure 2 reproduces part of an air traffic control radar-like scope. At first, two aircraft (AFR124 and BAW678) can be identified as conflicting (crossing on the top left under the acceptable separation gap) if nothing is done. The third one (BAW678) is not conflicting. Following the usual rule (that governs relations between the speeds), the (human) air traffic controller decides to make AFR124 go behind BAW456. As soon as this intention is formulated, the contextual aircraft BAW678 enters into the conflict, in this instance with AFR124. A second deviation decision is made and the problem is completely solved.

This presentation of the problem is very analytical as opposed to the representation likely to be elaborated by human controllers who use powerful pattern recognition processes (Klein, Orasanu, Calderwood, & Zsambok, 1993). As a matter of fact, controllers recognize a three-aircraft conflict immediately and the two-step solution is envisioned straightaway. The first ACRD utilized in the experiments was a two-aircraft conflict resolution device. The task unit represented by the controllers is not of this kind. The two successive two-aircraft conflicts are not resolved separately, but as a means (function applications) of executing the three-aircraft task. In addition, if the device turns AFR124 to the left in the two-aircraft conflict (AFR124 and BAW678), it can create a more complex problem, involving several aircraft on the left, than the initial three-aircraft problem. This analysis also shows that the way a task is defined is not independent of intention and that task decomposition is governed by the reduction of interference between sub-tasks.

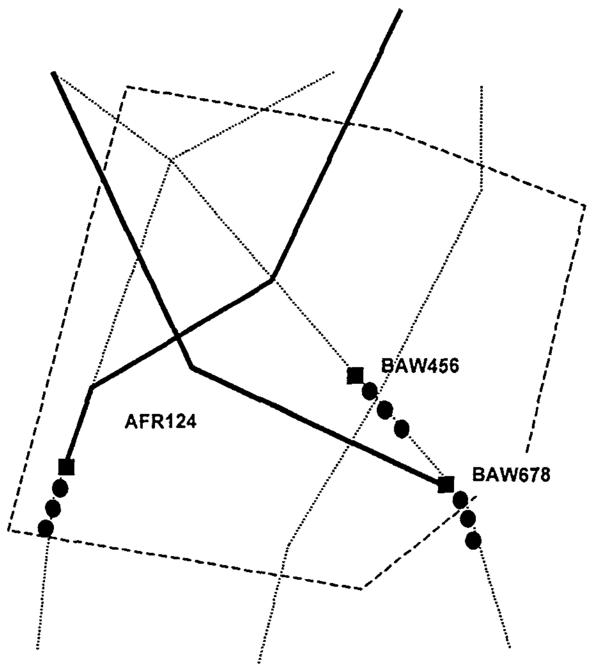

Figure 2: Resolution of a three-aircraft conflict in air traffic control. A square (followed by after-imagery dots in relation to speed) represents an aircraft. A thin line represents an airway. Two aircraft — BAW456 and BAW678 — are going from South-East to North-West. AFR124's trajectory crosses the others' trajectories. Bold lines indicates the effect of the deviation instructions given to the aircraft

Dynamic Task Allocation

Task Definition

Dynamic Task Allocation (DTA) assumes that the tasks (and subtasks) to be allocated, either to the human or to the machine, can be defined beforehand in a generic way. This generic definition will then be applied in real time to identify sub-tasks of this kind, resulting in a decomposition of the overall task. More often than not, the definition relies on competency of the automatic device, since it is crucial to that it can take the place of the human (redundancy). The first part of the Air Traffic Control (ATC) research program (SPECTRA) explored the concept of DTA. It assumed that ATC controllers could accept DTA when two-aircraft tasks are actually considered (Hoc & Lemoine, 1998; Vaderhaegen *et al.*, 1994). It was found that the benefits of using the ACRD were considerably reduced, because of a number of refusals by controllers to allocate (or to see allocated) two-aircraft conflicts belonging to three- or four-aircraft problems. It was felt that the ACRD would render the problem more complex to solve. Despite this, however, the ACRD still appeared to be effective.

Implicit and Explicit Allocation

A first version of the platform (simulator and assistance: SPECTRA V1: Vanderhaegen *et al.*, 1994) was developed to compare two allocation modes: *implicit* and *explicit*. Only *Radar* controllers (in charge of safety and expedition in the sector) were employed for night traffic duty. *Planning* controllers, in charge of regulating the radar controllers' workload and inter-sector coordination, were not present. The implicit mode consisted of imposing the allocation on the basis of an evaluation of the radar controller's workload and the maintenance of this workload below a certain level. In the explicit mode, the radar controller decided on the allocation. These two modes were compared with a control situation where no ACRD was used. Despite using an inappropriate experimental design (one that lacked balancing order effects), a high degree of consistency was found between different kinds of variables (objective and subjective measures). This led the researchers to draw two main conclusions.

- The two modes led to a better performance than the control situation, in correlation with the number of conflicts allocated to the ACRD.

- The implicit mode was better than the explicit mode, in terms of performance, because the latter mixed strategic (allocation) and tactical (conflict resolution) activities, which led to an overload. However, despite its positive effect on performance, the implicit mode was less appreciated by the controllers than the explicit mode. They reported that they were very anxious to keep control over the entire situation.

A second platform (SPECTRA V2: Hoc & Lemoine, 1998) was developed in order to reduce the explicit allocation demands. This necessitated two kinds of controller — a radar controller and a planning controller. Two explicit modes were defined — a fully explicit mode and an assisted explicit mode. The fully explicit mode enabled the two controllers to allocate the conflicts. In the assisted explicit mode, the machine made a proposal, the planning controller could exert a veto right, but the radar controller was not in charge of the allocation. The two modes were compared with a control situation and the order effects were balanced. Looking beyond the benefits of the two modes over the control situation, the main results were as follows (obviously, the problem of task decomposition remained).

- The assisted explicit mode was more effective than the fully explicit mode, in terms of performance, but also in terms of private and cooperative activities. Private strategies were more anticipative, because time was saved by the ACRD resolutions (including re-routing) and the planning controllers' contribution to DTA. Cooperative activities (between human controllers) appeared to be easier to develop, possibly because of a richer external COFOR on the interfaces.
- However, some evidence of a complacency phenomenon was found in the protocols. The radar controllers could not allocate conflict and thus felt themselves less responsible for the tasks performed by the machine.

The Demands of Dynamic Task Allocation on Design

From these SPECTRA experiments, three conclusions can be drawn when it comes to designing an efficient DTA between a human and an artificial agent.

- There must be compatibility between task decompositions. The best results ought to be attained by decomposition into almost independent sub-tasks, considering the human intentions. If the machine is unable to produce such an almost independence and to infer intentions, DTA cannot be entirely satisfactory.
- The human control should be maintained over the situation. Explicit DTA is always the best and purely implicit DTA should be avoided. A compromise, between the two modes is the production of proposals, which are then validated. However the machine should be able to produce acceptable proposals on a frequent basis.
- The human responsibility should be retained within the situation. The humans should commit themselves in the allocation process in order to avoid complacency, that is to say a split in the supervision field, where the humans only supervise their own action fields. Consequently, implicit DTA should be avoided.
- A mixture between strategic and tactical tasks should be avoided. There is a compromise to manage between the human implication in the allocation and the possible overload.

Dynamic Function Delegation

Task, Intention and Function Definition

In dynamic situations, tasks and intentions are defined in real time. Dynamic Function Delegation (DFD) implies that the human operator defines the tasks. The second step of the ATC program (AMANDA: Debernard *et al.*, 2002) has led to the design of a new platform where the two controllers are in charge of defining tasks, shown as "clusters" of related aircraft (clicking on the interface). The ACRD does not intervene without any imposed task definition (e.g., the cluster in Figure 2). Within a task, a function is defined as an under-specified plan to be fully specified, for example, "make AFR124 go behind BAW456" (and "re-route it as soon as possible" is always implied by any plan). The machine is then used as a super-calculator to compute an acceptable deviation. If necessary, the controllers can introduce further constraints. If they have not noticed the problem with the third aircraft (BAW678), the ACRD tells them that the plan is not feasible because of this other conflict. Then, the controllers can add the second plan — "make BAW678 go behind AFR124" — and receive a final validation of the solution. DFD takes place when the controller orders plan execution.

The Demands of Dynamic Function Delegation on Design

This new principle enables a quite simple machine to cooperate with the controllers without introducing negative interference (destroying a correct task representation, producing new problems to solve in the future, etc.). It also enables the machine to participate in the mutual control activity (improving task representation). Delegating a function is not a strategic activity since it is fully integrated into the tactical conflict resolution activity. An evaluation of this principle is in progress in order to validate the balance between the development of costly attentional activities inside what could be routinized activities and the benefits of delegation. In comparison with DTA, DFD is less demanding on machine design since there is no need for task decomposition and no incompatibility problems. Human control and responsibility over the situation are protected. Demands on design are restricted to direct manipulations on interfaces fully compatible with radar scopes to avoid destroying those routinized activities that are absolutely necessary in ATC.

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Conclusion

Dynamic activity allocation and adaptive automation are both reactions to numerous criticisms of full automation and illustrates its drawbacks (Hoc, 2000; Parasuraman, 1997) including: a decrease in the HMS adaptive power, an increase in risks because of human complacency about a badly designed machine, and so on. Certainly there should be continued research into the design of machines with more know-how and more ability to cooperate. Complex task decomposition, intention recognition, and cooperative planning should also be greatly improved. However, with the present state of affairs, dynamic task allocation (DTA) remains difficult to accept in real dynamic situations where human expertise should be promoted rather than impoverished or badly advised by narrow-minded machines. That is why, after having explored DTA in ATC, we have adopted the best benefit of dynamic function delegation (DFA).

Now, returning to the main topics of this workshop, our experience suggests the followings remarks.

- The human agent should decide the allocation (possibly with computer support).
- Intention recognition is needed in task definition, but human intentions can be transmitted to the machine at low cost (schematic plans).
- Monitoring (mutual control) can be promoted in both directions, in other words, not only from the human to the machine, but also in the reverse direction.
- Shared knowledge and plan (COFOR) is necessary. As is function delegation within common problem representations where feasible at a low cost.
- The machine's autonomy must be restricted if it is likely to produce negative interference in human activity.

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