Hierarchical Model and Communication by Signs, Signals and Symbols in Multiagent Environments

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Abstract

In this paper, a framework based on the skills, rules and knowledge taxonomy of Rasmussen is proposed. Precisely, a reflexive level is developed so as to reflect the fully automated activities, then a rule level to reflect stereotyped actions, and finally a knowledge level to reflect conscious activities involving distributed decision making. In fact, the basic goal of this framework is twofold: first, not to force processing to a higher level (i.e. the knowledge level) than the situation requires, and to support each of the three levels of cognitive control. More precisely, the proposed framework should allow agents to prefer the lower skills and rules levels rather than the higher knowledge level because it is generally easier to obtain and maintain coordination between agents in routine and familiar situations than in unfamiliar situations. The framework should also support each of the three levels because complex tasks combined with complex interactions require all levels. To permit agents to rely on low levels, a suggestion is developed. When it is possible, agents have to communicate by signals and signs since signals generally invoke a stimulus or a reaction that is a routine situation, whereas signs generally activate familiar situations. Finally, implementation and experiments demonstrated, on some scenarios of urban traffic, the applicability of concepts developed in this article.

1 Introduction

In a multiagent environment, the agents are autonomous, potentially preexisting and typically heterogeneous. Research here is concerned with coordinating intelligent behaviors among a collection of autonomous agents, that is, how these agents can coordinate their knowledge, goals, skills, and plans jointly to take action and to solve problems [1, 3]. In this type of environment, the agents may be working toward a single global goal, or toward separate individuals goals that interact.

Coordination is central to multiagent systems (MAS), without it any benefits of interaction vanish and the group of agents quickly degenerates into a collection of individual with a chaotic behavior. To produce coordinating behaviors in MAS, most research has concentrated on developing groups in which both control and data are distributed. Distributed control means that agents are autonomous (to some degree) in their actions. This autonomy of course can lead to uncoordinated activities because of the uncertainty of each agent's actions. In this context, a number of coordination techniques have been deployed. However, no technique investigated the relation between uncertainty and the situation addressed by agents. Indeed, the uncertainty decreases when the degree of familiarity of the addressed situation increases.

Our work presented in this paper is a step toward remedying this problem by providing a framework for designing multiagent systems in which agents are capable of coordinating their activities in routine, familiar and unfamiliar situations. We begin in Section II by motivating our framework. We then outline basic elements of our framework relative to three levels of cognitive control in Section III. Section IV presents a new model of communication based on signs, signals and symbols, and corresponding to the skill level, the rule level and the knowledge level respectively. Section V provides technical details on our implementation and presents results of our experiments. Finally, Section VII discusses issues about our framework and the underlying concepts and concludes with some open problems.

2 Coordination between Agents: Guiding Principles

Our work has been motivated by our efforts to coordinate intelligent agents in domains like air traffic control [4] or urban traffic (see Section VI). The framework presented in this paper reflects an effort that has extended over several years. In this section we summarize the guiding principles which have led us to develop this framework.

2.1 Coordination is easier in Routine than in Unfamiliar Situations

In MAS, agents should coordinate their distributed resources which might be physical (such as communication capabilities) or informational (for instance, information about goals, skills and plans). Clearly, agents must find an *appropriate technique for working together in harmony* [14]. In fact, if all agents had complete knowledge of the goals, actions and interactions of their members, it would be possible to know exactly what each agent is doing at the present moment and what it is intending to do in the future. In this context, it would be possible to avoid conflicting and redundant efforts, agents could be perfectly coordinated and the effort of achieving this state would not be prohibitively high.

However, such complete knowledge about actual actions and reactions is only feasible in routine situations. In real-world domains, there are also familiar and unfamiliar situations. In familiar situations, agents can generally coordinate their behaviors since individual acts are carried out under expectations of future actions of other agents' actions and beliefs. In unfamiliar situations however, the coordination between agents is difficult to obtain and maintain because agents need to be constantly informed of all developments in order to elaborate their decisions. In fact, a complete analysis to determine the detailed activities of each agent is impractical in unfamiliar situations, and agents should have the capability to reason about others.

In multiagent systems, we are therefore interested in three kinds of interactions between agents: interaction in routine situations, interaction in familiar situations and interactions in unfamiliar situations. For these categories of interactions, the coordination between agents is generally more attainable in routines than in unfamiliar situations. Whereas the communication between agents is generally more invoked in unfamiliar situations than in routines (Figure 1).

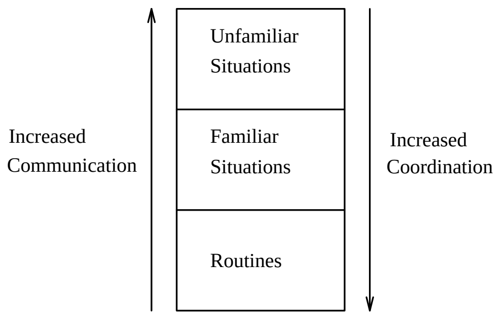

Figure 1: Coordination in different situations in a multiagent environment

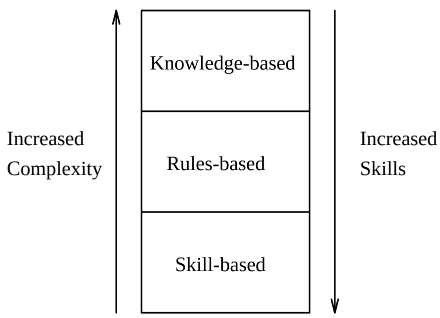

Figure 2: Hierarchical model of human behavior and reasoning techniques

A goal of our research is developing an architecture of agents with the conceptual models to investigate the three kinds of interactions. Generally, conceptual models have a hierarchical structure defined best by the skill-rule-knowledge (S-R-K) levels (Figure 2) of Rasmussen [15]. In the S-R-K perspective, the skill-based level denotes almost routines performances. At this level, agent performance is governed by stored patterns of predefined procedures, that map directly from observation (i.e. perception) to an action. The rule-based level represents more conscious behavior when handling familiar situations. The rule-based behavior is conventionally described by a set of heuristics, that is by a set of stocked rules. The knowledge-based level accounts for unfamiliar situations for which know-how or rules are not available. Indeed, for these situations the control of performance must move to a higher conceptual level, in which behavior is controlled by goal and utility and more generally by the reasoning about others.

2.2 Communication by Signals and Signs Lead Agents to Prefer their Lower Cognitive Levels

Generally, a skill-based behavior refers to "automated" behavior typical in frequently encountered situations. At this level, the external information should act as signals which define the space-time relations, deviations, variations, etc. from the environment. The rule-based behavior is governed by a set of rules or associations, which are known and followed. At this level, the external information serves as signs both to identify the situation and to be able to associate the appropriate set of rules. Consequently, signals and signs refer to low levels of cognitive control where the coordination between agents is easier and where agents' behavior is expected to be less prone to mistakes or misjudgments. In this case, the communication by signals and signs between agents should be preferred when it is possible, in order to allow agents to rely on low levels of their cognitive control.

2.3 A Knowledge Representation for Increasing Coordination

In conformity with interactions in routine, familiar and unfamiliar situations, the mode of knowledge representation adopted should have the following characteristics:

- it should represent mental constructs, models or structures for skill, rule and knowledge-based reasoning,

- it should make *abstraction* easy, particularly abstracting behaviors that can represent goals or objectives representing *what* is being achieved, and plans, procedures or tasks representing *how* the results are being achieved [7]. A behavior in this context can also have dimensions for *when* and *where* activities are taking place, for *who* are involved in the activities, and for *why* the behavior has been adopted. Notice that a hierarchical behavior with these dimensions allows agents to improve their coordination, and can propose alternative behaviors that lead to better coordination.

- it should make case-based reasoning possible in order to reflect *adaptation* to an unfamiliar situation from similar situations or cases. In this way, agents use their own experience if they have a relevant one, or they make use of the experience of others to the extent that they can obtain information about such experiences. This adaptability allows a flexible reconfiguration and consequently help agents to coordinate their activities, particularly in unfamiliar situations.

We have taken a step in this direction by adopting a knowledge representation based on memory organized packages (MOPs). Further details on this representation are given in [5].

3 An Agent Model based on Hierarchical Model of Human Behavior

It is becoming widely accepted that neither purely reactive nor purely planning systems are capable of producing the range of behaviors required by intelligent agents in a dynamic, unpredictable multiagent environment. Indeed, in these environments, agents require skills to respond quickly to familiar situations or routines, while simultaneously being able to carry out unfamiliar situations such as conflicts. Furthermore, in multiagent environments, an unfamiliar situation for an agent can be a familiar situation for another, and the former can request the latter to carry it out. Therefore, agents in complex, real-world domains need to combine the benefits of reactive and planning systems to control their behaviors. Recently, some approaches try to integrate these two levels [6, 9, 10]. However, these approaches still seem incomplete to us since they do not incorporate the decision making process that is important in multiagent environments [18]. Therefore, our agent model combines advantages of reactive, planning and decision-making systems. Precisely, the proposed model in this work has been influenced by the skills, rules and Knowledge (S-R-K) levels of Rasmussen [15].

The skills, rules and knowledge-based processing proposed by Rasmussen reflects differences in consistency of response and conscious control of human behavior. Skill-based behavior refers to fully automated activities such as tracking or guiding, rule-based behavior to stereotyped actions such as test point checking in troubleshooting electronic circuit, and knowledge-based behavior to conscious activities involving problem solving or decision making. We believe that this differentiation between the three cognitive levels is also applicable for multiagent environments where it is important to analyze the behavior of many agents with reference to their cognitive levels. Furthermore, we should concentrate on developing groups of agents in which both control and data are distributed. Distributed control means that agents are autonomous to some degree in their actions. This autonomy can however lead to uncoordinated activities because of the uncertainty of each agent's actions. To reduce this uncertainty, agents should have the propensity for skill-based and rule-based behaviors rather than knowledge-based behavior.

These considerations have led us to adopt Rasmussen's conceptual model as a framework to develop an agent architecture that evolves in a world inhabited by other agents. This model is driven by the goal of combining the complementary advantages of reactive, planning and decision-making systems in order to take into account different situations which arise in multiagent environments: routines, familiar and unfamiliar situations. First, it needs to be reactive to be able to quickly respond to changes in its environment. Secondly, it should be capable to plan its activities for a recognized task or goal. Finally, the model must also allow reasoning about others since agents should be capable of making decisions that take into account their own intentions and also others' intentions.

The proposed model (Figure 3) has been developed from the analysis of human behavior and includes the following phases. First, perceived information from the environment leads the agent to execute an action if the corresponding situation is perceived in terms of action. If this is not the case, the agent tries to recognize the situation. It can recognize the considered situation in terms of an action or in terms of a goal. In the first case, it tries to execute the corresponding action, and in the second case it invokes the planning module. Finally, if the agent faces an ambiguity and cannot come to a decision, or faces many alternatives, then it invokes the decision-making module (based on a Cognitive Map) to make a decision in order to commit to achieve a goal or an action. A goal leads an agent to plan, that is to produce a sequence of actions that achieve the chosen goal. The reader interested by the details of this architecture can refer to [5]. finally, we can summarize in TABLE II, the relationship between the proposed model and the three levels of control of human behavior.

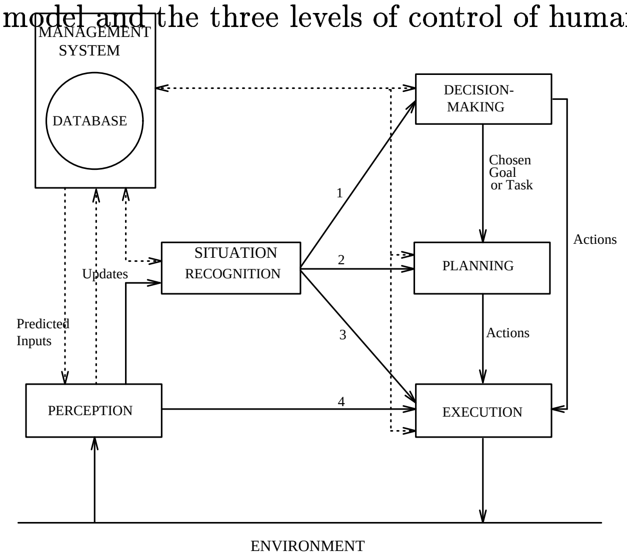

Figure 3: An agent model based On S-R-K framework—1 corresponds to an unfamiliar situation that needs decision-making; 2 is a situation recognized in terms of a goal; 3 is a situation recognized in terms of an action; 4 is a situation perceived in terms of patterns to execute (i.e. stimulus)

TABLE I

The relationship between the Proposed Model and the three Levels of Control of Human Behavior

Knowledge	perception - recognition - decision - planning - execution perception - recognition - decision - execution perception - recognition - planning[a] - execution
Rules	perception - recognition - planning[b] - execution perception - recognition - execution
Skills	perception - execution

[a]the planning process adapts old cases to the new situation, and the adaptation is significant.
[b]the planning process adapts old cases to the new situation, and the adaptation is generally minor

4 Communication by Signals, Signs and Symbols

In previous research in DAI environments, the possible solutions to the communication problem ranged between those involving no communication to those involving high-level, sophisticated communication. Solutions between these two extremities were: use of primitive communication, plan and information passing, information exchanges through a blackboard and finally, message passing. In the *no communication* case, an agent rationally infers other agents' plans without communicating with them. To achieve this, researchers [11, 17] have used game-theoretic approach characterized by pay-off matrices that contain agents' pay-offs for each possible outcome of an interaction. In the *primitive communication* case, the communication is restricted to some finite set of fixed signals (usually two) with fixed interpretations. Georgeff [12] has applied this work to multiagent planning to avoid conflicts between plans involving more than one agent. In the *plan and information passing* approach, an agent A_1 communicates its total plan to agent A_2 and A_2 communicates its total plan to A_1 [17]. In the case of *exchange through the blackboard*, the agents use a shared global memory on which agents write messages, post partial results and find appropriate information. On the other hand, several works in DAI have used classical *message passing* with a protocol and a precise content [7]. Finally, the *high-level communication* approach focuses on dialogue between agents [19, 21]. This dialogue allows the generation and the interpretation of utterances which are speech actions planned to convey the information that the speaker is in particular mental states (beliefs, commitments and intentions) which consist of inducing a particular mental states in the hearer.

In our work, we adopt a new approach to communication. This approach firstly distinguishes between communications by signals, communication by signs and communication by symbols. Notice that the fact that information or indications going to and from agents can be perceived in different ways is not new [8, 15], but curiously enough, it has so far not been explicitly considered by multiagent systems designers.

Signals can be viewed as data representing time-space variables from a dynamic, spatial configuration in the environment and they can be processed directly by the agents as continuous variables. In communication by signals, the signal delivered by an agent i has the end of simply being a releaser for the receiving agent j – of simply eliciting a reaction by j. That is, the signal generally invokes a stimulus or a reaction, without passing through the memory (or the database in our model). In this case, we have a *non cognitive communication* characterized by

$$perception \longrightarrow action$$

An example of communication by signals in urban traffic is the case where a driver follows the signal delivered by another driver in front of him, in a situation of dense fog.

Signs are another kind of information that agents can exchange. Signs indicate a state in the environment with reference to certain norms for acts. In the case of communication by signs, the sender makes a sign which refers to some state of environment and which has the end of signifying, of letting the receiver knows the same reference. Of course, the sender and the receiver should share a set of signs with their references in order to communicate efficiently. For instance in urban traffic, communication between a driver and a policeman at a crossroad is generally done by signs. The policeman makes a specific sign which refers to a certain action and which is addressed to certain driver(s). The addressee(s) recognize(s) the reference of this sign and activate(s) stored patterns of behaviors.

Note that information perceived at the rule level (see TABLE 1) acts generally as signs activating familiar situations. Furthermore and conversely to signals, signs pass through the memory (or the database in our model). In this case, the communication can be viewed as a *cognitive communication*.

Finally, agents can also communicate by symbols. *Symbols* represent variables, relations and properties and can be formally processed. They are abstract constructs related to and defined by a formal structure of relations and processes, which according to convention can be related to features of the external world [15]. In urban traffic for instance, a dialogue between a policeman and a driver in natural language reflects a symbol-based communication. Another example of symbolic communication is "honk the car horn", etc.

Information at knowledge and rule levels can act as symbols depending on the situation and the language used for communication. In familiar situations corresponding to the rule level, agents can use a specific language (derived or not from a natural language). This language is generally constructed from repeated activities. When unfamiliar situations occur, agents do not dispose of any operative knowledge nor of any specialized language. They must then make use of a non specialized language (for example natural language), which is less concise but more flexible than their operative language used in familiar situation.

In summary, with signals and signs, agents do not force their cognitive control to a higher level (i.e. the knowledge level) than the demands of the situation requires. In contrast, agents have a propensity for behaviors based on skills and rules. These behaviors are generally fast, effortless and propitious to a better coordination between agents.

5 The Urban Traffic As Illustrative Example

Building on major ideas developed in this work, we now give details about an illustrative example and its implementation using the hierarchical architecture and the communication by signs, signals and symbols developed in this paper. Urban traffic is generally a highly interactive task between various agents. These agents can be people (drivers, policeman, pedestrians, etc.) or machines (vehicles, traffic-lights, etc.) and have to continuously adjust their actions in order to avoid conflicts such as traffic-jams, and in severe cases, crashes.

The urban traffic application is a relevant area of research for multiagent paradigm. Consequently, we might demonstrate the applicability of the major concepts developed in this article for this application. We particularly focus on investigation of global aspects such as interaction between agents in routine and less routine situations and communication between agents using signs, signals and symbols. More precisely, in this section we investigate a multiagent scenario showing traffic situations at an intersection (Figure 9).

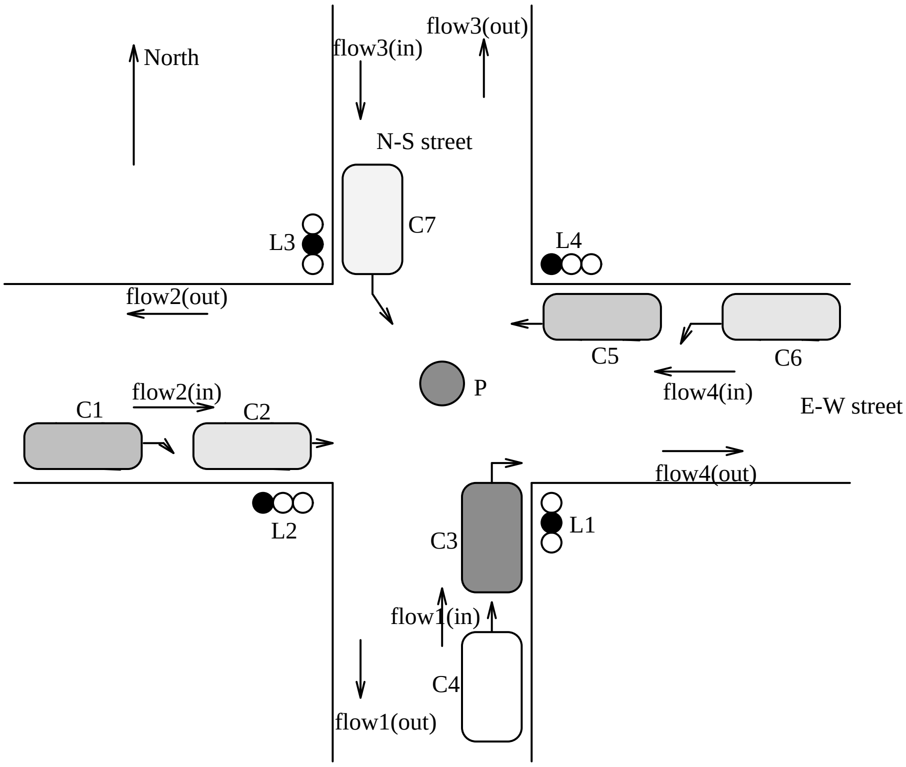

Figure 4: A multiagent scenario in urban traffic: the crossroads : C denotes a car, L traffic-lights, and P the place of a policemen

This scenario captures 1) agents' behaviors in routine and familiar situations (e.g. the agents' behaviors are coordinated by traffic lights); 2) agents' behaviors in complex situations (e.g. the agents' behaviors are coordinated by a policeman); 3) agents' behaviors in unfamiliar situations (e.g. the agents' behaviors are coordinated by social laws, because traffic lights are off).

5.1 Implementation

The architecture presented in Figure 3 depicts a general model and can be adapted to a vast number of fields. We implemented each component of the architecture (in Common Lisp) while keeping in mind this idea of generality. In order to validate this architecture in a multiagent environment, we have implemented the crossroads scenario using our architecture and the communication based on signs signals and symbols. The crossroads scenario has been simplified and instead of striving for a comprehensive simulation of reality, emphasis has been put on the applicability of the major multiagent system aspects developed in this work. One type of agent used to model the considered scenario is the human agent and more particularly drivers and policemen (pedestrians are not yet modeled since they are not considered in this first work). This type of agent is implemented using the architecture presented in Figure 3. Notice that drivers use cars as prosthesis that widen the range of human senses by providing information to other agents. More precisely, in our scenario, each association driver-car is represented by a car (e.g. `C1`, `C2`, etc.) whose flow of information adheres to model presented in Figure 3. In these conditions, a car $\in$ {`C1`,`C2` etc.} has to pass the traffic-lights by coordinating his activities with other cars. He can communicate with others through signals and signs, particularly the signals and signs delivered by other cars (parking-lights, turn-lights, brake-lights, stop-lights, etc.), signs and symbols delivered by a policeman (go-ahead, turn-right, stop, etc.) and signs delivered by traffic lights.

To represent a car, we have adopted the following properties: **`f_s_e`** (i.e. the frontal surrounding environment); **`b_s_e`** (i.e.the back surrounding environments); **`dir`** (i.e. the direction of the car's next move that might be **`turn_left, turn_right, straight_ahead`**). These properties are represented by MOPs and those relative to surrounding environment are periodically updated to reflect any change.

We have implemented a simple model of a crossroads in order to simplify the sequencing of traffic-lights (which is generally very complex) and the process of decision-making when the traffic-lights do not work . In this model (adopted from Lux's model [13]), the intersecting streets are represented simply as a pair of queues. This simplification allows to do without traffic lights showing arrows for the different directions of traffic flow, and simplifies light sequence control considerably. Furthermore, a crossroads is assumed to have no *capacity* and consequently flows of Figure 9 adhere to:

$$\sum_{I=1}^{I=4}(flowI(in) - flowI(out)) = 0.$$

In this simplified crossroads model, traffic-lights `L1`, `L2`, `L3` and `L4` (see Figure 9) are interdependent since opposite directions always switch in synchrony. Thus, opposite flow volumes, `flow2(in)`, `flow4(in)` and `flow1(in)`, `flow3(in)` are controlled by exactly the same sequence. Furthermore, when `l1` and `l3` show green the `l2` and `l4` must show red and vice versa. For the control regime reflecting the functionality of the `Crossroads`, there are different strategies, each with its own set of rules to follow. The objective is to control the flow so that all directions are served equally. Based on our simple model of crossroads and on what we seek to achieve, we have adopted the following strategy:

> As long as no significant differences in traffic flow volumes are detected, `L1`, `L2`, `L3` and `L4` adhere to a standard value. When the traffic flow in one of the intersection streets becomes extremely small, the lights of the busier direction stays green until one or more cars approach the intersection in the less busy street. Then the light turns green in the latter direction as needed, up to a predetermined maximum time.

In our scenario, each car has a `RoutePlan` determining its route. Guided by this `RoutePlan`, the agent finds its way and turns the desired direction at a crossroads. To do this, the agent periodically interrogates its `RoutePlan` to know what to do. For example, being in street `N-S` at traffic-light `L1` and knowing the direction of the next step suffices to determine which street to enter next.

Finally, all agents implicated in our scenario share common knowledge including social laws about the highway code and other social behaviors.

5.2 Experiments

As stated previously, there are three levels (S-R-K: skills, rules and knowledge) of cognitive control in multiagent systems (MAS). These three levels can be grouped together into two general categories [16]. K is concerned with analytical problem solving based on symbolic representation, whereas S and R are concerned with perception and action. S and R levels can be only activated in routine and familiar situations because these low levels require that agents know the perceptual features of the environments and the knowledge relative to these situations. The K level, on the other hand, is only activated in unfamiliar situations. These considerations have been taken into account in designing our agents.

With these agents, we have developed implementations and experiments in urban traffic to verify our intuitions about the distinction between the two modes of processing: perceptual processing and analytical problem solving [20]. Perceptual processing is fast, effortless and is propitious for coordinated activities between agents, whereas analytical problem solving is slow, laborious and can lead to conflicts between agents. To this end, we are conducting a series of experimental studies on three policies of the crossroads scenario. The policy 1 refers to a routine of urban traffic. In this routine, agents' activities are coordinated by traffic lights. Policy 3 refers to an unfamiliar situation of the crossroads scenario. In this situation, agents should rely on social laws to make decisions because traffic lights are off, and there is no policeman to coordinate their activities. Finally, the policy 2 refers to a complex situation where agents' activities are coordinated by a policeman, that is by a knowledgeable agent.

We examined for the cars three performance indices when comparing the policies: communication, processing time for each mode of reasoning (skills, rules and knowledge), and task effectiveness. The effectiveness is specified by two distinct parameters: errors and waiting time. A summary of the main experiments is given in TABLE II. For the policeman who intervenes in the policy 2, we examined two performance indices: communications and processing time for each level of the agents' cognitive control. The results about these indices are given in TABLE III.

TABLE II

Experiments Summary for the Cars

(these results are averaged across 10 scenarios)

Performance\Policies	Policy 1	Policy 2	Policy 3
Communication (i)	1.9	3.1	5.3
Proc. time for S (ii)	140	145	30
Proc. time for R (iii)	17	130	17
Proc. time for K (iv)	6	60	420
Waiting time (v)	163	335	467
Errors (vi)	0.2	2.7	4.1

(i)mean messages (signs and/or symbols) sent per car while waiting to pass

(ii) mean Sun Sparc cpu seconds per car for reasoning at the skill level, while waiting to pass

(iii) mean Sun Sparc cpu seconds per car for reasoning at the rule level, while waiting to pass

(iv) mean Sun Sparc cpu seconds per car for reasoning at the knowledge level, while waiting to pass

(v) mean Sun Sparc cpu seconds per car for the total waiting time at crossroads

(vi) mean number of near misses or collisions for all cars in a scenario

TABLE III

Experiments Summary for the Policeman

(Parameters in this table are measured during the total waiting time per car)

Performance\Policies	Policy 2
Communications	8.7
Proc. time for S	40
Proc. time for R	90
Proc. time for K	205

As we had anticipated, our implementation and experiments successfully demonstrated that perceptual processing is fast, effortless and is propitious for coordinated activities between agents. Policy 1 is in this case, since it is considered (in our implementation) as routine of urban traffic.

More precisely, *policy 1* which reflects a routine, performed best overall. Particularly, this policy allows agents to have the best waiting time and there is no effort since the processing time at the skill level is much higher than at other levels. As we had anticipated, our implementation and experiments successfully demonstrated that with a routine, the number of near misses or collisions between cars is the fewest. In addition, the number of messages sent per car in this routine is also the fewest. Consequently, our expectation that coordination at the skill level is more easy to obtain and to maintain than at knowledge level, is proved true. In the same context, our expectation that routines are not generally communication intensive is also proved true. What happens in this routine is that agents share social laws that allow them to respect traffic lights, and therefore to coordinate their activities without communicating intensively.

The *policy 3* is considered (in our implementation) as an unfamiliar situation where agents reason at the knowledge level to elaborate their decisions. In this context, we had also expected that the analytical problem solving, that is the knowledge level, would be slow and effortful. These expectations are proved true as indicated by our results. Precisely, policy 3 performed worst overall. Indeed, agents have the worst waiting time and their major processing time is at the knowledge level where reasoning is about itself and about others. This reasoning mode is considered as requiring effort since it needs knowledge about others' intentions in order to predict dimensions relative to actions or plans such as for instance what (to do) and who (is the actor). By doing this, agents try to improve their coordination. Finally, with the policy 3, the number of near misses or collisions between cars is the greatest. This result is also in accordance with what we had expected, that is that the analytical level is more propitious to errors and therefore to poor coordination between agents.

Finally, the *policy 2* is a complex situation where cars are coordinated by a knowledgeable agent who is the policemen. In this type of situation, we had expected that cars reason at low levels and the policeman at a high level. Our implementation and experiments confirm this expectation. Precisely, processing times in TABLE II indicate that agents consider the situation relative to policy 3 as a situation which is more familiar than policy 3 but less routine than policy 1. In the same context, processing times in TABLE III show that the same situation is considered by the policeman as a unfamiliar situation with a certain degree of familiarity. These considerations led in the context of cars, to a policy which is intermediate in performance as shown in TABLE II, since the waiting time of policy 2 is intermediate between the waiting times of policies 1 and 3.

Our implementation and experiments demonstrated also that the presence of policeman improve the coordination between cars since the number of near misses or collisions is lower than the number of near misses of the policy 3 where there is no coordinator. The number of messages sent per cars is also lower than the number of messages of policy 3 since cars in policy 2 only follow indications given by the policeman. However, implementation and experiments show that the coordination in the case of policy 2 is not as efficient as the coordination in the case of policy 1.

Collectively, our implementation and results are consistent with what we had expected.

6 Discussion and Open Problems

There are two characteristics of realistic multiagent environments that it is worthwhile to note. First, agents in complex work domain need to be highly skilled as for instance operators of such systems which have extensive experience in controlling the environment. Second, agent design for these environments consists of specifying an agent for a single, specific application. In this case, we do not need to design a general agent. Thus, issues associated with transfer between various applications do not play a significant role in MAS because we will almost always be dealing with the same agents for the same application.

These two considerations make perceptual processing, (i.e. skill and rule levels) an attractive possibility for the designer of MAS. This recommendation does not mean that perception is always better than knowledge but that the characteristics of multiagent domains are generally propitious for perceptual processing. In other words, if one can design agents that effectively take advantage of perceptual processing, then the benefits can be great. In particular, communication is minimized and coordination is easier to obtain and maintain. However, to be truly effective, a MAS should also support higher levels of cognitive control in order to reason about others to be able to reduce negative interactions between agents in the case of an unfamiliar situation.

In summary it is important to note that for MAS design:

1. lower levels are easier for efficiency interactions and consequently agents should be designed in a way that allows them to rely on low levels in routine and familiar situations (greater the skills, lower the level),

2. complex tasks including routines, familiar and unfamiliar situations require all levels and consequently all levels (skills, rules and knowledge) need to be supported.

Communication by signals and signs allow agents to rely on low levels. Indeed, signals invoke generally a stimulus or a reaction, without passing through the high levels, whereas signs generally activates familiar situations.

7 Conclusion

The framework described in this paper was motivated by a problem: how to permit agents to coordinate their activities in routine, familiar and unfamiliar situations. The first step taken toward solving this problem was to determine what model of agent was associated with these situations. Common sense revealed that coordination is generally more easy to obtain and maintain in routine than in unfamiliar situations. Conversely, unfamiliar events must face the problem of reasoning about others and consequently agents which are in this situation can use communication intensively if they do not succeed in making a decision about what to do next with other agents. In addition, for unfamiliar situations, agents are more propitious for making negative interactions. In these conditions, a viable approach to agent design for multiagent systems must be able to combine benefits of reflexive, planning and decision making systems in order to produce skill-based behaviors, goal-oriented behaviors and commitment-based behaviors as required by real multiagent environments. To this end, we have proposed an architecture for agents that reflects three levels of cognitive control as specified by Rasmussen's taxonomy: a skill-based behavior, heuristic-based behavior, and knowledge-based behavior. We also argued that communication by signals and signs allow agents to rely on low levels since these levels are easier for efficiency interactions. In the remainder of the paper, we showed how our proposed model can be used in multiagent environments. Finally, our implementation and experimentation was consistent with what we had expected, in particular: the lower levels (i.e. skills and rules levels) are easier for efficiency interactions.

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