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# Quantitative Cognitics and Agility Requirements in the Design of Cooperating Autonomous Robots

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**Abstract.** The paper makes two main theoretical contributions and also presents a cooperating robot for domestic use, as a practical study case, where the concepts agile control can be illustrated. The first contribution relates to quantitative cognitics, an approach which helps in analyzing complex situations and in designing advanced systems involving cognition, such as cooperating robots. Cognitive systems usually feature a hierarchy of subsystems. For humans, as for autonomous, cooperating robots, the functions of perception, decision, or in a more refined fashion yet, vision or trajectory planning, are good examples of (sub-) processes and tasks, which can be addressed per se, in specific subsystems. In particular, vocal communication is discussed below, as instance of a very stochastic process. For such cases, the probability of error is to be taken into account for the relevant assessment of knowledge quantities. The second contribution relates to a critical feature: relative agility of control elements. For complex cases, where many resources are necessary (e.g. groups of robots), a multi-agent structure may be useful, but then interactions occur and this involves loops, where information flows, and consequently stability becomes increasingly of concern. Several elements of solutions are proposed.

**Keywords:** Cognitics, cooperating robot, agility, multi-agent architecture.

## 1 Introduction

Automated processes allow for humans, today, to control systems in rather complex and demanding tasks and applications. We shall not refer here to energy nor material components, usually also necessary, but will focus instead on information-related flows and processes.

Nowadays, many data flows are commonly processed without direct human action, i.e. in an automated fashion, involving cognitive operations in complex and demanding applications. Novel formal definitions and units for cognitive properties need be defined (re. e.g. [1,2]). Such flows are far beyond the complexity and abstraction levels of early « messages » , which used to consist in a few bits only, directly related to physical signals, and were typical of telephone communications around which the “information theory” has been invented, in the middle of last

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century [3]. This new need, which relates to progresses to be achieved in the cognitive world (knowledge management, abstractions, learning, and more broadly speaking, cognitics – this word has been coined to describe the science and techniques of automated cognition) is widely recognized and very acute today, appearing in one way or another in many fields ranging from technical domains such as in manufacturing workshops, to computer-based context and even further to social sciences and humanities areas [e.g. 4-6]. Assistance at home is one field of particular interest for us.

In order to progress in such areas, several contributions are presented in this paper. In general, a quantitative approach is recommended (quantitative cognitics) and in particular the assessment of knowledge for cognitive systems which sometimes make errors is shown below. Another point involves considerations about the agility of controllers, which is shown below to be a critical factor to take into account for the design and stability of multi-agent systems; the latter may consist in very different forms: e. g. a group of robots, a set of internal components of a single robot, or a mixed group of humans and robots. The case of designing autonomous, cooperating robots, as for domestic applications in Robocup-at-Home league [7,8], provides a good example where such considerations can be practiced.

The paper is organized as follows. Section 2 presents knowledge quantity estimation when delivered information is not totally error-free , as is typically the case in vocal communication. Section 3 discusses the fact that cognitive processes can be distributed at different levels of granularity, usually including, at a high level, perception, decision and action functions; it also shows where is typically the largest load. Section 4 reminds the reader of the crucial importance of relative agility for control units in any single loop (action and feedback paths), and shows that a multi-agent system architecture may lead to many loops, which may each set specific, different requirements; this provides the basis for Section 5 where it is shown that time and delays must be tracked, or at least represented in a model when tracking is not feasible in order to keep distributed, complex, multi-agent systems stable and effective; alternately, architecture may sometimes need be adapted. Section 6 provides a practical case, a cooperating robot for domestic use, where above theory can be illustrated, practiced and tested.

## 2 Knowledge Estimation in Presence of Errors

In the MCS model [e.g. 2], the concept of knowledge is usually presented for the basic case, namely for the case of systems that deliver correct information; possibly limited to a small domain, but nevertheless always correct.

Let us remind the reader of the MCS equation for assessing knowledge, K, which is the following:

$$K = \log_2\left(n_o \cdot 2^{n_i} + 1\right) \text{ [lin]} \quad (1)$$

where $n_i$ is the quantity of information entering the system, and $n_o$ is the quantity of information delivered by the system.

Equ. 1, includes, in its core, a quantity M, defined below, which can be viewed as the complexity of the process, or, in principle, as the size of a (virtual) memory containing all the possible messages delivered, for all possible input configuration (this memory is virtual, in the sense that in nearly all cases, it would be totally impossible to realize such a memory ; yet this is an interesting equivalent model, to be considered as a reference for quantitative assessment).

$$M = n_o \cdot 2^{n_i} \text{ [bit]} \quad \textbf{(2)}$$

An extension is very useful for assessing cognitive properties in the case where a cognitive system delivers information flows that are not totally error-free[1]. In such a case the system does not perfectly know a given domain $D_m$.

A particular output message, $d_{osj}$, does not necessarily correspond to the correct corresponding one, $d_{oj}$. Equation 1 is still applicable, but the part of out-flowing information that does not correspond to $D_m$, which could be called "noise" or "error", should be removed from the equation. The quantity of correct information delivered by the system, $n_{osc}$, must then be estimated in each case, and injected into Equ. 1:

$$M_s = n_{osc} \cdot 2^{n_i} \text{ [bit]} \quad \textbf{(3)}$$

The quantity $n_{osc}$ is defined in the following way:

$$n_{osc} = \sum_{j=1}^{n} p\left(d_{os\,j}\right) \cdot p\left(d_{os\,j} = d_{o\,j}\right) \cdot \log_2((p\left(d_{os\,j}\right))^{-1}) \text{ [bit]} \quad \textbf{(4)}$$

where $p(d_{osj})$ is the probability of occurrence of message $d_{osj}$ flowing out of the system, and $d_{oj}$ is the corresponding correct result, i.e. the result that belongs to the knowledge domain under consideration when a specific message, $d_{ij}$, enters the system. The term $p(d_{osj} = d_{oj})$ is the probability of the jth output message of the system to be correct. The basic idea here is that the information quantity delivered by each output message should be weighted by its probability of being correct. If system answers actually are all correct, the second term on the right side of Equ. 4 has a null effect (factor equal to 1) and consequently the three quantities no, nos, and nosc will be the same. On the other extreme, if output messages are not related to the knowledge domain, or, to put it briefly, answers are wrong, $n_{osc}$ will be zero, leading to zero [lin] of knowledge, even if $n_{os}$ is much larger than $n_o$.

## 3 Cognitive Quantities in Perception, Decision and Action Processes

In principle, the MCS model can describe as well human processes as those processes running on man-made systems. Nevertheless, « cognitic » rather than « cognitive »

[1] An early version of this extension can be traced to [10], even though other symbols were used there.

could be used, when relating specifically to man-made systems rather than to human beings. The quantitative assessment of cognitic and cognitive properties show that in real world systems, the performance levels of cognitive or cognitic systems may not always lie where expected.

Observing humans, the overall cognitive system could be validly considered as a single black box, characterized in particular by overall input and output information flows. At the other extreme, it might also been useful in many circumstances to analyze things at a much finer granularity level and this is also possible within MCS model. We shall consider here the traditional fragmentation of overall process into three main parts : perception, decision, and action.

In general, perception processes imply much larger cognitic/cognitive quantities (in particular complexity and knowledge) than action, and, even more so, than decision. In A.I. however, attention tends to be focussed on decision processes, while for real-world systems, perception and action processes cannot be ignored.

Considering the elementary task of starting or stopping a car at a crossroad, as a function of red or green states of a traffic light, the following quantities may be estimated.

$$K_{decision} = \log_2 \left(1 \cdot 2^1 + 1\right) \approx 1 \quad \text{[lin]} \tag{5}$$

$$K_{perception} = \log_2 \left(1 \cdot 2^{30000} + 1\right) \approx 30'000 \quad \text{[lin]} \tag{6}$$

assuming a good enough traffic view, compatible in quality with what a 100 row x 100 column, color camera can acquire

$$K_{action} \approx \log_2 \left(200 \cdot 2^1 + 1\right) \approx 10 \quad \text{[lin]} \tag{7}$$

assuming a 1 meter long trajectory to be travelled, with 1 cm accuracy, in 3-D space, for a leg actuating the gas or the brake pedals.

## 4 Behavioral Stability of Groups

It has been shown in [1] that the agility of closed-loop controllers, relative to the dynamic behaviour of systems to be controlled, is critical for success (re. fig.1).

In the case of multiple systems, such as a group of cooperating robots, interactions will usually occur, thus creating a potentially large number of individual, elementary control (decision) loops.

For a successful overall system behaviour, it is critical that in all control (decision) loops, the relative agility be good enough. Taking the relative agility as an indicator provides a sound basis for task allocation and decision priorities in group negotiations.

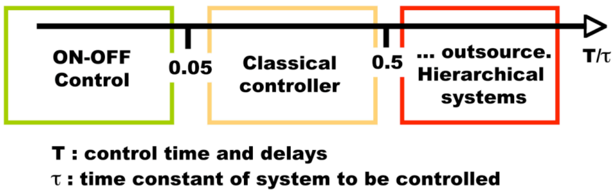


**Fig. 1.** Control may be easy to be achieved, or quite impossible, depending on the relative agility of controllers.

## 5 Necessity of Time Modelling and Time Reference in Complex, Distributed, Multi-agent Systems

Interacting systems exchange information and thereby may yield numerous control loops. The danger in those cases is that when systems grow, involving more agents and processes the global, collective behaviour becomes unstable. As shown in previous paragraph, an interesting indicator of the reliability of decision making in any considered loop is provided by the agility of the control (decision-taking) element, including communication delays, relatively to some dynamic properties of controlled system elements (characteristic time constant).

In complex, distributed multi-agent systems (consider for example a group of robots as in a soccer team, or the water-circuit management resource of a warship, as presented by Rockwell Automation), the number of interaction loops may be very large, with very different agility features. The situation is even more difficult to manage if reconfigurations may dynamically occur. In such cases it seems difficult during design phase to forecast all possible configurations and to predefine all the appropriate decision paths and units.

In a soccer game for example instability will suddenly occur if a robot can move fast, but is controlled through an information path (loop) relatively slow, because of including communication through several team members.

Approaches worth to be considered include the following ones: 1. to characterize extensively signals (samples) in terms of phase (add accompanying time-stamps). 2. to dynamically identify the time responses of elements to be controlled (for all relevant loops). 3. to reduce as much as possible the occurrence of loops by organizing subsystems in as decoupled a way as possible (functional and topological autonomy). When feasible, approach 3 is drastic in avoiding loops and thereby the risk of instability. Approaches 1 and 2 allow applying in real-time the agility criterion mentioned in the previous paragraph for allocating instantaneous decision rights.

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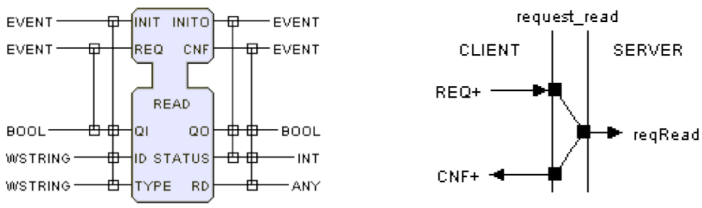


a b

**Fig. 2.** Example of functional block in IEC61'499 framework (a), and example of associated elementary signal sequence (b) [9].

For example, in novel proposals for so-called intelligent control, such as in particular in O3NEIDA context [e.g. 6,10], a good basis is already provided by the formalism of functional blocks (FB). As shown in fig.2, time is already explicitly taken into account in terms of sequence and causality. An additional modelling step making delays explicit seems to be practically feasible for FB's and would provide the basis for robust, distributed behaviour in complex systems in this context.

Other interesting examples are numerous in the domain of cooperating robots.

## 6. Case study – Quantitative Assessment of Cognitive Performance Levels for a Mobile, Cooperating Robot, in Domestic Environment

This section relates to mobile, cooperating robots. It presents and illustrates the general idea that perception tasks are usually much more demanding, in cognitive performance levels, than action and, even more so, than decision tasks. It also helps demonstrating how MCS metrics can be practiced and prove useful.

**Fig. 3.** RH3-Y, our mobile, cooperating robot for demonstrations in domestic applications. Blue trays, with individual covers, are there for user purpose, in « at home » applications. The lower level contains electrical and electronic devices, servo controller and PLC ;. the supervision computer can be lying on top of the trays, for development phases, but is normally smaller and also confined in the lower part of the robot; or is replaced by a fixed, regular computer, operating remotely via Ethernet and TCP/IP connection.

Fig.3 presents RH3-Y, the third version of our mobile, cooperating robot for demonstrations in domestic applications, which has followed previous designs for Eurobot. The first version, RH1-Y, has taken part in competitions [7] and has for example proven capable, in principle, to follow a human, which is a basic ability for many potential home applications (carrying goods, accompanying persons in order to be ready for services, being trained for preferred paths, etc.).

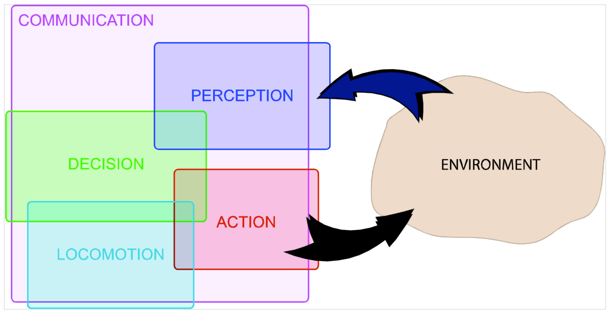


**Fig. 4.** Overview of main cognitive functions of a mobile, cooperating robot.

As overviewed in Fig.4 , and shown in a more detailed form in Fig. 5, the main cognitive processes can be more or less distributed in specialized functional units: perception (in particular word recognition, visual object recognition, obstacle localisation), decision, action, etc

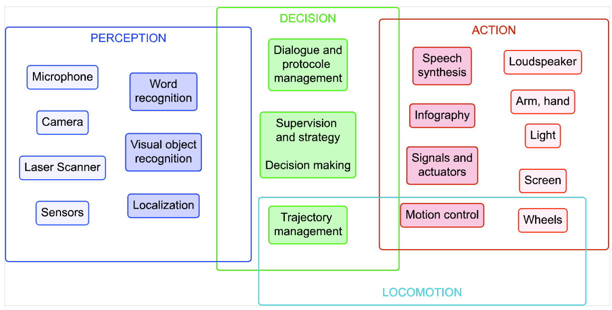


**Fig. 5.** Refined view of main cognitive functions and resources of RH2-Y (This robot is RH1-Y augmented by the addition of basic arm and « hand », among other improvements).

Let us consider some specific tasks to be handled by RH1-Y. In the context of Robocup-at-home, very precise tasks have been defined in 2006, and they are updated every year. There has been in particular a « navigation » task, which required in principle that the system visit 3 locations, according to user's choice, among about 10 specific predefined possible locations

In order to have a convenient human-robot interaction, vocal dialogue is particularly well suited

As stated so far, and globally, the quantity of information as input of the system is about 10 bit, considering that we have 3 words, each one being equally probable

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among 10 possibilities. Here the output quantity is the same, the cognitive process being purely to transfer on the output what is fed as input.

$$n_i = n_o = \log_2(10) * 3 \approx 10 \text{ [bit]} \quad \textbf{(8)}$$

These input and output quantities provide the essential substance in order to qualify the necessary amount of knowledge required for the task as stated.

$$K_{global} = \log_2\left(10 \cdot 2^{10} + 1\right) \approx 13 \text{ [lin]} \quad \textbf{(9)}$$

This quantity is small.

In practice, the global view is, schematically speaking, also the view at the level of the decision unit. However the user does not feed the decision unit with a nicely encoded, 10 bit signal. The user « just speaks », in English, with the restricted vocabulary mentioned (3 times one word among 10 possible topological names).

Consequently, the robot needs a perception stage. As shown on Fig. 5, the sound path starts with a microphone, connected to the perception unit. At the input interface of the latter, the amount of information received is about 50'000 bit per word. At least 150'000 bit for all three of them (assuming a 0.5 s duration per word, 10 kHz of sampling frequency, and 1% accuracy; classical information theory).

When everything works perfectly, the three words (out of ten possible) are abstracted from the sound-wave, i.e. recognized, which means that about 10 bit of correct information is indeed delivered by the perception unit to the decision unit. (In case the recognition is not totally error-free, the equation of paragraph 2, above, should be taken)

Thus the knowledge quantity required for the perception stage is the following:

$$K_{WordPerception} = \log_2\left(10 \cdot 2^{150'000} + 1\right) \approx 150'000 \text{ [lin]} \quad \textbf{(10)}$$

On the other hand, once decided, a destination location has still to be reached. Assuming, first, a 10 cm accuracy, second, an average coordinated motion along a 5 m path, to be done three times, and third, a motion in the plane (3 degrees of freedom), the action function has to concretely deliver (« synthesize ») about 2'500 [bit] of (correct) information in order to define the trajectory:

$$n_o = 3 \cdot \frac{5}{0.1} \cdot 3 \cdot \log_2\left(\frac{5}{0.1}\right) \approx 2'500 \text{ [bit]} \quad \textbf{(11)}$$

Thus the knowledge quantity required for the action (or locomotion) stage is the following:

$$K_{TrajectoryPlanning} = \log_2\left(2'500 \cdot 2^{10} + 1\right) \approx 30 \text{ [lin]} \quad \textbf{(12)}$$

Looking back at Equ. 9, we can see that the estimation of knowledge required is not realistic there. In the case we review, the input information is vocal, and on the output side a full trajectory is to be defined (and travelled). The perception stage and the action stage should not be overlooked.. Consequently the following expression appropriately describes the amount of knowledge required for the task to be successfully performed:

$$K_{global2} = \log_2\left(2'500 \cdot 2^{150'000} + 1\right) \approx 150'000 \text{ [lin]} \quad \textbf{(13)}$$

The design of cognitic systems featuring such a large amount of knowledge is usually not obvious. Fig. 4 gives an overview of the control resources and architecture adopted for the design of RH1-Y.

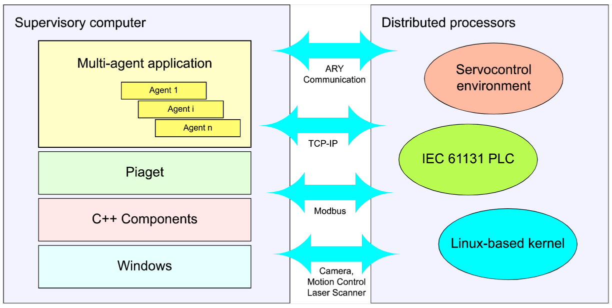


**Fig. 6.** Overview of the control resources and architecture of RH1-Y.

It can be observed in the figure that a variety of embedded agents are used, in order to match very different time-scales: supervisory computer for large-scope, relatively less agile control loops; and, for more agility in reflex loops a PLC (re. IEC 61'131 programming standard), complemented with yet more agile servo controllers and specialized processors in smart sensors (in particular color camera, laser scanner). These various resources are interconnected but remain to a large extent autonomous. This is well in line with the measures proposed in paragraph 5: adapting the agility of each controller to the specific requirements of the task they control; and keeping to a minimum level the amount of interaction between agents.

## 7. Conclusion

The paper has presented several contributions to the field of cognitics and multi-agent systems.

The first main contribution relates to a quantitative approach for cognitive systems, and in particular to the importance of abstraction and concretization processes, Cognitive systems can be viewed as single black-boxes, processing information, However they can also be considered as a structure where more detailed processes are present (or conversely as larger systems, such as a group of robots for instance). For humans or autonomous, cooperating robots, perception, decision, or, in a more refined fashion yet, vision or trajectory planning are good examples of (sub-) processes that can be addressed independently, as specific functions. The MCS metric system is generally helpful in order to guide understanding and developments of cognitive

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systems, Applying this metrics shows that typically the largest cognitive load is put on perception, then much less is required for action, and even less, for decision functions; while by intuition people usually tend to refer mostly to the latter.

The second main contribution shows how time and time-related properties are crucial indicators for the design and operation of complex, distributed, and in particular multi-agent systems. For complex cases, many resources are necessary, a multi-agent structure may be useful, but then interactions occur and this implies loops where information flows, and consequently stability becomes increasingly a concern. The paper shows that a critical property in every loop is the relative agility of control elements, and therefore time and delays must be tracked, or at least represented in a model when tracking is not feasible, in order that decision power be allocated dynamically to the appropriate elements, thus keeping distributed, complex, multi-agent systems stable and effective. Another element of solution is to reduce interactions and loops by isolating components, giving each of them as much autonomy as possible.

The third and final main contribution of the paper relates to a cooperating robot for domestic use, as a practical study case, where above concepts have been illustrated, practiced and tested. In particular, vocal communication has been shown to be very demanding in terms of cognitive performance and, with current implementation, does not always behave totally without errors. For such cases, the probability of error is to be taken into account for the relevant assessment of knowledge quantities.

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