

## More on MCS Ontology for Cognition: Revising Selected Concepts, Including Cognition and Time, Considering Cognition Links with Philosophy and Implementing Automated Cognition in the Real World

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**Abstract**—Designing advanced cognitive technologies and applications requires a formal ontology, such as the Model for Cognitive Sciences (MCS), the theoretical foundations now proposed for automated cognition, cognitics. Cognition has the ability to create and deliver pertinent information. Discussion is made in the current paper of a number of cognitive notions including those of reality, time and revisited “speed”, change and discontinuity, innate and learned behaviors, as well as the human-inspired basics of communication in a group. These newly defined notions conveniently complement the existing MCS ontology. Notions are delineated in conceptual frameworks and can moreover be made operational, deployed in the real world, for validation purpose and for the benefit of users. All these elements confirm the rightness of our current approaches in solving concrete Artificial Intelligence problems and this is illustrated below by some concrete examples taken in domestic context, including robots capable of learning. Cognition would not make much sense per se, and the paper also shows how it can be implemented in the real world, notably using our Piaget proprietary environment for development and programming of smart robotized systems. Experiments prove that the resulting smart systems can indeed successfully operate in the real-world, and in particular interact with humans, performing with large quantities of cognitive components: knowledge, expertise, learning, etc. The quantitative approach of MCS and the operationalization of its cognitive concepts in real-world systems allow as well for a fruitful dialogue about core issues in philosophy as an effective design and realization of smart systems for the benefit of humans.

**Keywords** - cognitive robotics; MCS ontology for cognition; cognitics; cognition; time; cognitive speed; discontinuity; reality; innate behavior; communication basics

### I. INTRODUCTION

The current publication extends some of our past published works, and in particular largely revisits the recent paper [1], adds a new presentation of the concepts of cognition and time, discusses significant links between cognition and philosophy, as well as addresses the challenge of implementing cognition in the real-world.

In the past century, a major step in evolution has been made when information has been formally defined [2], and infrastructure has been provided for communication and processing of information in a massive scale.

In the early days of signal processing, in technical terms, information was neatly provided by some transmitters, typically originating from some other electronic devices, control panels, microphones or sensors. Machine-based sources of information were limited to signal generators, such as for sine waves or pseudo-random sequences.

Things have now become much more complex and cognition is the new domain to domesticate, where pertinent information is autonomously created by expert agents (e.g., [3]). It is with this very relevant goal that the MCS theory for cognitive sciences has been created (Model for Cognitive Sciences [4] [5]). See also the cognitive engine of Figure 1, the cognitive concept pyramid of Figure 2, and the metric system of Figure 3). The material published so far has already brought interesting benefits in terms of understanding the core cognitive properties, assessing quantitatively their values, and allowing for convincing implementation of cognitive robots in selected areas [6].

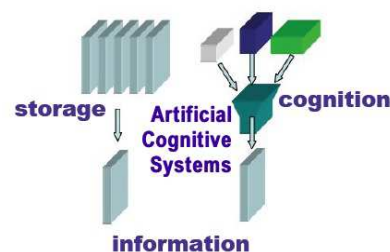


Figure 1. Cognition and, effectively, cognitive systems, allow for generating relevant information, exactly similar to pre-stored information - when the latter is available. Some kind of cognitive engine is necessary (e.g. human-based or artificial, implemented on machines).

Traditionally, people have developed context-dependent cognitive indicators (e.g., for expertise, Elo points for chess-players, Association of Tennis Professionals points for tennis-players, grading systems in schools, or IQ scores), but unfortunately, beyond the case of information, no other work, in our knowledge, has addressed the formal, technically-prone definitions of cognitive entities with associated units.

Figure 2 schematically presents the main cognitive entities in MCS theory context, and Figure 3 presents the equations for their quantitative assessments. Let us briefly review their definitions.

The top group is green, referring to MCS essentials. Knowledge is, for an agent (human or possibly machine-based) the property to deliver the right information; fluency, the cognition speed; expertise, the property to deliver information right and fast, the product of knowledge and fluency; learning, the ability to increase expertise levels; intelligence, the capability to learn, and quantitatively, the ratio of learning to experience; experience, the amount of information witnessed in terms of input and output associations (“examples”, “experiments”); complexity, the amount of information necessary to exhaustively describe an object; abstraction, the property of delivering less information than it is incoming; concretization is the inverse of abstraction.

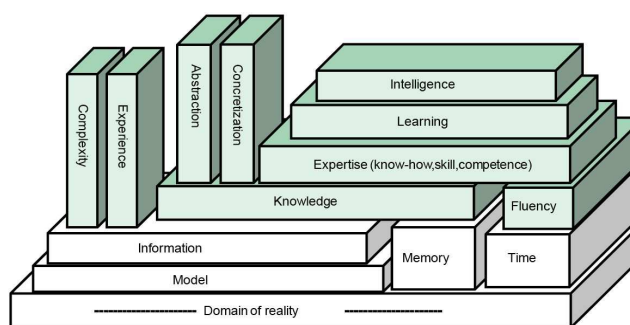


Figure 2. Main cognitive entities in MCS theory. Important cognitive concepts, defined in MCS theory, are colored in green (left). They are based on a few classic entities, including reality and time, which, though classic, also need a discussion from a cognitive perspective

The lower group is white. Even though in principle the corresponding concepts are classical, experience shows that their limits are not well understood, and this is especially disturbing as the new, green concepts are built on them. Thus information is very much time-dependent, the delivery of it essentially making its repetition useless; information is essentially subjective, which means that the same message may convey different quantities to different users; memory is considered here as a support for the permanence of messages, such as an engraved stone, i.e., without the typically associated writing and reading processes; the last 3 quoted concepts, reality, model and time, are further discussed in the sequel of this paper.

In cognitive systems, scale and time are dimensions that are typically much more important than usually perceived. In particular, individuals can collectively yield groups, systems can often be analyzed as a network of subsystems; and in all control loops, occurring in single agents or multi-agent systems, strict dynamic constraints allow – or not – for stable outcomes. Partial autonomy may have to be granted to ancillary subsystems/agents (re. Figure 4).

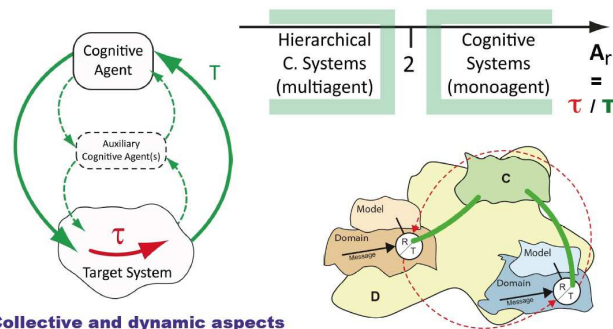
In general, commonsense, classical concepts, and corresponding MCS concepts are quite synonymous and can be described by the same words; nevertheless, there remain often subtle differences, and in the sequel of this article, when the respective distinctions should be made, the “c-” prefix will be added for the terms defined in MCS Ontology;

for example c-speed (1/s unit) is not the usual displacement, motion speed (m/s unit).

Information:	$n = \sum p_i \log_2(1/p_i)$ [bit]
Knowledge:	$K = \log_2(n_{out} 2^{n_{in}} + 1)$ [lin]
Fluency:	$F = 1/\Delta t$ [ $s^{-1}$ ]
Expertise:	$E = K \cdot F$ [lin/s]
Learning:	$\Delta E = E(t_1) - E(t_0); > 0$ [lin/s]
Experience:	$R = r(n_{in} + n_{out})$ [bit]
Intelligence:	$I = \Delta E / \Delta R$ [lin/s/bit]
relative Agility:	$A_r = \tau / T$
T: Fluency <sup>1</sup> and communication delays	
$\tau$ : Reaction time of target system, to be controlled	

Figure 3. Equations for assessing quantitatively the core properties in cognition. Information keeps its classical definition though (re. Shannon 1948 [2]).

Today another step is considered, whereby artificial cognitive agents should effectively approach human cognitive capabilities for three complementary reasons: better functional services (including those involving human-machine cooperation), better understanding of human nature, and implementation possibility of theories in order to make them operational, and thereby possibly validate them. Proceeding should now be done in incremental steps along two complementary ways: the understanding of concepts, and the operationalized implementation of cognition in machines.



> **Collective and dynamic aspects**

Figure 4. Time and scale matter. Cognitive agents may have to be organized in a hierarchy, for large scope, and dynamically stable control. They can aggregate to form groups or be analyzed at a lower scale as a network of sub-systems.

In this endeavors, a first surprise had been to experience that the prerequisites, the basis on which the MCS theory was built, were not at all as widely understood as expected (re. general surveys [7] [8] and focused discussions below). A complement had to be progressively brought in MCS, re-discussing classical topics, namely those relating to the notions of information, models and memory.

Now, at the moment of addressing in its “generality” the cognitive faculty of humans, another necessary pre-condition for implementing it in machine-based agents appears. A

further analysis, of deeper foundations yet on which the MCS theory is grounded, cannot be escaped. What is reality? What is time? How to cope with the infinite complexity of reality? How much innate or wired can be the cognitive capability we are considering?

The paper addresses these questions in successive sections: Section II for reality; Section III for time; Section IV for ways to cope with the infinite complexity of reality, in particular including the innate versus learning paradigms for producing new cognitive agents. The general presentation made so far will be illustrated in Section V with detailed concrete examples, taken from the field of cooperative robotics; they will address cooperation both for human and machine-based cases, relating to cognitive aspects and operations. The final 4 sections will additionally discuss cognition in three different contexts: conventional AI and aspects of implementation in the real-world (VI), Piaget as a key example of environment allowing to automate and implement cognition in the real-world (VII), illustrating applications (VIII), and considerations relating cognition and philosophy (IX).

## II. WHAT IS REALITY?

In MCS theory, reality is in principle viewed as everything, including not only physical objects but also immaterial ones, including information repositories, models, assumptions, novels and if-worlds. It corresponds to the universal definition of Parmenides: What is, is. As illustrated in Figure 5, reality is infinitely complex (re. the definition of complexity in MCS ontology: an infinite amount of bits or megabytes of information would be required for the exhaustive description of reality), so much so that even any tiny part of it, in practical terms, is infinitely complex as well. Reality, including self, is also always the ultimate reference. All subjects facing reality are bound to adopt a constructivist approach [9], relying on means initially self-provided, as innate or “wired”, and later on, hopefully improving those means, in particular by proceeding with exploration and learning by experience (Concretely, a human starts in particular with DNA; a typical robot of ours is given in particular a computer and an executable program; then they explore and learn and ultimately successfully achieve many new, unforeseen operations).

This position is similar to the one of Kant [7], for whom innate, pre-existing “categories” are initially required, allowing cognitive agents to perceive. And simultaneously, by careful axiomatic contributions, complex cognitive structures including possible collective, shared models (culture) can be elaborated.

In summary, in a first stage where a single individual is considered, we do not need to know what is reality, as we benefit from the beginning, of an innate (or “wired” in machines) capability to cope with it (models). Moreover, in parallel, rational processes can also develop, and, with automated cognition, with possible exploration tasks, and on the basis of acquired experience, this can usually yield significant improvements.

At the next stage, where the creation of a new capacity to cope with reality is considered, ingenuity is the key, as defined in MCS ontology [5].

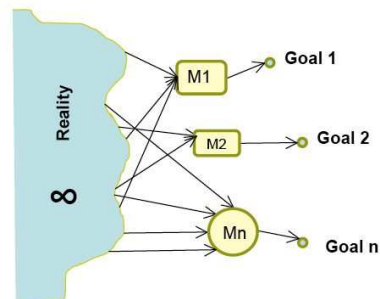


Figure 5. Experience strongly suggests that reality is infinitely complex. Models may be simple and validly serve singular goals, but they should always be considered as very specific for those goals and infinitely lacunary with respect to reality

## III. WHAT IS TIME?

Strangely, time is far from well defined in classical terms. The proposal of Kant is interesting with his complementary attitudes, leaning on one hand towards intuition, whereby everyone has a spontaneous understanding of the time concept; and leaning on the other hand towards rationality (Weltweisheit, philosophy), by which a rigorous, “mathematical”, definition could be elaborated – with no guarantee but chance however to have this latter construct coincide with the former one. Similarly, St-Augustine claims to know very well what is time - as long as nobody asks for a formal definition of it! Even in the contemporary time where philosophy and science have both well developed, Rosenberg apologizes for simply defining time as follows: “time is duration” and “duration is the passage of time” [8].

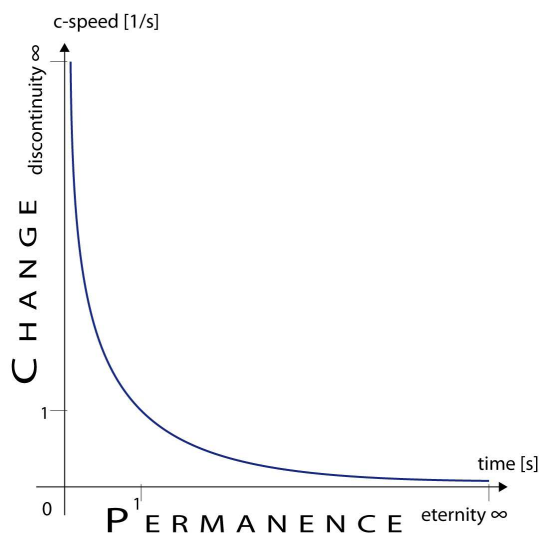


Figure 6. Time characterizes permanence, and speed as defined in MCS ontology, i.e., “c-speed”, does it for change.

It is well known that dictionaries tend to have circular definitions. This should be accepted for at least two reasons: as clearly stated by Kant, reality and cognitive world are disconnected; in this sense, a “first” definition, i.e., relating directly to reality is impossible (convenient complements to circumvent this definition obstacle include gaining experience by direct confrontation to reality, visits to museums, science parks, touring and lab experiments). Now, with circular definitions, the cognitive world appears as a maze with multiple entry points. In a chain of 10 so-related concepts, the reader has ten chances to hop with his/her/its intuition from reality to the cognitive world (which includes libraries, languages, dictionaries and Wikipedia).

Time has already been addressed in MCS ontology, as well as two other closely related concepts fluency and agility. Here, however, things improve: a clearer articulation is made between time and change; speed is defined in a universal way, which then helps, with appropriate, specific complements, better handle changes in a variety of domains. Fluency, thus, becomes the speed of expert information delivery and agility the speed of action.

We propose here to define time as a distributed axiom, in a cloud of 6 interconnected concepts: time, permanence, eternity, change, speed, and discontinuity (re. Figure 6):

- Time is a measure of permanence, and is quantified by the “second” as a unit.

- Permanence is the property of things that do not change.

- A permanence that is persistent for an infinite amount of time is eternity.

- Speed is a measure of change, and is quantified, in MCS ontology (“c-speed”), by the inverse of a second (notice that this is more general than the usual motion speed, assessed in meter per second; it can also apply to all dimensions other than linear in distance, e.g., speed of rotation, heating, speech, sedimentation, or general cognitive operations).

- Change is the property of things that do not remain same, stable, permanent over a certain time.

- A change that occurs at an infinite speed is a discontinuity.

If any single one of the six previous statements is intuitively understood, this evidence can be rationally propagated to all the other 5 associated concepts.

Changes can be of different orders: the speed of change may be permanent, constant over a certain time (1<sup>st</sup> order change); or the speed itself may change at constant speed, yielding the notion of permanent acceleration (2<sup>nd</sup> order change), etc. (re. “jerk” for 3<sup>rd</sup> order change).

In summary, even though time has somehow been defined in various ways in the fields of philosophy and physics, in MCS ontology it gains in clarity and compatibility with other entities crucial for natural cognition and automated cognition.

#### IV. HOW TO COPE WITH THE INFINITE COMPLEXITY OF REALITY?

Section II has shown that reality should be considered as infinitely complex. Yet, it appears that much can often be achieved in practice. So, what paradigms allow for such

positive outcomes? The current section presents 5 of them, including the selection of (prioritized) goals, the pragmatic exploration of local circumstances, the generation of agents with some innate or wired initial capabilities, an iterative process improving performance, and the accelerated progress resulting from setting multiple, coordinated actions in parallel.

##### A. *Necessity of selecting a goal*

As illustrated in Figure 5, experience shows that numerous goals can be reached while ignoring most aspects of reality. Numerous simple ad hoc models prove effective. To the point where even bacteria not only survive in our often-hostile world, but even usually live well and multiply.

A basic paradigm consists in focusing attention on selected contexts, successively considering them with as many constraints as possible. A good example of this approach is notably the famous “hic et nunc – here and now” framework in Jesuits’ case studies. Here, are some other typical cases: “under assumption”, “with abstract and holistic views”, “with more detailed analytical representations”, etc.

Critical for success is the proper selection of a goal. A goal in practice always has a number of peculiarities that open possibilities for effective and simple modeling (re. also Figure 5). In AI, it is often said in substance that experts know what to ignore in a given situation.

For example, we have stated above what is the main goal of the research we refer to in this paper: to make possible the design of artificial cognitive agents effectively approaching human cognitive capabilities, with further possible positive impacts in three areas (see Introduction section). Toward this goal, an effective model implies in particular the proposed extensions of MCS ontology.

Some other, more intuitive arguments for selecting a goal include the following two:

- It may be useful to map in cognitive context the well established A\* algorithm for navigation in space [10] crucial elements are the location of goal-site and the one of current position.

- As reality is infinitely complex, non-oriented efforts would get as diluted and ineffective as curry powder thrown in a river (re. Thai motto recommending humans to focus on selected goals).

##### B. *Pragmatic approach adapted to circumstances*

Careful attention must be given to “current” status, as the latter typically evolves. In a pragmatic way, we propose to start with the world as is, modeled as simply as necessary for reaching the considered goals. In cognition, backtracking is the rule. From the selected goal, specifications are derived, which then lead the cognitive process, and in particular an active perception (“exploration”) faculty capable of acquiring useful information and the possible experience elements eventually allowing for improvements (re. Figure 7).

##### C. *Innate goal and capabilities*

A prominent place is initially given to innate and current capabilities (re. Figure 8).

In practice, it is precious to be aware that even humans do not start, individually, from scratch. At birth time, they already know for example how to grasp, crawl, find their food; these tasks are not necessarily obvious for a robot.

Some chicken for example have such an elaborate pre-design that they can be industrially grown without any social assistance; they can get out of their egg and develop without the help of previous generations.

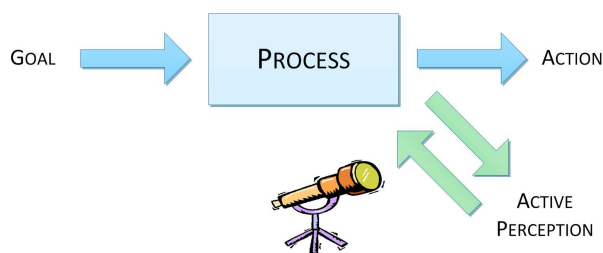


Figure 7. In cognition, backtracking is the rule. From the selected goal, specifications are derived, which then lead the cognitive process, and in particular an active perception (“exploration”) faculty capable of acquiring the experience necessary for improvements.

Therefore, it is legitimate also for machine-based agents under study to start from some predefined (let us say “wired”, or pre-programmed) initial state. And humans have created robots.

#### D. Improved goal and capabilities

In the paragraph about reality, care had been taken to keep things as simple as possible. Nevertheless, multiple cognitive processes, including some innate capabilities, and possibly newly acquired experience elements could already been mentioned, opening the way for improvements and learning.

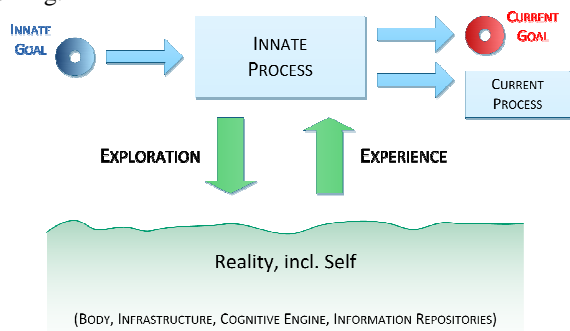


Figure 8. Current goals and processes may result from exploration performed and/or experience acquired by an agent running a given cognitive process in a certain domain of reality. Initial goals and processes are innate (or “wired”).

The next interesting stage occurs when the design and creation of a new capacity to cope with reality is considered (Figure 9). For connecting directly to reality, chance (as in Darwin’s theory,) or ingenuity (as defined in MCS ontology [5]) are the main keys.

#### E. Collective approach; elements of communication, credibility, reputation, and trust

Experience shows that the coordinated forces of multiple agents – groups- increase the possibilities of successful actions in the world.

This paradigm can be exploited in a multiplicity of ways. Of particular interest for our context, we find groups of humans, of robots, and of hybrid resources – robots cooperating with humans.

Groups have already been defined in MCS ontology. In this context a critical ingredient has been identified as the culture of the group, and, in reference to it, the communication channel and some kind of formalism, protocol or language.

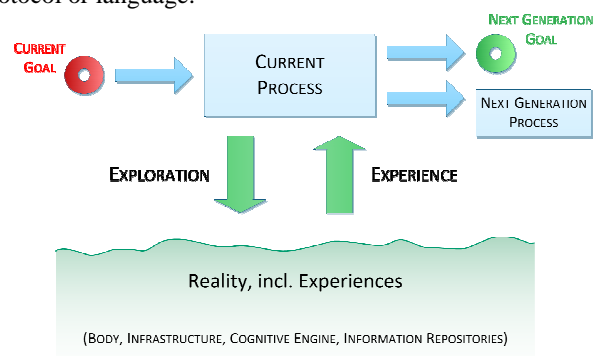


Figure 9. Current goals and processes may lead to improvements in next generation system (in particular for humans or machines).

Two new elements come now under scrutiny. The first one is, for inspiration, the case of baby communication, a case reasonably simple for the purpose of progressive transfer of approach to machine-based systems. The second one is the sharing of error probability of a source, among humans, which expands at group-level a feature already taken into account for individual cognitive agents.

In their early months of existence, babies appear to have at least 4 types of communication capabilities. In some circumstances, babies can express strongly (high arousal) their emotions [11], their states of happiness and unhappiness (positive or negative valence); they cry, or smile, which typically leads to corresponding correcting or sustaining actions from their parents. They also test the good understanding and adequacy of key behaviors and gestures by imitating, and mimicking; they also sometimes just synchronize with others in their attitudes and actions (they join in or trigger yawning, and laughing).

The MCS theory has introduced a value, in terms of probability of error, for cognitive agents delivering information. This affects the quantitative estimation of knowledge characterizing these sources. Now we can add a similar, interesting property at group level, which allows for appropriate propagation of the expected error-rate. In this framework, agents would take into consideration the credibility of sources and in particular of other group members; if shared at group level, this credibility could form the basis for, collectively, building up a reputation. Thus when receiving a message, such agents could associate to it a

trust value, based on reputation. Improvements would result in terms of modulation of risk-taking and in the respective weighting of multiple conflicting sources being integrated (fused).

## V. DETAILED EXAMPLES IN COOPERATIVE ROBOTICS

Let us consider a typical test task of Robocup@Home (RaH) competitions, “Fetch and Carry” (F&C). In substance, team members can in particular talk to their robots, giving a hint about what to fetch (e.g., “a grey box”), and where it stands (e.g., “near the front door”); the robot should by then know enough about topology and navigation to be able to autonomously reach there, locate the object accurately enough to get it in the “hand”, grasp it, lift it up, and transport it back to the starting location (re. Figure 10).

The results of Sections II and IV, including §A to E in the latter case can be illustrated here, both in human and in machined contexts.

### A. Illustration in human context

In a first stage, a group of international experts have elaborated a rulebook where the general goal of designing systems useful for humans (re. to Section II, in short SII) is focused towards a domestic goal (re. to Section IV.A, in short SIV.A), and then backtracked into the specification of even more focused subgoals: elementary capabilities to be devised. One of them is the task called “Fetch and Carry”, addressing a “natural” way for a robot to find, grasp and transport an object (SIV.A). This intermediary goal is then searched in parallel by multiple teams (SIV.E). This task adapts to local infrastructure (SIV.B) and is iteratively considered, year after year (SIV.C-D).

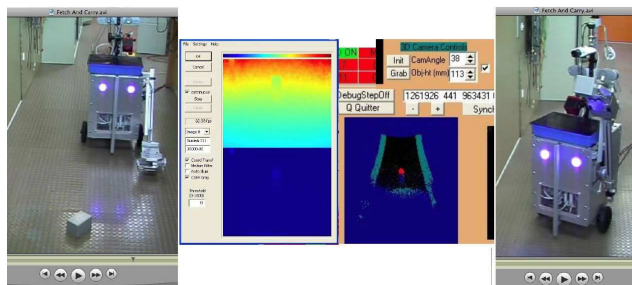


Figure 10. In the F&C task, our proprietary robot RH-Y uses in particular a vocal dialogue, a navigation capability typically using a ranger for navigation purpose, a time-of-flight camera for recognising and locating objects (*center*) and position and force controlled arm and gripper (*left and right*).

### B. Illustration in robotic context

The demonstration system is real and thus very complex. An overview of the task can be seen on a video available online (e.g., [12]) and multiple aspects are presented elsewhere. Here we shall discuss a minimum of aspects for purpose of example.

Consider first as an analogy, the problem for a human to jump over a wall. This can be easily achieved, or may remain totally impossible, depending on how high is the wall; the metric height is critical. Similarly, in the cognitive world,

properties must be precisely defined and metrically quantified in order to allow for meaningful descriptions and effective requirement estimation.

For the F&C test task, referees typically retain about 20 objects, which may be randomly put in 20 possible locations. Robots may more or less be wired with initial expertise, e.g., in terms of topologies and functions; a common culture is also defined (“names” of standard objects and locations are published on a wall one day or more before the test). Let us practice a quantitative estimation of requirements in terms of cognitive entities (re. concepts of Figure 2). Ignoring here many processes, such as e.g., word perception and recognition, or navigation and handling, let us focus on the cognitive task of understanding which object is where. The input space would consist in about 10 bits of information for each object and rough location specified. On this basis, at the most abstract level, one out of  $20 \times 20 = 400$  possibilities should be resolved (i.e., about 9 bits) to know which object is to be fetched, and where it is roughly located. In this very minimal form, the necessary knowledge for correctly understanding the vocal dialogue amounts to approximately  $K=14$  lin. With a dialogue lasting for 5 s, the amount of expertise for this cognitive task amounts to  $E=14/5=2.8$  lin/s. Learning is demonstrated and can be quantitatively estimated on this domain: without dialogue the task cannot be achieved in the 5 min allotted to the task (roughly,  $K=0$  lin, and therefore,  $E=0$  lin/s), while with a successful dialogue, lasting for, say 5 s,  $E$  increases to about 3 lin/s. The MCS intelligence index is thereby of  $i=3/5=0.6$  lin/s<sup>2</sup>.

In the specified location (e.g., “near the door”) the object is manually moved by referees by  $\pm 20$ cm just before the test, making it impossible for robots to have it fully (pre-) wired. Therefore exploration as in SIV.B is performed, using Time-of-Flight (TOF, distance) perception. Notice that here, as in most usual cases, the perception process features (or requires) a lot more knowledge and expertise than the above cognitive operation: in particular the input space includes here  $176 \times 144$  samples, each with 1cm accuracy in a 500cm range, i.e., about  $150'000$  bits of information; similarly, the output stage is relatively large for successful trajectory specification (about  $10'000$  bits of output information), and the processing time is short (say, 0.1s).

Time is a very important feature for success, in many contexts of these applications (motor control, parallel agent management, sensor-based exploration process, etc.). In our proprietary “Piaget” environment [13], agents run in parallel, with very short, individually granted, time slots, lasting for about 100 nanoseconds each in average. Therefore, at low level, Piaget defines its own fine-grained time basis (“TicksPerSecond”); permanence quantities are estimated as numbers of scheduler cycles (“Ticks”), which individually last for about 1 microsecond in average. At higher level and for longer time increments ( $>10$  ms) time is managed on the basis of the system clock, and is thereby compatible with the general culture, common to multiple robots and humans, that makes effective cooperation possible.

## VI. CONVENTIONAL AI, COGNITION AND IMPLEMENTATION OF COGNITION IN THE REAL-WORLD

(Artificial) Intelligence is but one concept in a broader field, which is (Artificial) cognition.

AI has been addressed for half a century and longer (Turing 1950 [14]), yet no formal theory about it has been widely accepted today. Worse than that, experience shows that most people intuitively feel that, ultimately, intelligence is a property to be exclusively found in humans, implicitly thereby making AI, i.e., machine-based intelligence an empty set. As a stronger line of defense, the limits for this latter case are sometimes restricted to the frontiers of the so-called general intelligence.

The situation is really hard for conventional AI. Consider even some researchers who address explicitly the goal of designing intelligent machines (e.g., [15] Konidaris et al., 2012). They state their aim at bringing together intelligence and machines, implicitly stating once more that machines have no intelligence. A better concept and wording would be to develop the intelligent capabilities of machines.

In science and engineering, there have always been some researchers looking for integrated solutions, systemic answers. For this kind of people, in the case of AI in particular, beside the core aspects of world representation and information processing at a cognitive level, complementary aspects of autonomous implementation and immersion in the real world have also been part of the target. Some have even gone further to consider that cognition could only emerge from an autonomous, real-world, structure (e.g., discussion in [16]).

Traditional difficulties in providing a formal theory, or even simply in delineating an appropriate ontology for cognition may in particular have come from two major facts: first attention has traditionally been deviated from “what is it?” to “how to let it operate?”; and the second is that connection has not been sufficiently made to the well-defined information theory (consider e.g., [17]).

Now as developed above, with MCS theory, reality appears as infinitely complex and yet for selected goals, much simpler models can be effective.

## VII. PIAGET FOR IMPLEMENTING COGNITION IN THE REAL-WORLD

Cognition has some interest per se, nevertheless, its main value relates to the ability to change the world. In this section, four aspects of this topic will be treated: the necessity of implementing automated cognition in the real-world, the strategy for ensuring the best possible design, the requirements for a new environment supporting development and control in this regard, and finally an overview of Piaget, which provides solutions in this context.

### A. Necessity of implementation of cognition in the real-world

As discussed above, implementing cognition in the real world is a crucial requirement for smart machines. In our view input information for subsequent reasoning must be acquired – perception. And cognitive operations are useless

if they do not yield results, information to be somehow converted into world changes – action.

Again, let us insist and remind the reader that if he/she dogmatically defines intelligence to be exclusively human, intelligent machines are obviously impossible. By this token, to *try* to merge intelligence and robots is the most that can be done, and do not hope for success. On the contrary, by the definitions we advocate above, experience shows that AI is not only feasible, but also in fact already largely deployed. So the merge has already been done, yet of course significant improvements are still clearly expected.

Notice first that cognition does not only imply information and knowledge, but also critically requires an engine – step 1 into the real world. In practice we have cognitive systems, in particular humans, or artificial cognitive systems (ACS).

And adding the perception and action capabilities to cognition is a second step into the real world. This already defines a robot; to be possibly augmented with some locomotion and communication capabilities.

Moving along this road, we have searched for the best possible design.

### B. Strategy for the best possible design

The goal just stated in previous paragraph calls for a very complex system, embedded in the real world, and in particular operational in real-time, capable to address the most advanced applications in terms of automation and cognitive, human-related tasks.

To be tractable, the proposed system must be organized as a hierarchy of coordinated, specialized resources (e. g. Figure 11), contexts, and points of view, each being individually much simpler

Another element of strategy is, at all levels of the hierarchy, starting from the very top, to rely in as much as possible on existing elementary solutions – subsystems.

Here where lots of integration must be done, the first priority in selecting potential components, strangely, is less on the top functional capabilities of these elements than on their safe availability and operational robustness.

Possible candidates in terms of possible components may be found, from case to case, on the market, in scientific and technological publications, or other sources yet, including new proprietary developments.

### C. Requirements for a new set: architecture and language

On day one, back in 1998, like today still, the system we aimed at could not be found, ready-made, on the market or in other labs. Nevertheless, more and more powerful components were being developed. At the hinge between these two realities, the first component to appear as necessary for our goal has been the design of a novel set, architecture and language, which we have called “Piaget” in reference to the famous psychologist of same name, recognized scientist of human cognition, who had made major contributions especially in the context of young children development. It is in fact a computer-based

environment, favorable for developing and intelligently controlling mobile cooperative agents and industrial robots.

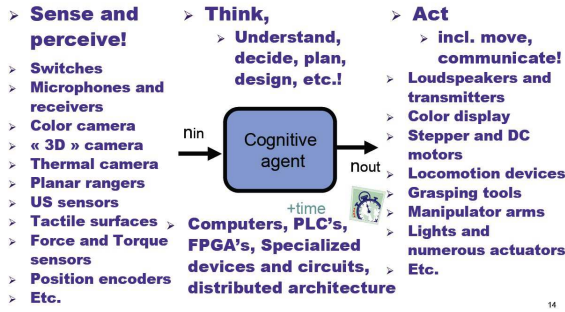


Figure 11. Smart systems sense, perceive, think and act. The table names some of the underlying physical resources we have been using in Piaget context.

D. Overview of Piaget

The “Piaget” concept for architecture and language has evolved in two or three major stages, and is described in detail in Dessimoz, Gauthey and Omori 2012 [13]. For convenience, a few elements about this concept are also provided in this paragraph.

Computers have been around for some time, as well as standard products in electronics, precision engineering and microtechnologies. Some of such major real-world components integrated in our intelligent robots with Piaget are shown in Figures 11 and 12.

The cognitive components of the processes involving the real-world resources of Figures 11 and 12 typically relate to large amounts of information (>> 1 Mb), and operate at high speed (up to 10<sup>7</sup> [1/s] and more).

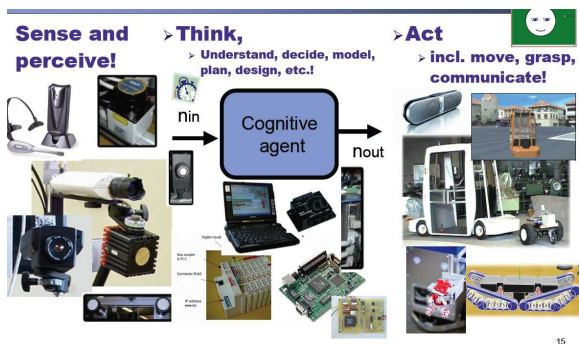


Figure 12. Smart cognitive systems sense, perceive, think and act. While the previous figure includes general names, the current one illustrates by pictures the corresponding elements. Other elements not shown here include Kinect sensor, Katana arm, Aldebaran NAO humanoid, and Kuka / Stäubli industrial robots for example.

The cognitive components of the processes involving the real-world resources of Figures 11 and 12 typically relate to large amounts of information (>> 1 Mb), and operate at high speed (up to 10<sup>7</sup> [1/s] and more).

The first crucial component that appeared to be missing though, was an application-oriented environment, with

parallelism and real-time capabilities, and very open possibilities for integration of numerous, heterogeneous, products and services.

```

.....
11: SleepAGN(0.05);                               break; case
12: if(!SignalIn(NSISStart))
    GoState(6);
    else
    GoState(20);                                     break; case
20: DemarrerMatchAGN();                             // start 90 s timer etc.
                                                break; case
21: SignalOutAGN(NSOAspirateur, true);             // start motor vacuum
                                                break; case
22: SignalOutAGN(NSORouleauIN, true);             // start motor brush
                                                break; case
23: ApproAGN(HoleNb1, 15);                          break; case
24: MoveAGN(HoleNb1);                                break; case
25: MoveAGN(Trans(173,90,-90));                     break; case
26: ObserverLigneAGN(NL, NCStart, NCStop) // Visual analysis of a row
    if (N2Jaune>0) // totems are yellow; balls are white
        {PositionTotemOuBalle[1].TypePosition=Totem;
        nbTotem = nbTotem+1;}
    else
        PositionTotemOuBalle[1].TypePosition=Balle;
                                                break; case
27: ...
    
```

Figure 13. Example of instructions in Piaget language.

In Piaget instructions are numbered (re. Figure 13). A meta-level program counter is defined for each task and is typically realized in the implementation, lower level language as a switch paradigm. A possible “AGN” suffix explicitly indicates, when present, that, for the next allocated time slot, the program proceeds at the next numbered Piaget instruction.

Our applications make typically use, on the supervisory computer, of about 20 parallel agents. And experience shows that common, current computers can in average visit (enter, do the work, and step out) each task in a single 100 nanosecond long time slot.

The Piaget language includes in principle very specific, application-oriented instructions, such as for example the “ChooseTheBridgeVisually” instruction. It has been found useful also to integrate in it a kind of subset of the excellent VAL language for robotics, derived from AL [18]. This decision brings two main advantages: 1. VAL keeps a relatively general view at robotic and automation level (e.g., “Signal i” instruction to turn on the digital output number i), useful for the early phase of a new application. And 2. this paves the way to a common standard for novel, mobile agents and classical, industrial robots. Val can be traced back to the beginning of industrial robotics, or even further to the above-mentioned AL language, and keeps evolving.

Piaget supports direct and inverse kinematics as well as extensive support for transformation and frame ancillary computations, in matrix form and homogeneous coordinates. Motion control is typically hierarchized in three levels: programming, coordination and joint control, with elementary cycle speed respectively situated at about 500, 15, and 0.5 milliseconds.





“I have heard: go to door”, and if this is critical, the dialogue manager will ask for a confirmation (“is this correct?”).



Figure 17. On the left, Piaget panels and text-typed fields illustrate typical vocal dialogues: e.g., recognized commands are shown in green (here “”) and synthesized text in yellow; yes/no buttons can at will simulate microphone inputs. On the right a face is recognized for “Who is Who” test.

Advanced tests in terms of cognitive capabilities and human robot interaction capabilities have been demonstrated in Robocup@Home world competitions, e.g., “CopyCat”: programming by showing – the robot learns what to do; (Figure 18) and “FastFollow”: leading and training a robot in new homes just by walking –the robot learns a path, and can for example guide the human back to the starting point; “OpenChallenge”: in Singapore our robotic group included three coordinated robots, and in particular a humanoid for the purpose of mediation between human and machines (Figure 19).



Figure 18. On the left, RH-Y robot visually analyzes and immediately replicates each of the object displacements manually performed by President Asada. On the right, RH-Y moves fast, following its guide, crossing another team, and completing first the imposed visit of a home.



Figure 19. “Open Challenge” (Robocup@Home world competition, Singapore). Nono, a NAO-typed robot, discusses with “Daniel”, moves on OP-Y platform and then calls RH-Y, which brings drinks and snacks. Application developed and programmed in Piaget

Like for Eurobot competitions, in Robocup-at-Home contests, results have always been reasonably good, in both

cases reaching the 4<sup>th</sup> place in rank for the best year. Many videos of past competitions are available, on our server and/or on YouTube.

*B. Piaget and cognitics for intelligent robots in industrial applications*

Industrial applications can also be driven by Piaget. Figures 20 and 21 illustrate two cases, the former one involving a Staubli robot and the latter one a Kuka.



Figure 20. “Chip count and accuracy test”: Application mostly developed and programmed in Piaget, including the industrial robot arm visible on the picture and other resources: optical fiber, PLC, camera, motorized rotating table, servocontroller, Ethernet switch, PC and other components yet.

In both cases, the robot arms are driven, at elementary, lowest level, by manufacturers’ controllers (incl. KRL for Kuka; Val3 for Stäubli) and, at higher levels, by a program developed in Piaget environment and expressed in Piaget language.

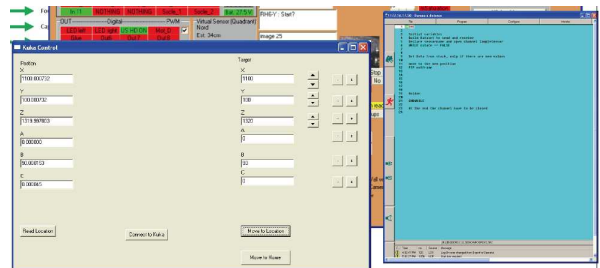


Figure 21. Three windows relating to an industrial application involving a Kuka robot (The first two belong to Piaget environment; the third one is a remote desktop linked to Kuka controller).

Piaget supports fast and robust vision, in many modes (infrared/BW, color, thermal, 3D-time of flight sensors; various processes).

*C. Integrated capabilities in Piaget for quantitative estimation of cognitive properties*

A particular interest of Piaget environment is to provide a tool for convenient, quantitative estimation of core cognitive properties: knowledge, expertise, experience, speed/fluency, intelligence, as well as low-level ingredients: probability

calculus, quantization, sampling rate, input and output information signals and quantities, all this along with an interactive example (Figure 22).

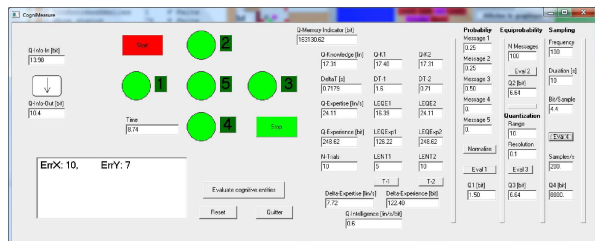


Figure 22. Piaget environment includes a form for the quantitative estimation of cognitive properties in general, along with a specific example: learning how to accurately click in the center of 4 targets.

### IX. COGNITION AND PHILOSOPHY

Cognition was given ontology above, including notably definitions for time, reality and wisdom. This overlaps to a large extent with domains of interest in classical philosophy though. Nevertheless, each fields retains important distinctive properties. This section suggests that a cross feeding of results achieved in the respective fields mutually helps and it shows some concrete examples in this regard.

Philosophy literally means "love of wisdom" and was used in Ancient Greek to refer to any pursuit of knowledge [21-24]. In that era, the field was very broad, including not only core cognitive elements, such as formal logic and syllogisms but also domains considered today on their own, such as physics, sciences and politics. In fact even today philosophy keeps the universal view, and in this sense keeps including the latter domains, though in their most abstract forms only.

On the other side advances in tools and techniques have progressively led to automation and, more recently, out of necessity, to a formal and quantitative theory of cognition. In this evolution, the scientific approach has led to epistemic observation and a theory including axiomatic definitions of core concepts and the proposal of related metrics [5] [25-27]. Cognition is essentially the faculty to deliver correct information, ensured by specific internal structures and operative flows, typically processing information rationally, with high performance levels, for example in terms of complexity, knowledge, abstraction, learning, or expertise. While historically rather exclusively considered in human context, cognition is also, today, and increasingly, concerning man-made artifacts (re. artificial cognition, traditionally commonly described as AI).

In philosophy, cognition is central, and yet as the etymology of the former word can doubly prove it, philosophy is much more than that. Interestingly, Thomas Aquinas has formally distinguished behavior in two main categories. While indeed the cognitive category is one of them, there is also a decisive other one, which encompasses the affective components, feelings and emotions [28]. Precisely with the notions of «love» and «wisdom», philosophy strongly refers to non-cognitive components: the former case is evident, love is a feeling; the latter case requires more explanations. Wisdom is a specific property of

cognitive agents, referring to their ability to take good decisions (to be expert in delivering the messages that make agents reach a given goal); here at least two problems remain out of cognitive reach: which goal is appropriate? And are the required non-cognitive components, necessary to reach the goal, also ready for action (e.g., availability of energy, affects, physical elements or social partnerships)?

In consequence, philosophy is necessary for addressing problems at both ends of the reasoning chain, typical of cognitive processes: 1. the intuitive, experimental process extracting initial, axiomatic data and model features from reality; 2. the selection of relevant goals (re. ethics and, ultimately for humans, the choice of individual roles in universe).

Reciprocally, as is shown below in five points, the formal framework initially developed for advances in machine-based cognition, with means for quantitative assessments, suggests that other distinctions can be beneficial and allow for a novel clarity of many philosophical issues.

Rational, cognitive processes, for humans as for machines, can only develop in formal, well-defined structures that finally remain necessarily extremely simple with respect to reality; they develop in the scope of ad hoc models. Figure 5 above has qualitatively illustrated the fact that the simplicity of models has a huge cost: a similarly extreme restriction in terms of respective goals that any model can help to reach. The mentioned framework for cognitive sciences quantitatively defines complexity (and in an analog way, simplicity) as a direct function of the quantity of information (for which quantitative assessment is well-founded). Everyone knows that models are never complete with respect to reality, but going quantitative shows that the ratio in their complexities with respect to reality tends to zero ("zero-plus"?). This has tremendous consequences in philosophy: in particular what debate with respect to truth can be meaningful? How not to underestimate the importance of goal setting? The fact is that faith cannot, ultimately, be the defense of any truth, but in priority should represent adherence to a certain freely chosen goal.

Research in cognition has brought other, new results in terms of system granularity and group nature. A similar scheme can repeatedly be observed at very different scales, whereby apparently "individual", autonomous systems can appropriately be merged thereby yielding the emergence of a new holonic entity (a "group"), or on the contrary those same structures can be observed as coherent, collective entities (i.e., as "groups" as well), and consequently be analyzed in finer cooperating substructures. In particular, from a cognitive perspective, much of the paradigm is similar 1. as neural networks cooperate at brain/body level (re. "thinking"), and 2. as individual agents cooperate at a collective, higher level, yielding a group behavior (re. "society").

Experience shows that the effective, integral capability of groups is not always guaranteed, at any level, and the challenge gets more serious when, as is most of the time the case, a same resource may simultaneously be part of multiple groups, of different "cultures" and boundaries. Consider for example the risk of schizophrenia and possibilities of

membership conflicts for a human involved in several allied families, an employing company, various friendship circles, one or multiple religious entities, political parties cooperating in broader, secular frameworks, spaceship Earth, etc.

A particular advantage of automated cognition is that it allows theory in cognition to be operationalized. Coherence between a theory and the corresponding praxis has probably never been so close to guarantee. The very equations and structures that describe a cognitive phenomenon can now be computed in real-time and used to guide actions accordingly in the real world, as embedded computers and cooperating robots start routinely to do so.

Research in automated cognition has brought further, crucial results in terms of system dynamics. Careful, quantitative estimations and specific structural aspects can for example detect instability conditions and may call for changes in organization, such as granting autonomy to selected subsystems. Consequences can be drawn with benefits in the context of social philosophy. Reciprocally, it is also true that classical models in philosophy can help design novel automated systems featuring machine cognition (including AI).

#### X. CONCLUSION

Designing advanced cognitive technologies and applications requires a formal ontology, such as the MCS Model for Cognitive Sciences, the theoretical foundations now proposed for automated cognition, cognitics. Cognition has the ability to create and deliver pertinent information, both for the case when it is embedded in humans, and also for the case when it is machine-based, automated (re. « cognitics » in this latter case).

Starting in a pragmatic way from where we stand, in particular with humans creating robots, progressing with distributed axioms, navigating through small contexts in direction of selected goals (the design of high performance machines, of robots cooperating with humans, and a better understanding of cognition in humans), we adopt a constructivist approach in conceptual framework and validate them gradually by making them operational in test tasks.

Past works had taken for granted that reality and time were notions evident for everyone. Now, at the moment of attempting a practical implementation of those notions in robots, the situation is quite different. Early results in the context of MCS theory had made it clear that reality is infinitely complex, practically out of reach for cognition, under condition of exhaustivity.

Discussion has been made above of a number of cognitive notions including those of reality, time and revisited “speed”, change and discontinuity, innate and learned behaviors, as well as the human-inspired basics of communication in a group. These newly defined notions conveniently complement the existing MCS ontology. Notions are delineated in conceptual frameworks and can moreover be made operational, deployed in the real world, for validation purpose and for the benefit of users. All these elements confirm the rightness of our current approaches in

solving concrete Artificial Intelligence problems and this is illustrated below by some concrete examples taken in domestic context, including robots capable of learning.

Further research has been performed and the current paper could sketch ways to cope with the infinite complexity of reality. Several other cognitive notions could also be newly discussed, including those of time and revisited “speed”; change and discontinuity; innate and learned behaviors; as well as the human-inspired basics of communication in a group. On the basis of the proposed MCS ontology, and taking often advantage of innate/wired expertise, it can be concluded that robots can be effectively deployed in quantitatively bound domains, as illustrated in several concrete examples.

Cognition would not make much sense per se, and the paper has also shown how it can be implemented in the real world, notably using Piaget, our proprietary environment for development and programming of smart robotized systems. Experiments prove that the resulting smart systems can indeed successfully operate in the real-world, and in particular interact with humans, performing with large quantities of cognitive components: knowledge, expertise, learning, etc.

The quantitative approach of MCS and the operationalization of its cognitive concepts in real-world systems allow as well for an effective design and realization of smart systems for the benefit of humans as a fruitful dialogue about core issues in philosophy.

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