Some New Concepts in MCS Ontology for Cognitics;

Permanence, Change, Speed, Discontinuity, Innate versus Learned Behavior, and More

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Abstract—**Paving the way for advanced cognitive technologies and applications, an ontology for automated cognition, cognitics, has been proposed. 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 (design of high performance machines, of robots cooperating with humans, and better understanding of cognition in humans), we adopt an incremental, constructivist approach, in conceptual and operational frameworks. 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 Model for Cognitive Sciences ontology. 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.**

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

I. INTRODUCTION

In the past century, a major step in evolution has been made when information has been formally defined, 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, originating from some other electronic devices, control panels, microphones or other sensors yet. Machine-based sources of information were limited to signal generators, such as for sine-waves or pseudo-random sequences.

Then, however, things have become much more complex and cognition is the new domain to domesticate, where pertinent information is autonomously created by expert agents (e.g. , [1]). It is with this very relevant goal that the MCS theory for cognitive sciences has been created (Model for Cognitive Sciences [2, 3] and the cognitive pyramid of Fig. 1). This has been published and 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 [4]. So far, people have developed context-dependant expertise indicators (e.g. Elo points for chess-players, Association of Tennis Professionals points for tennis-players, or IQ scores), but unfortunately no other work, in our knowledge, has addressed the formal, technically-prone definitions of cognitive entities with associated units, beyond the concept of information.

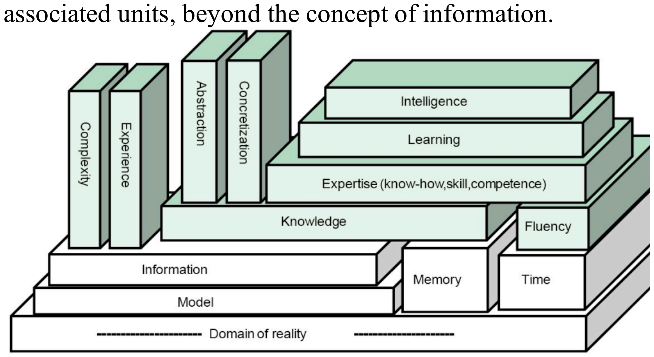

Figure 1. Main cognitive entities in MCS theory. Important cognitive concepts, defined in MCS theory, are colored in green (left). They are based on a few classic entities, including reality and time, which, though classic, also need a discussion from a cognitive perspective

Fig.1 schematically presents the main cognitive entities in MCS theory context. Without giving here again 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.

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-dependant, 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 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).

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.

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 [5,6] and focused discussions below). A complement had been progressively brought, 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. Finally, the general presentation made so far will be illustrated in Section V with detailed concrete examples, taken in the field of cooperative robotics, addressing both human and machine-based cognitive aspects and operations.

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 Fig. 2, 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 [7], 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 [5], 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). Nevertheless, rational processes can also develop in parallel, which, with automated cognition, possible exploration tasks, and on the basis of acquired experience, should yield various 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 [3].

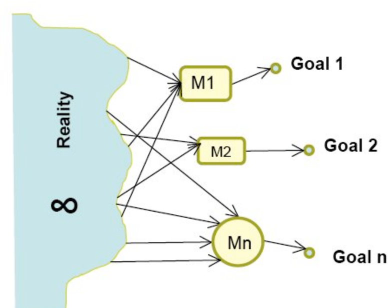

Figure 2. Experience strongly suggests that reality is infinitely complex. Models may be simple and validly serve singular goals, but they should always be considered as very specific for those goals and infinitely lacunary with respect to reality

III. WHAT IS TIME?

Strangely, time is far from well defined in classical terms. The proposal of Kant is interesting with his

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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 noone 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" [6].

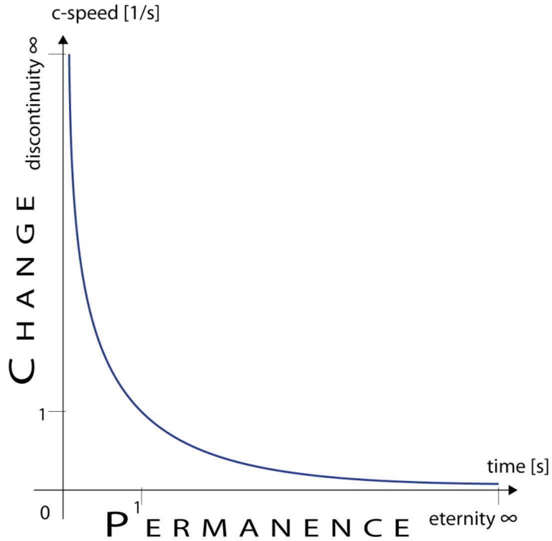

Figure 3. Time characterizes permanence, and speed as defined in MCS ontology, i.e., "c-speed", does it for change.

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 obstacle include 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 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. Fig. 3):

- 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 (1st order change); or the speed itself may change at constant speed, yielding the notion of permanent acceleration (2nd order change), etc. (re. "jerk" for 3rd order change).

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 Fig. 2, 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 Fig. 2). 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 [8]; 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 in a river (re. Thai word recommending humans to focus on selected goals).

B. *Pragmatic approach adapted to circumstances*

Then care must be given to current status. 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. Fig. 4).

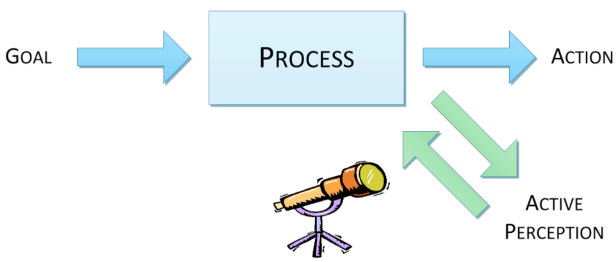

Figure 4. In cognition, backtracking is the rule. From the selected goal, specifications are derived, which then lead the cognitive process, and in particular an active perception ("exploration") faculty capable of acquiring the experience necessary for improvements.

C. *Innate goal and capabilities*

A prominent place is initially given to innate and current capabilities (re. Fig. 5).

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.

It is therefore 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.

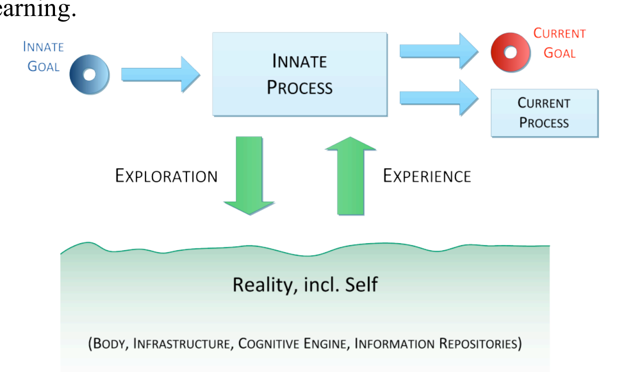

Figure 5. Current goals and processes may result from exploration performed and/or experience acquired by an agent running a given cognitive process in a certain domain of reality. Initial goals and processes are innate (or "wired").

The next interesting stage occurs when the design and creation of a new capacity to cope with reality is considered (Fig. 6). For connecting directly to reality, chance (as in Darwin's theory,) or ingenuity (as defined in MCS ontology [3]) are the main keys.

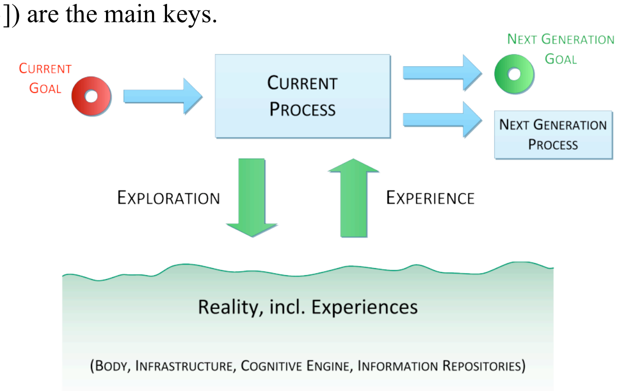

Figure 6. Current goals and processes may lead to improvements in next generation system (in particular for humans or machines).

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.

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

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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 [9], 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. Fig. 7).

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 (SII) is focused towards a domestic goal (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).

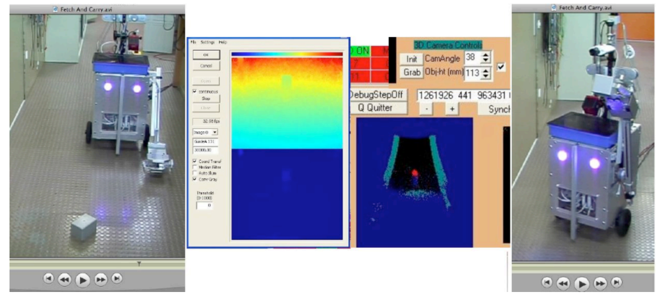

Figure 7. In the F&C task, our proprietary robot RH-Y uses in particular a vocal dialogue, a navigation capability typically using a ranger for navigation purpose, a time-of-flight camera for recognising and locating objects (*center*) and position and force controlled arm and gripper (*left and right*).

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., [10]) 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 Fig. 1). 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 bit of information for each object and rough location specified. On this basis, at the most abstract level, one out of 20x20=400 possibilities should be resolved (i.e. about 9 bit) 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^2.

In the specified location (e.g."near the door") the object is manually moved by referees by +/- 20cm 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 176x144 samples, each with 1cm accuracy in a 500cm range, i.e., about 150'000 bit of information; similarly, the output stage is relatively large for successful trajectory specification (about 10'000 bit of output information), and the processing time is short (say, 0.1s).

Time is a very important feature for success, in many contexts of this applications (motor control, parallel agent management, sensor-based exploration process, etc.). In our proprietary "Piaget" environment [11], 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 time basis ("TicksPerSecond"); nevertheless, 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. Conclusion

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. The paper has first briefly revised MCS, an ontology for cognition, 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). 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. Further research has therefore been performed and the current paper could nevertheless 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.

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References

[1] Bernard Claverie, "Cognirique - Science et pratique des relations à la machine à penser", Editions L'Harmattan, 2005, pp. 141.

[2] Jean-Daniel Dessimoz, "Cognition Dynamics; Time and Change Aspects in Quantitative Cognitics", Second International Conference on Intelligent Robotics and Applications. Singapore, 16 - 18 December, 2009; also in Springer Lecture Notes in Computer Science, ISBN 978-3-642-10816-7, pp. 976-993.

[3] Jean-Daniel Dessimoz, "Cognitics - Definitions and metrics for cognitive sciences and thinking machines", Roboptics Editions, Cheseaux-Noréaz, Switzerland, ISBN 978-2-9700629-1-2, pp. 169, January 2011.

[4] Wisspeintner, T., T. van der Zant, L. Iocchi, and S. Schiffer, "RoboCup@Home: Scientific Competition and Benchmarking for Domestic Service Robots", Interaction Studies, vol. 10, issue Special Issue: Robots in the Wild, no. 3: John Benjamin Publishing, pp. 392--426, 2009.

[5] Frederick Charles Copleston, "A history of philosophy", Volume 6, Continuum International Publishing Group Ltd.; Édition : New edition (June 5, 2003), pp. 528.

[6] Alexander Rosenberg, "Philosophy of science: a contemporary introduction", Routledge comtemporary introductions to philosophy, 2005

[7] George E. Hein, "Constructivist Learning Theory", The Museum and the Needs of People CECA (International Committee of Museum Educators) Conference, Jerusalem Israel, 15-22 October 1991, Lesley College. Massachusetts USA.

[8] Hart, P. E.; Nilsson, N. J.; Raphael, B., "A Formal Basis for the Heuristic Determination of Minimum Cost Paths", IEEE Transactions on Systems Science and Cybernetics SSC4 4 (2), pp. 100–107, 1968.

[9] Julie A. Jacko (Ed.), "Human-Computer Interaction. Novel Interaction Methods and Techniques" 13th Internat. Conf., HCI Internat. 2009, Proc. Part II, San Diego, CA, USA, Springer.

[10] http://rahe.populus.ch /rub/4 , last downloaded on June 3rd, 2012.

[11] Jean-Daniel Dessimoz, Pierre-François Gauthey, and Hayato Omori, "Piaget Environment for the Development and Intelligent Control of Mobile, Cooperative Agents and Industrial Robots", accepted for publication, ISR 2012, International Symposium for Robotics, Internat. Federation of Robotics, Taipei, Taiwan, Aug.27-30, 2012.