Embodying Intelligence in Autonomous and Robotic Systems with the Use of Cognitive Psychology and Motivation Theories

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Abstract. The article discusses, on a certain level of abstraction and generalization, a coherent anthropological approach to the issue of controlling autonomous robots or agents. A contemporary idea can be based on appropriate modeling of the human mind using the available psychological knowledge. One of the main reasons for developing such projects is the lack of available and effective top-down approaches resulting from the known research on autonomous robotics. On the other hand, there is no system that models human psychology sufficiently well for the purpose of constructing autonomous systems. Nevertheless, to combat this lack, several ideas have been proposed for embodying human intelligence. We review recent progress in our understanding of the mechanisms of cognitive computations underlying decision-making and discuss some of the pertinent challenges identified and implemented in several systemic solutions founded on cognitive ideas (like LIDA, CLARION, SOAR, MANIC, DUAL, OpenCog). In particular, we highlight the idea of an Intelligent System of Decision-making (ISD) based on the achievements of cognitive psychology (using the aspect of 'information path'), motivation theory (where the needs and emotions serve as the main drives, or motivations, in the mechanism of governing autonomous systems), and several other detailed theories, which concern memory, categorization, perception, and decision-making. In the ISD system, in particular, an xEmotion subsystem covers the psychological theories on emotions, including the appraisal, evolutionary and somatic theories.

Keywords: cognitive architecture, cognitive development, decision-making, human-computer interaction, perception, intelligent agents

1 Introduction

Creating a system functioning in a human-like way, has long been a principal subject of artificial intelligence and robotics. As can be seen from the many known results of robotics, a significant number of artificial creatures and humanoids have been constructed [32], and some of them even try to communicate in natural language [55]. Moreover, considering the inner aspect, the well-known artificial neural networks (of a convolutional type) have been conceived and applied for different system control and recognition purposes [23,9]. All such minor steps are being made towards creating an artificial humanoid, synthetic organism, or android robot, designed to look and act like a human.

Artificial Intelligence is being developed in a continued effort to solve engineering problems, such as reasoning, problem solving, knowledge representation, machine learning, natural language processing, machine perception, and others. Eventually, solving these problems should lead to an invented humanoid system similar to a human being, to a certain extent. A few principal types of approaches to artificial intelligence are worth mentioning here:

- cybernetic – which postulates to follow an imitation of some aspects of real, physical, or biological systems in a virtual world (using neural networks, evolution algorithms, swarm algorithms, etc.) [53],
- statistic – which seeks to build rigorous, usually sophisticated, mathematical tools necessary for statistical modeling of processes [49],
- symbolic (top-down, synthetic, 'neats', clean) – which uses high-level logic (simplistic, black-box) mathematical modeling, knowledge-based processing, and machine learning [47],
- sub-symbolic (bottom-up, analytic, 'scruffies', *ad hoc*, embodied) – which involves the use of small (white-box, physical, neuronal) models to first create a low-level, and next, by the *ad hoc* rules, higher-level solutions [8].

The variety of known AI branches strive for (usually partially) modeling of the human mind, and none of them fulfills this objective fully. Modeling the human mind can be performed by applying the symbolic (top-down) approach and the sub-symbolic (bottom-up) method. These two approaches are complementary, and both are related to the cybernetic method. Certainly, the statistical tools developed in a mathematical way are of great use. Probably, solely an intelligent combination of many methods will be able to satisfactorily reflect the effects of the human brain.

Embodied Intelligence (EI) represents the sub-symbolic approach. It is an extension of the genuine cybernetic projects from the 50s, which tried to reproduce simple phenomena of 'intelligence' identified at a low level of cognition [17,3,8,7]. We can recall here the early cybernetic projects, like the construction of *homeostat*, a device which retains stable despite external disturbances, or *tortois*, a robot which follows an assumed intensity of light [53]. Quite promising results can be obtained by following *baby steps*, that is, by simulating a certain basic functionality using simple elements (note that the tortois had only two neurons, for instance). On the basis of such affirmative experience, a new branch of behavior-based robotics has emerged [4].

Most issues, such as finding an optimal trajectory or recognition of environmental objects, require rather complex operation, whereas inference and reasoning are relatively simple (from the biological and computer science points of view). It is Moravec's paradox that applies to this problem [46]:

> *Encoded in the large, highly evolved sensory and motor portions of the human brain is a billion years of experience about the nature of the world*

> *and how to survive in it. The deliberate process we call reasoning is, I believe, the thinnest veneer of human thought, effective only because it is supported by this much older and much more powerful, though usually unconscious, sensorimotor knowledge. We are all prodigious olympians in perceptual and motor areas, so good that we make the difficult look easy. Abstract thought, though, is a new trick, perhaps less than a hundred thousand years old. We have not yet mastered it. It is not all that intrinsically difficult; it just seems so when we do it.*

It seems natural that different achievements from the fields of embodied intelligence, behavior-based robotics, and top-down approaches in AI, are indispensible in modeling the effect of the human mind. However, to reach an intelligent interaction of an artificial agent with the environment it is also important to clearly define what 'embodied intelligence' means [60].

In this paper the concept of 'embodied intelligence' will be understood in a slightly different way than the 'classical' notion. Recall that mathematical modeling providing a description of a hypothetical fragment of an existing reality, reflects the behavior of a real system in a particular environment. Such an environment generates different distal signals determining the so-called experimental setting. At each stage of the process of modeling of physical phenomena, the results of the next simplified mathematical model are thoroughly referenced to the previously conducted experiments. This is in line with the bottom-up approach (analytic, physical, white-box). On the other hand in natural sciences, psychology, philosophy, and cybernetics, the top-down approach (synthetic, mathematical, black-box) is most frequently in use. Ignorance of the aforementioned principles may easily lead to confusion and inadequate interpretations.

1.1 ... Intelligence

One of the first definitions of intelligence has been proposed by Spearman in [59]:

> *...all branches of intellectual activity have in common one fundamental function, whereas the remaining or specific elements of the activity seem in every case to be wholly different from that in all the others.*

It appears, however, too vague for the aim of determining the intelligence for robot purposes. Though clear, other definitions like: „*The ability to deal with cognitive complexity*" or „*Goal-directed adaptive behavior*" [20,61] also seem to be overly general. Nevertheless, due to such definitions, you can at least imagine what is the essence of human-like intelligence:

Definition 1. *Intelligence is the ability of active processing of cognitive information in order to adapt to the changing environment and to gain own, specific purposes or common goals.*

In an extremely simple case, an intelligent agent, by being completely focused on searching for a source of energy necessary to survive, can function completely selfishly. Clearly, the latter brings to the mind the aforementioned tortois and cybernetic theories.

1.2 Embodied ...

Embodiment in the human case means that the entire perception of the real world completely relies on its physical components and senses. Embodiment is also associated with the philosophy of mind, and, in particular, with the whole mind-body problem as formulated by Descartes [2].

Certainly, intelligence could not be developed without embodiment [60]. It is also clear that any virtual or robotic agent ought to be designed for, and located in, a certain environment to have a chance to implement a two-way interaction. Then one can talk about *engineered intelligence*, having the *environmental embodiment* (or foundation) defined as:

> *Mechanism under the control of an intelligence core that contains sensors and actuators connected with this core via communication channels.*

Such embodiment of a robot or agent can be easily extended with various kinds of tools (like glasses, spectacles, drives, or even a mobile or car), which augment both the agent's perception and possibilities of reaction.

2 Decision systems

The idea is to build a system that – in line with the increasing capabilities of computers and their power – would be able to take autonomous decisions, according to current circumstances. Certainly, there exist, and are being developed, increasingly sophisticated decision-support systems, such as: expert systems [1,5], and systems based on Bayesian networks [16,65] or neural networks [57,66]. Such systems usually support human decision making (for diagnostic purposes, for instance). In most cases they are strictly tailored to pre-defined conditions. In general, however, there are two known paths for decision-making:

- classical, which finds the most optimal decision for a well-defined problem,
- cognitive, aiming at finding a solution to real problems defined or recognized only partially.

Thus the classical decision theory treats about taking decisions in a strictly optimal sense for mathematically well-modeled tasks and well-defined problems. Whereas the cognitive theory shows how to take proper decisions for difficult real-world problems, which are usually uncertain and not well defined [19].

An early elaboration on human decision-making processes was delivered in 1910 by Dewey [15]. According to him, there are five stages in the decision making process: Defining the problem, Indication of its character, Finding possible solutions, their Evaluation, and Selection of the appropriate solution. A similar and a bit more universal division, referred to as *GOFER*, presented in 1991 [41] suggests the following phases:

1. Goals – searching for selecting the objectives,
2. Options – considering a wider spectrum of alternative actions concerning the goals currently considered,
3. Facts – gathering additional knowledge about actions (options) and goals,
4. Effects – evaluating (usually hypothetically) the results of the chosen options,
5. Rating – final evaluation of the decisions, and selecting the best one.

In addition, there are many other interesting approaches to the analysis of complete decision processes [54,6,44]. Not far from, in its simplest form, the decision making process can always be described in solely three phases [58]:

1. definition of the problem,
2. finding possible solutions,
3. selection of the optimal solution.

In order to achieve the effect of autonomous decision-making suitable for a current situation, the system should not only take the opportunity of learning (knowledge extension), understanding and recognizing (known) objects, but also it should have some motivations which compel it to take action.

There are a great number of decision-making systems based on human motivation factors. Human is the highest of all species in terms of adaptation to the changing environment, thus the human system of motivation appears to be most adequate as a template of behavior. Ethical foundations for such systems can be derived from the existing variety of the available models of psychology and human intelligence. These achievements have also notably contributed to artificial intelligence. Among them one can distinguish the following types of conceptual solutions:

– behavioral [4,14],
– BDI (Beliefs-Desires-Intentions) [25,13,52,21],
– emotional [42,33] (sometimes they are assigned to BDI),
– driven by needs [22,56,43,45,50],
– cognitive (**LIDA**, **CLARION**, **SOAR**, MANIC, DUAL, OpenCog, ...).

To give you a taste of the existing spectrum of complex systems, we will discuss below three (in bold) of the above-listed representatives of cognitive systems.

2.1 LIDA

Learning Intelligent Distribution Agent, LIDA, originally developed by Stan Franklin [18], is a cognitive system which intends to model biological cognition [40,18]. It implements an architecture of sub-sumption [8] and other aspects of the sub-symbolic branch of AI. This is one of the most advanced projects aiming at modeling the results of psychological and neuro-psychological theories, in

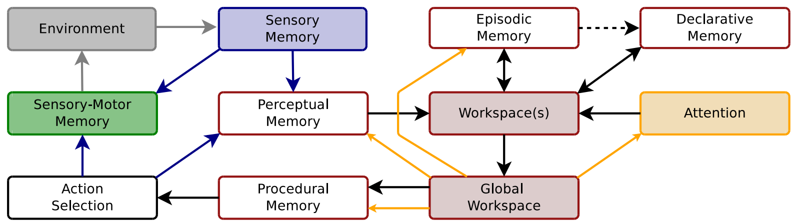

Fig. 1. Cognitive architecture of Lida: the grey lines represent interaction with the environment, blue lines show low-level processing, orange lines indicate learning process, and dotted lines portray consolidation of the memory.

particular, embodied knowledge, symbolic systems of perception, different types of memory, and the different ways of learning mechanisms, overt attention and motivation in the form of emotion (Fig. 1).

LIDA is executed using cognitive cycles (repeated in each executive run), each of which consists of the subprocesses of perception, selection of appropriate response (relative to the perceived environmental facts), and implementation of the selected reaction. Advanced cognitive processes, such as planning, can be synthesized as an aggregate of the perception-action cycles. Motivational aspects in the LIDA system concern feelings, which have their own valence (positive or negative), associated with satisfaction, or pain (which evidently attributes LIDA also to the emotional developments and solutions).

Stimuli recorded by sensors and pre-processed, are next analyzed in a working/operational memory referring to various types of long-term memory (perceptual, episodic, declarative and procedural). Memory is instrumental in creating a current model of actual circumstances, which constitute an executive groundwork for the process of selecting the desired reaction (using the procedural memory). *Conscious contents* are intended to add an external context to this model, and to enable learning processes. Once selected, the reaction is directly implemented by the actuators.

2.2 CLARION

Connectionist Learning with Adaptive Rule Induction On-line, CLARION, represents a cognitive architecture based on theories from cognitive and social psychology [63,62,11,64]. CLARION implements several AI results to ensure the effect of creating an *intelligent* system. CLARION's architecture, developed and implemented by Ron Sun, is composed of four units shown in Fig. 2:

- ACS – (procedural) Action Centered Sub-system,
- NACS – Non-Action Centered Sub-system,
- MS – Motivational Sub-system,
- MCS – Meta-Cognitive Sub-system.

In each of the above sub-systems the data and structures are represented dually: at a higher level (overt/explicit) and at a lower level (covert/implicit). This dual representation in CLARION, connected with (different) philosophic theories and with the issue of memory representation [35,51], enables autonomous learning in two ways: bottom-up (induction) and top-down (deduction). The assumptions applied are fully compliant with the requirements of the embodied intelligence design discussed earlier.

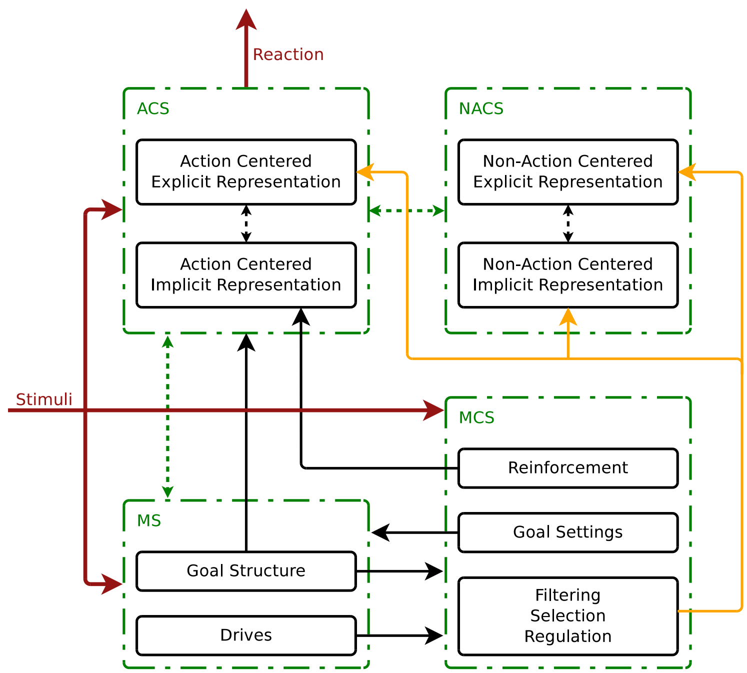

Fig. 2. Cognitive architecture in Clarion: the orange lines present attention (in general), green lines indicate data exchange, and red lines show interaction with the system's environment.

The action oriented sub-system (ACS) is responsible for all kinds of the agent's reactions, both internal and external (concerning the environment). The covert (implicit) part is implemented as a neural network, while the overt (explicit) layer represents a rule base. The non-action centered sub-system (NACS), which mimics the role of the semantic and episodic memories, is responsible for the storage and delivery of knowledge. It is also divided into two parts. Its hidden part takes the form of an associative neural network, while its explicit layer can be described with the use of symbolic notations and rules. The inference performed in this module is founded on similarities.

Motivation means are also important to the design of the cognitive structure of CLARION. Corresponding motivational elements of the MS sub-system are of both the explicit and implicit type. Explicit (higher) elements include targets (explicit goals), such as: belonging, recognition, power, autonomy, respect, and honesty. On the other hand, the lower motivational factors (prime movers) of the CLARION system, realize the idea similar to the concept of *needs* (discussed later), which are of a physiological nature (consider eating, drinking, sleep, security, and reproduction). In addition, CLARION's MS sub-system allows you to program your own *secondary needs* to define a more subtle motivation (in order to achieve a certain goal).

The MCS sub-system is responsible for a meta-cognitive function resembling attention or awareness. It monitors and regulates all other cognitive processes of the agent and fulfills the idea of *consciousness*. More specifically, MCS chooses which goals are most important, with autonomous inferencing and learning, and how to adjust the gain of the learning process. It is also responsible for information filtering and for selecting the method of data interpretation.

2.3 SOAR

State, Operator And Result, SOAR, is a cognitive architecture invented by Laird, Newell, and Rosenbloom [39,36,24,48,10,38]. It is one of the earliest systems of this type (its first version is dated back to 1983), whose main purpose is behavior resembling an intelligent agent. Its architecture is suitable for operation under varied conditions, from routine tasks upto creatively difficult open problems. It requires appropriate forms of knowledge representation, and suitable types of memories (procedural, semantic, episodic and iconic). To be consistent with the assumptions of embodiment, the agent needs to interact with the ambient world, and to learn constantly about its features. The decision making in SOAR is based on the current situation perceived from the environment, whereas the necessary information and knowledge is acquired by suitable dynamic processing of the data gained through the sensors. An internal expert system plays the role of fundamental processing unit.

SOAR's cognitive architecture has several components concerning [37]:

- memory functioning, for the task of knowledge storage,
- processing module of attention, used for extraction, mixing and remembering knowledge,
- semantics and syntax of the language used for storage and processing of knowledge.

Similarly to LIDA, SOAR is based on a certain decision cycle. A perception sub-system manipulates the data stored in a symbolic short-term memory. Deductive rules are used to test the agent's capabilities in the context of possible actions. Another layer of rules is applied to suggest optimal reactions (operations) adequate to the current situation evaluated by perception and motivational subsystems, and next the agent's preferences are calculated. Finally, according to

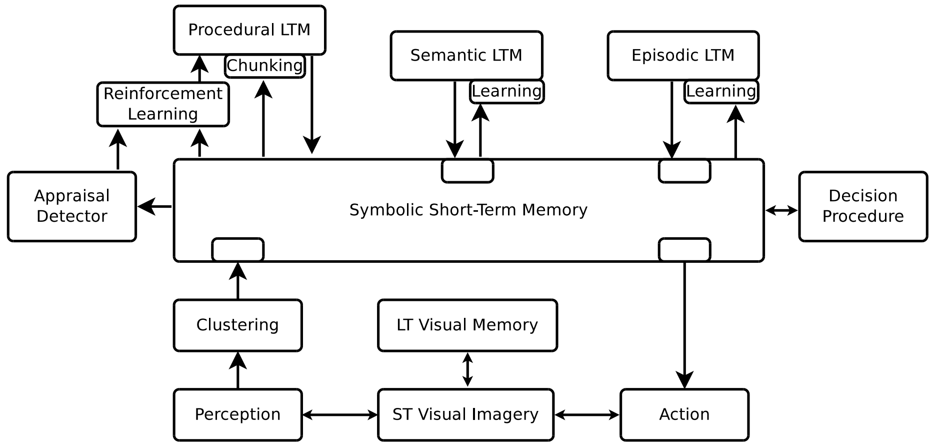

Fig. 3. Cognitive system of SOAR (ver. 9).

the perceived state (situation), and given a pre-processed set of possible reactions and preferences, SOAR is ready to select one of the estimated reactions, and then to apply it using the system actuators.

The cognitive structure of SOAR is shown in Fig. 3, where decision cycle is implemented by the block of decision procedure. In the SOAR system, emotions are generated in the appraisal detection block, and next they serve as reinforcement applied in learning processes (indirectly through *mood* and *feelings*). Semantic memory is an essential element in the treatment of procedural and episodic knowledge (using long-term memory). It allows the agent to store information about the environment. On the other hand, the episodic memory contains the knowledge related to the execution and effects of various types of actions, including the degree of fulfillment of the rules and operations performed by the agent (and others). Long-term visual memory as well as imagination assist in the agent's mind operations concerning spatial processing.

2.4 Intelligent System of Decision-making

Intelligent System of Decision-making, ISD, as presented in the recent papers [26,27,28,29,30,31,12,35], is a control system of an agent that intends to covert and implement the contemporary theory of embodied intelligence and decision theory, and in particular, the models of cognitive psychology and motivation theory. It mimics roughly the way people make decisions, from the arrival of the stimuli to the generation of a reaction. As a consequence, the ultimate design of the ISD unit is the result of a thorough modeling of human psychology embedded in elementary findings of an extensive literature study. In practice, ISD is a universal system which can control robots and unmanned ground vehicles, including cars, as is presented in [12]. A view on ISD is presented in Fig. 4.

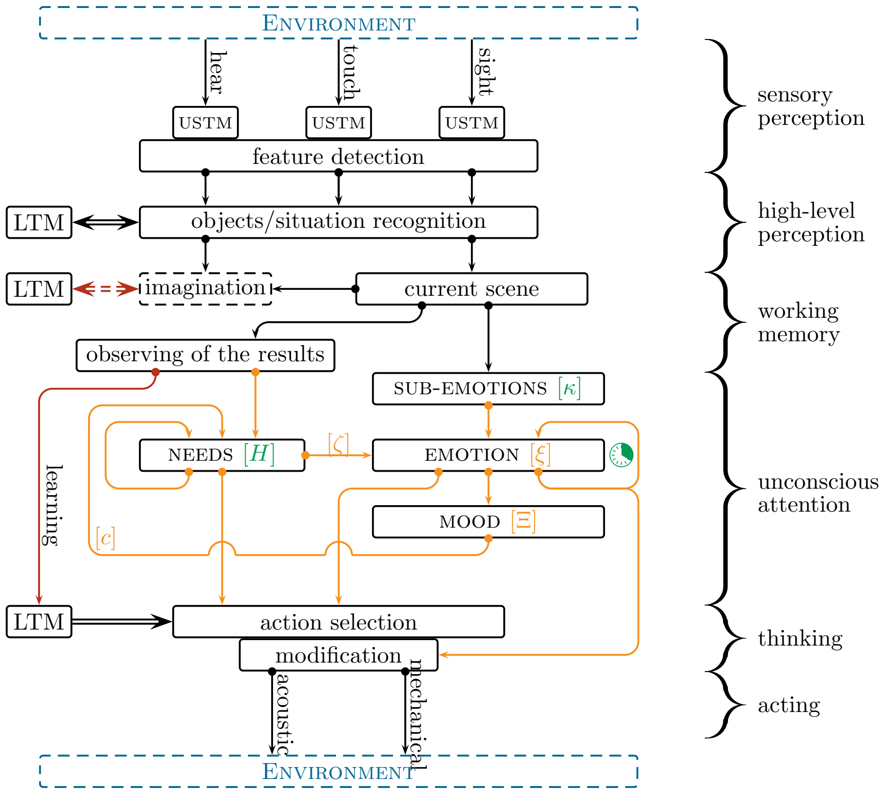

Fig. 4. Schematic view on the Intelligent System of Decision-making.

ISD is a cognitive decision-making system, which implements all of the stages of decision-making, presented earlier. The main mechanism of decision-making in ISD is based on the concept of needs, which are principal drives for acting. Needs are variables programmable by the user. They can also be possibly created autonomously by the agent and adjusted for certain situations. Thus, different sets of needs may be used to shape the characteristics (personality) of the agent, according to its environmental conditioning. Observed objects and events, and actions performed by the agent (namely their inner and outer results) have impact on the state of the agent's needs.

ISD presents also cognitive abilities with respect to the *understanding* of the environment (in practice, without them the system would not be consistent). It means that from the robotic point of view, the agent is 'conscious' of its environment, it knows its position, and the position of surrounding objects and their definition. Stimuli perceived by the agent's senses (sensors) are stored in an ultra-short-term memory (USTM). Simple features of perceived objects (impressions), such as colors, shapes, textures, etc. (like red flat rectangle), are extracted from USTM, and stored in a short-term memory (STM). To recognize a simple impression, the agent can apply various mechanisms, developed as filters, masks, neural networks, fuzzy systems, decision rules and others. For example, a Haar cascade can be used for recognizing head shapes (impressions). During extraction, certain stimuli may cause an immediate unconscious action of the agent (like: 'step back' in response to pain). On the basis of the observed features (impressions), complete discoveries/objects are 'mentally' created, taking into account the relative location of the features in space. In a simple translation, the discovery consists of impressions in a specific location. Next, they are compared to known objects stored in a long-term memory (LTM). If the 'mind' detects a certain level of similarity between the perceived discovery and a know object from LTM, the discovery is recognized/identified with the object from LTM. A suitable recognition procedure is described in [12]. Some of the discoveries may result in half-conscious activities, previously learned through multiple repetitions.

Recognized objects are transferred to the agent's operational memory that represents the current scene, where they are analyzed from different angles, taking into account:

- the impact of external (environmental) facts/objects, as they may affect the needs or cause sub-emotions, which can, in turn, change the agent's proper emotion; Remember also that both the needs and the sub-emotions must be previously stored as connected to certain discoveries (e.g. a pink blanket from childhood can connect with the need for security), and thus affect the agent's current system of needs;
- the effect of the internal (*body*) facts/states, as they can also modify the agent's system of needs (e.g. an energy sensor connected to the need of energy, can directly change the need of the agent, according to its value).

According to the above, the states of needs are constantly updated, creating, and pointing to, new goals. The agent tries to find (or formulate) a conscious action to be implemented by the system in order to fulfill its most important or painful needs [27,28,29]. The action undertaken by the ISD unit is then tracked by the part of the thinking process which is referred to as the observer of results. This process always seeks to see a desired effect of the previous action (for instance, in the change of the degree of fulfilment of the agent's needs) by penetrating the contents of the operational memory. It is also related to the learning process in ISD. The achieved results of the previous activities are memorized (for future searches of optimal actions).

In line with the human motivation theory, emotions are one of the most important factors of human behavior. Systems, based on human psychology (both cognitive and motivative), but deprived of emotions would be ineffective. Emotions in ISD perform their function at a higher level of control than the basic ISD control ruled by the system of needs. In our robotics applications, emotions allow us to narrow down the set of possible reactions to those that are most adequate (in the view of the system designer) for the current time moment and the state of the ISD system [30,34].

Pre-defined sub-emotions (emotions associated with identified objects) do influence the current state of the proper emotion of the agent, which strikes (assumes) one of 24 possibilities, according to the theory of Plutchik. The degree of satisfaction of all the agent's needs, the former emotional state, and the effect of calming down (emotion simply decays with time), all influence the state of the emotion of the agent. Changes in emotion affect the mood, which, in turn, tune the fuzzy parameters of the needs models. As mentioned earlier, emotion effectively preselects (narrows) the set of possible reactions. In addition, it can modify some reactions (for instance, by using additional forms of expression, like wording, gestures, or facial expressions).

There are different types of long-term memory in the ISD system [31]:

– semantic (abstract and realistic),
– episodic,
– procedural.

Knowledge in ISD is stored in the form of (abstract or instance) discoveries, consisting of many different features/impressions (including those related to needs and emotions), labels, and relations to other discoveries [35]. Episodic memory is used to describe events on the time axis, and with reference to respective discoveries stored in the semantic memory. A forgetting phenomenon decays the activity level of remembrances (the events remembered in the episodic memory). Depending on this level, the more frequent the remembrances (memories) are, the faster they can be recalled. Procedural memory contains specifications (declarations) of the agent's actions.

3 Comparison

The above-presented systems represent a cognitive approach to the problem of decision-making. All of them are trying to combine the bottom-up and top-down approaches and methods. In practice, however, they are very different in the aspects of implementation and concept. There is no great sense to compare them in terms of parameters such as computational complexity, speed of response, accuracy and performance of individual activities, because of the large variety of implementation and use of these systems. Certainly, there are several useful tests for autonomous cognitive systems like user-end tests for *coffee-making* or *student behavior*, but they have a limited use, due to the lack of the necessary actuators. The utility of such one-sided (one goal) tests is also controversial due to their selectivity, at which some cognitive systems appear to be better than the other ones, depending on the particular test task. However, one may always compile a multi-purpose comparison of the cognitive architectures in terms of structure models, driving systems, and implementing concepts, as has been shown in tab. 1.

4 Synchronization of cognitive systems

Each of the presented systems approaches the issue of modeling the human cognitive processes in its own way. They appear to be more or less explanatory,

Table 1. Comparison of cognitive architectures.

	LIDA	CLARION	SOAR	ISD
structure	perception-action cycles	explicit and implicit sub-systems (parallel)	cycles	cycles with interruptions
stimuli	internal and external	external	dependent on designer	internal and external
perception memory	Slip-Net (associative)	connected to working memory	*not known*	impressions
basic memory unit	codlet	chunk	rule	discovery
short-time or working memory	global workspace theory	limited (visuospatial, auditory, other)	symbolic short-term memory	current scene and imagination with activation levels (limited)
long-time memory structure	perceptual, episodic, declarative, procedural	Non-Action Centered Subsystem (semantic, associative knowledge)	procedural, semantic, episodic	semantic (abstract and instance), episodic, procedural
drivers	*not known*	similar to human needs, goals	emotions	needs & emotions
emotions	feelings (positive or negative)	*not known*	appraisal (mood and feelings)	based on Plutchik
decision-making	based on current environmental situation	rules and neural networks	rules and reasoning	motivation driven
programming language	Java	C#	Java & C++	Python
usage	medical diagnostic	simulations concerning wide spectrum of cognition	simulations from towers of Hanoi to quakebot	partial simulations

and usually to some extend (partially) support the psychological theories on these processes. This knowledge allows us both to evaluate the psychological theories and generalize or adapt the cognitive processes for autonomous agents. For example, each of presented systems has some basic memory entity, which let the agent to comprehend particular real objects, and an overall semantic memory, necessary for grasping the actual situation by an autonomous robot.

Note that cognitive architectures are primarily designed to make decisions under the circumstances of autonomous work. Nevertheless modeling the environment of the agent appears to be even more difficult than the inferencing itself. Therefore, it is important that the developed systems also indicate how to describe the environment for the purpose of autonomous agents (letting the necessary and inevitable interaction).

For comparative purposes and definite concluding results, each of the presented systems should be implemented on a platform of an autonomous (mobile) robot, and then tested under identical conditions (this would be more effective than partial simulation, certainly). In particular, the cognitive architectures should be tested at different angles, highlighted below:

- perception - estimated in terms of speed and accuracy of environmental recognition,
- attention - to determine the importance of objects due to agent's security and decisions,

– decision-making - adequate for practical uncertainty,
– learning and reasoning - enabling the agent to correct its mistakes and to expand its *knowledge* about the surrounding environment,
– computing power - necessary for proper functioning of the system.

5 Summary

The paper discusses the idea of embodied intelligence as an approach that combines both the cognitive modeling of complex systems (top-down approach), as well as the (bottom-up) implementation of systems designed to detect and comprehend the basic characteristics of the environment. Needing a variety of tools, the creation of such architecture principally relies on established theories, and thus results in workable reformulations of several essential definitions concerning intelligence.

The agent that has the ability to actively process cognitive information using its sensors and mechanisms to adapt itself to the changing environment and to achieve its objectives (at least to strive for them), possesses embodied intelligence. In our pursuit of the goal of embodied intelligence, we used a systematic approach to the cognitive decision-making process through the implementation of several major ideas of cognitive psychology and motivation theory, which led us to design of the Intelligent System of Decision-making (ISD).

Though the presented cognitive systems have been developed for different purposes, all of them model the decision-making process in a very interesting, instructive and practicable way, using differently defined motivational aspects. In the near future, such systems will have the opportunity to achieve a high level of sophistication in terms of both the design conception and technical implementation - with great hope to achieve at least some level of intelligence of simple living creatures (like lizards, for instance).

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