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Artificial cognitive control system based on the shared circuits model of sociocognitive capacities. A first approach

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ABSTRACT

A first approach for designing and implementing an artificial cognitive control system based on the shared circuit models is presented in this work. The shared circuits model approach of sociocognitive capacities recently proposed by Hurley in *The shared circuits model (SCM): how control, mirroring, and simulation can enable imitation, deliberation, and mindreading. Behavioral and Brain Sciences* 31(1) (2008) 1–22 is enriched and improved in this work. A five-layer computational architecture for designing artificial cognitive control systems is proposed on the basis of a modified shared circuits model for emulating sociocognitive experiences such as imitation, deliberation, and mindreading. In order to show the enormous potential of this approach, a simplified implementation is applied to a case study. An artificial cognitive control system is applied for controlling force in a manufacturing process that demonstrates the suitability of the suggested approach.

1. Introduction

There is as yet no such complete scientific theory of intelligence (Sanz and Gómez, 2008). Recent results in different disciplines, such as neuroscience, psychology, artificial intelligence, and robotics, and results related with new machines and intelligent processes, have laid the foundations for a computational theory of intelligence (Meystel, 1994). There are many definitions of intelligence, one of them is the ability of human beings to perform new, highly complex, unknown or arbitrary cognitive tasks efficiently and then explain those tasks with brief instructions. It has spurred many researchers in areas of knowledge such as control theory, computer science, and artificial intelligence (AI) to explore new paradigms to achieve a qualitative change and then to move from intelligent control systems to artificial cognitive control strategies (Albus, 2008).

A natural cognitive system displays effective behavior through perception, action, deliberation, communication, and both individual interaction and interaction with the environment. What makes a natural cognitive system different is that it can function efficiently under circumstances that were not explicitly specified when the system was designed. In other words, cognitive systems have certain flexibility for dealing with the unexpected (Vernon et al., 2007). A cognitive system can also *reason* in different ways, using large quantities of knowledge adequately represented in advance. In addition, a cognitive system can learn from experience to improve how it operates. Furthermore, it can explain itself and accept new directions, it can be aware of its own behavior and reflect upon its own capabilities, and it can respond robustly to unexpected changes. Thus, artificial cognitive agents must share with natural cognitive systems key traits and some *cognitive and neurobiological* principles.

General systems analysis about the heterogeneous aspects of cognitive phenomena demonstrates that, bearing in mind the known mechanisms of human mind, cognition can be defined as model-based behavior (Huerta and Nowotny, 2009; Ito, 2008; Rabinovich et al., 2006). During cognitive or executive control, the human brain and some animal brains process a wide variety of stimuli in parallel and choose an appropriate action (task context), even in the presence of a conflict of objectives and goals. Thus, there is a shift from attention control (a selective aspect of information processing that enables one to focus on a relevant objective and ignore an unimportant one) to cognitive change in itself.

At present there is a wide variety of strategies and initiatives related with the partial or full emulation of cognitive capacities in computational architectures. Each one is based on a different stance regarding the nature of cognitive capacity, what makes a cognitive system, and how to analyze and synthesize such a system. However, there are two widespread trends, the *cognitivist* approach (reflected, for example, in architectures such as *Soar*, *EPIC*, and *ICARUS*), based on representational systems as a tool for processing information symbolically (Pylyshyn, 1984), and the approach that describes *emerging systems* (*AAR*, *Global Workspace*, and *SASE*),

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which include connectionist systems, dynamic systems, and enactive systems (Thelen and Smith, 1994). They are all based to a greater or lesser extent on the principles of self-organization (Clark, 2001). The cognitivist approach rests on cognition's being developed on the basis of symbolic representations, while the connectionist approach treats cognition as an enactive system, that is, a system defined "as a simple network of processes that it produces itself and that constitutes its identity". This *sense-making* (Weber and Varela, 2002) has its roots in autonomy, an autonomous system being a distinguishable individual (Froese, 2007). There are also hybrid models that combine the two visions; i.e., they use representations which are only constructed by the system itself when it interacts with and explores its environment.

On the other hand, there are thousands of complex systems and processes which are waiting for artificial cognitive control strategies in order to behave adequately before disturbances and uncertainties (Sanz et al., 2007). In this century, the manufacturing is a clear example of a dynamic social and technical system operating in a turbulent environment characterized by continuous changes at all levels, from the overall manufacturing system network right down to individual factories, production systems, machines, components, and technical processes. Nowadays, the highest priority goes to the development of technologies that enable faster, more efficient manufacturing by means of cooperative, self-organized, self-optimized behavior through process control systems. In addition, manufacturing processes are conditioned by the presence of nonlinear and time-variant dynamics that are determined by forces, torques, and other variables—even, in the case of nano-scale processes, with strong interactions at intermolecular level. These characteristics increase the functional complexity of manufacturing due to nonlinearities, and they exponentially increase the functional and precision requirements of sensors, actuators, and computing resources.

This work is based on the shared circuits model (SCM) approach (Hurley, 2008). SCM approach serves as the foundation for designing an artificial cognitive control system where imitation, deliberation, and mindreading processes are emulated through computational efficient algorithms in a computational architecture. Hurley's approach suggests that these capacities can be achieved just by having control mechanisms, other-action mirroring, and simulation. An artificial cognitive control system should incorporate these capacities and therefore it would be capable of responding efficiently and robustly to nonlinearities, disturbances and uncertainties. The modifications introduced to the SCM approach make that this preliminary version can be applied to design a control architecture for a case study: a high-performance drilling process. In order to improve efficiency of a high-performance drilling process, the current study focuses on the design and implementation of a control system for drilling force.

This article is organized into five sections. A brief description of SCM as described by Hurley is given in Section 2. The modified shared circuits model (MSCM) incorporated to an architecture in which is implemented an artificial cognitive control system is explained in Section 3. Section 4 shows the experimental results of applying a simplified implementation of the MSCM applied to a case study represented by a high-performance drilling process. Finally, the conclusions are presented in Section 5.

2. Shared circuits model to enable imitation, deliberation, and mindreading. A review

SCM approach is supported on a layered structure to describe how certain human capacities (i.e., imitation, deliberation, and mindreading) can be deployed thanks to subpersonal mechanisms of control, mirroring, and simulation (Fig. 1). Basically, SCM is based on the observation of the human brain. Some brain regions are in charge of coding actions for reaching objectives and how other regions code means for reaching objectives. So, the brain may be envisaged as making use of not only inverse models that estimate the necessary motor plan for accomplishing an objective in a given context, but also a forward model that enables the brain to anticipate the perceivable effects of its motor plan, with the object of improving response efficiency. The first kind of behavior is covered by the action of layer 1 of SCM, while the behavior described in the forward model is covered by layer 2 of SCM. Layer 4 of the scheme is the layer in charge of controlling when to perform one type of behavior or another.

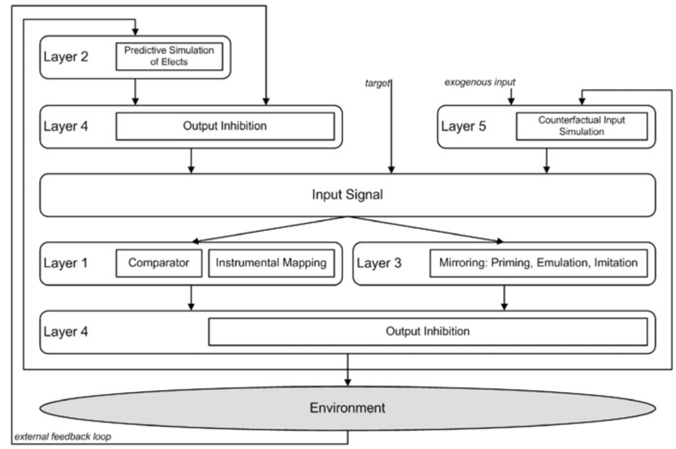

Fig. 1. Depiction of SCM. Layer 5 monitors simulation of input acts or evoking objects. Using layers 2 and 3, SCM can perform simulation at both ends and, with layer 5, enables strategic deliberation.

Other kind of behavior is the imitation that, in addition to playing an important role in both the sociability and the development of the human adult, is a means of learning. Imitative learning requires mirroring the actions of others in response to given circumstances. In order to perform this task, first the observer copies the input/output associations already observed, inhibiting the mirroring mechanism. SCM represents this mirroring capacity in its layer 3. The interaction between layer 3 and the inhibition control performed by layer 4 serves to emulate the agent's capacity to distinguish self from other.

SCM also describes, from a functional point of view, how the agent can carry out the cognitive skill of mindreading. This capacity is emulated by the operation of layer 5, which is in charge of simulating possible other-related inputs that are external (exogenous) to the agent.

3. An architecture for artificial cognitive control. Modified shared circuits model

A computational architecture for an artificial cognitive control system is proposed for high-performance manufacturing processes, underpinned by the modified shared circuits model (MSCM). Therefore, it is necessary to enrich SCM approach from a computational science viewpoint. To develop a complex cognitive agent, it is necessary to make a global structure that would be a collection of information processing elements, linked by information forwarding elements layered atop physical/information interfaces (Sanz et al., 2009).

This section explains the modifications introduced to SCM to enrich and improve its capacities, taking into account the suggestions reported in the state-of-the-art and the main constraints of the SCM approach. Since a layer-based model is incorporated in a