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Editorial

Special Issue "Cognitive Robotics"

Antonio Bandera [1,*], Luis Manso Fernández-Argüéllez [2] and Zoe Falomir [3]

1 Departamento de Tecnología Electrónica, University of Málaga, 29071 Málaga, Spain
2 School of Engineering & Applied Science, Aston University, Birmingham B4 7ET, UK
3 Bremen Spatial Cognition Center, University of Bremen, 28359 Bremen, Germany
* Correspondence: ajbandera@uma.es

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Within the realm of new robotics, researchers have placed a great amount of effort into learning, understanding, and representing knowledge for task execution by robots. The goal is to develop robots that can help humans with daily tasks. Cognitive robots need to explore and understand their environment, choose a safe and human-aware course of action, and learn—not only from experience, but also through interaction.

This Special Issue collects nine research papers in various fields related to Cognitive robotics. The relevance of the knowledge representation and its use by decision makers is present in the proposal by Martín et al. [1]. Specifically, the necessity of integrating behaviors and symbolic knowledge was solved by adding a graph-based working memory to a cognitive robotics architecture. The proposed framework has been successfully tested in robotics competitions such as the RoboCup and the European Robotics League. The aim of combining deliberative and reactive behaviors in a flexible way is also present in the work by González-Santamarta et al. [2]. In the MERLIN cognitive architecture, the process of integrating deliberative and behavioral-based mechanisms in robotics is normalized. The solution is empirically tested using a variation of the challenge defined in the SciRoc @ home competition. The relevance that cognitive robots can provide for improving task effectiveness and productivity in the industrial domain is highlighted in the work by Chacón et al. [3]. In this work, the authors show that a cognitive assistant robot is also able to provide autonomy for the human supervisor to make decisions, and to give feedback to the human operator in the loop. The approach is evaluated on variability reduction in a manual assembly system. The problem of transferring knowledge for the purpose of easing a robot from learning simpler tasks into learning complex ones is addressed in the work by Duminy et al. [4]. The proposed approach combines goal-babbling with imitation learning, and active learning with a transfer of knowledge based on intrinsic motivation, in order to self-organize this learning process. With a simulation and a real industrial robot arm, the authors show that task composition is key for tackling highly complex tasks. The importance of non-functional properties, such as safety or performance, and their evaluation at runtime are addressed by Romero-Garcés et al. [5]. In this work, the authors describe the integration of the modules that allow these properties to be monitored into the software architecture of a robot, providing information on the quality of its service. In a healthcare scenario, experimental evaluation illustrates that the defined quality of service metrics correctly captures the evolution of the aspects of the robot's activity, and its interaction with human users covered by the non-functional properties that have been considered. Detecting and positioning objects, as well as people, in an accurate semantic map are essential tasks that a robot needs to carry out. Instead of proposing the use of Deep Learning, Medina-Sánchez et al. [6] address these tasks from low-density point clouds provided by 3D LiDARs and segmentation methods for the detection of objects. Evaluation shows that this approach achieves comparable performance in object labeling and positioning, with a significant decrease in processing time compared to established approaches based on deep learning methods. The importance of how cognitive robots are perceived by people is studied by Sumitani et al. [7]. Through investigating pain experiences of a set of human subjects when observing facial expressions of a robot modelling affective minds, they conclude that we share empathic neural responses, which can intuitively emerge, according to observed pain intensity with a robot (a virtual agent). Finally, robots can be also useful for allowing humans to experience and perform actions in distant places. Considering the results from studies on human factors, Almeida et al. [8] provides a set of recommendations for the construction of immersive teleoperation systems. Moreover, they develop a testbed for studying perceptual issues that affect task performance while users manipulated the environment, either through traditional or immersive interfaces. A cognitive robot's ability to replace a person in a dangerous environment is conditioned by its capacity for learning the spatial semantics of the environment or object. Shrivastava et al. [9] deal with this problem by devising an agent that mimics the grid and placing neuron functionality in order to learn cognitive maps from the input spatial data of an environment or an object. A place sequence learning system is also considered for working as the episodic memory of the trip.

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