Knowledge representation for Cognitive Technical Systems

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The face of computers and computer-equipped technical systems has drastically changed over the last decade and will continue to do so for some time. Illustrative examples of these developments are mobile phones. Nowadays, mobile phones are – for entertainment and other reasons – equipped with continuous sensors for self localization as well as with general purpose sensors such as cameras and microphones. They are also seamlessly connected to the world-wide web, the world's largest information source. Phones also have substantial computational resources causing the borderline between mobile phones and computers to fade. Indeed, some of the computer and mobile phone manufacturers are now competing in the same market. A number of mobile phone applications make good use of computational resources, the web and the sensors in order to turn phones into smart assistants such as travel guides.

Entertainment electronics, in particular in the games sector, is strengthening this development. It has developed powerful graphical processing units and new sensors, such as novel low-cost depth sensors, that enable computer games to observe the movements of human players to control their avatars in game environments. In other words, technical systems are being equipped with the perceptual and information processing means for real world problem-solving.

The vision of generally useful technical systems implies its own big challenges. Today, it is still not technically feasible for an autonomous robot to pick and place chess pieces with the dexterity of a five-year old, while Deep Blue [1], a computer program for playing chess, successfully beats the world champion. While this might be surprising upon first glance, it has taught us researchers what the difficult computational and control problems really are. We now know that, in many application domains, the problem is less in solving the problem itself but rather in solving the problem flexibly, reliably and competently in a wide range of contexts, in real time, and under uncertainty. The human brain is a computational device that is tailored for flexible, reliable and efficient real-time motion control [2], [3].

The complexity of the motion and action control problems solved by humans and animals can be estimated by looking at how long it has taken nature and evolution to arrive at their highly specialized and optimized solutions. Anybody who has tried to develop autonomous robot control for a rather simple manipulation task, such as setting a table or cleaning up, deeply admires the solutions nature has come up with. It also suggests that understanding the information processing principles will help us in the development of flexible, robust and competent robots and other technical systems.

The methods that are used for realizing cognition-enabled control are, in particular, automated learning, reasoning and planning – methods that are key subject matters in Artificial Intelligence. So what is the difference between Artificial Intelligence and cognitive technical systems? Again, it is difficult to draw an exact line, but one can certainly see a strong difference in terms of emphases. While AI focuses on representations and algorithms, research in the area of cognitive technical systems is typically more system-oriented. Perhaps this difference is best illustrated by two research questions that are investigated in the respective fields. When applying AI methods to cognitive technical systems, AI researchers face the so-called *symbol-grounding problem* [4], the question of how symbolic representations are formed from the sensor data of the technical system and how symbolic action representations are translated into physical actions, i.e. voltages to motors.

In contrast, cognitive systems research often investigates the co-development of data structures and (computational and control) processes with symbolic representations being a subset of the suitable data structures. The latter view is particularly evident in the research directions of *embodied intelligence* [5] and *developmental robotics* [6], [7]. A success story of the AI-based research path is certainly *probabilistic robotics* [8], where symbolic representations can be learned, perhaps even as joint probability distributions, over sensed data and used to control robots such that they are reliable and can maximize the expected utility of their actions.

References

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