TOWARDS INTELLIGENT MACHINES: THEORIES, TECHNOLOGIES AND EXPERIMENTS

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Great efforts are being devoted in developing intelligent machines in Universities and Industry research laboratories all over the world. Intelligent machines will have strong social and economical impacts namely in manufacturing, defense, food industry, oceans and space exploration, medicine, rehabilitation, highway and urban transportation. Intelligent machines that can sense their environment, reason, self-acquire skills by learning, and act on it, require the integration of real-time software and modeling with sensors and precision mechanisms. In this paper, firstly theory and technologies for intelligent systems are examined concerning, namely, sensing, perception, learning and architectures. Secondly, experiments performed in these areas, in the framework of two projects under development in the Institute for Systems and Robotics are examined.

The first one, the RobChair project, was conceived with the aim to assist disabled people in the difficult task of operating a powered wheelchair. At its current stage, the wheelchair project supports semi-autonomous navigation with the following features: uses fuzzy-logic based reactive navigation, allows remote operation by Internet observers through a 3-D Graphical User Interface (GUI) and can be activated by voice.

The second project is concerned with self-learning of robot control skills and with mobile robot path-learning for the robot moving in unknown environments.

Keywords: Intelligent machines; powered wheelchairs; learning; reactive control

1. INTRODUCTION

Great efforts are being devoted in developing intelligent machines in University and Industry research laboratories all over the world.

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In [1], J. S. Albus presents a theoretical model of intelligent machines. Albus says, "at a minimum, intelligence requires the ability to sense the environment, to make decisions, and to control action. Higher levels of intelligence may include the ability to recognize objects and events, to represent knowledge in a world model, and to reason about and plan for the future. In advanced forms, intelligence provides the capacity to perceive and understand, to choose wisely, and to act successfully under a large variety of circumstances so as to survive, prosper, and reproduce in a complex and often hostile environment". From these sentences we can identify the most important abilities that are needed for an intelligent machine namely, sensing, perception, world modeling, reasoning, planning, skill acquisition by self-learning or with the help of an external teacher, cooperation, and control of actions. For instance, for a robot to carry out different tasks autonomously in unknown and changing environments it has to be intelligent to determine and control its own actions based on sensory information and perceived world knowledge. The robot makes observations by sensing the environment, and uses its perception capabilities to establish and maintain a correspondence between the internal model and the real environment. One of the functions of perception consists on extracting specific features from observations, about entities, states and connections existing in the real environment. On the other hand, the perception also includes processes of detection and recognition, which are fundamental for mapping the real environment to its image, the internal world model. Concerning this last aspect both sensory information and perceived knowledge are used. To be effective, the world model, which represents the intelligent system's best estimate of the real environment state, should be kept up-to-date. Self-adaptation and self-acquisition of new knowledge concerning uncertain or unknown environment are essential abilities of any superior intelligent system. Living beings adapt themselves to dynamic external world through learning; and over intervals spanning generations through evolution consubstantiated by transmission of genetic information. Like living beings, intelligent machines should be able to acquire new knowledge and new skills so as to be able to successfully adapt themselves to new situations and new environments. In this chapter, a skill is viewed as an activity for controlling some feature characterising the interactions between an intelligent machine and its environment. For interacting with its surrounding, the intelligent system plans and controls its actions having in view global behavioural objectives. For this purpose, it is required the ability to reason about internal and external parameters like space, time, and system's geometry and dynamics.

An important concept in the field of intelligent systems, originally adopted by the Artificial Intelligence (AI) community, is the concept of agent: an entity or computational process that senses its environment and interacts with it. An example of an agent, important for the purposes of this chapter, is a mobile robot embodied and endowed with its mechanical, sensory, and effector components. An agent can become more intelligent if it is endowed with learning capabilities.

Various methods can be used for learning: supervised learning, reinforcement learning [2, 3] and learning by demonstration assisted by a teacher [4]. Supervised learning methods require a training data set composed by input vectors and the corresponding desired output vectors. In the second case, the agent learns by experimentation, acting on its environment and receiving re-inforcement. The agent searches and tries different actions for every situation it encounters and selects the most useful ones. This search/selection process is guided by a reinforcement signal that is a performance evaluation feedback function. Like humans and other living beings, robots could learn by observing and imitating other agents. In this case we talk in teaching, and we define teaching as a mean of transferring human (or other agent) knowledge and skills to robots.

Many other topics concerning machine intelligence could be referred in this text, namely cooperation in the framework of multi-agent systems (MAS). Cooperation behaviour is a certain kind of intelligence that could emerge from a group of agents. In order that a MAS could perform some global task with the intervention of all its agents (or simply part of them) it is necessary some kind of coordination of the actions of each agent. Interest in this particular field has been growing steadily in the last few years [5, 6].

The chapter is organised as follows: the next section outlines control architectures of individual agents, computation tools for implementing
agents and reviews some of the projects/areas where intelligent machines are expected to produce in the near future strong impacts. In the following sections, experiments in the areas of control, navigation and learning performed in our Institute, will be examined.

2. AGENT’S CONTROL

The control architectures of individual agents can be classified according to three main categories: cognitive, sub-cognitive and hybrid architectures. In any case it is possible to simultaneously exist in the system elements like sensing, perception, planning and control of actions, even though under different organising forms.

In the cognitive model, the traditional organisation makes to correspond to each intelligent element one functional module, global to the overall system, with information flow structured vertically. This has been the traditional approach, which fits well with complex agents in well-structured environments. This means, environments that involve little or no uncertainties and that can be precisely modelled.

In the sub-cognitive model, initially proposed by Brooks [7], we may continue to have perception, planning and control functions but with local existence. The global control system is composed by a set of horizontal modules. Each module generates a behaviour that is a control mechanism for achieving or pursuing some goal. One feature that clearly differentiates the cognitive and sub-cognitive models is concerned with the knowledge structures. There is a global knowledge base in the cognitive model but not in the sub-cognitive model. The sub-cognitive architecture is a behaviour-based model where all the behaviours receive direct inputs from sensors and send commands directly to actuators. The behaviours run in parallel and compete to control the entire system or a given set of actuators. In its most simple case, behaviours are selected according to a very simple arbitration process based essentially on a priori assigned priorities to each module. This is a very inflexible structure since there is a need to redesign parts of the system for each new task. The emergency of more complex behaviours from the combination of basic behaviours is currently a popular topic of research [5, 8]. In contrast to traditional cognitive systems, the behaviour-based model is a bottom-up approach that placed agents with low levels of cognitive complexity evolving in highly unstructured, noisy and uncertain environments.

Finally, hybrid architectures that concurrently integrate and interconnect cognitive and sub-cognitive components have been widely proposed in the last decade [8-11]. Usually these architectures employ a reactive system for low-level control, and a planner for higher-level decision making, supported by a knowledge-based perceptual system.

2.1. Soft Computing Techniques

Traditional AI methods use a planning approach to execute each different task. These methods need a good symbolic representation of the environment to decompose a task in terms of goals, knowledge necessary to perform the goals and behaviours. The difficulty in interpret the environment by sensed data and the complexity of these methods, make other soft computing techniques (like Fuzzy Logic and Neural Networks) more successfully in the control of intelligent systems. This section addresses some of these techniques.

**Fuzzy Logic** can be regarded as an extension of classical binary logic where each member of a fuzzy set may have a numerical degree of membership between 0 and 1. A fuzzy system is composed by rules expressed with *if..then* statements. Each rule have an antecedent part (if) containing several preconditions and a consequent part which prescribes the value. One of the main advantages of fuzzy systems is the capability to represent linguistic concepts and the subsequent ability to model the expertise of trained human operators [12].

**Artificial Neural Networks** (ANNs) are composed by a group of processing elements (perceptrons) highly interconnected in a parallel architecture similar to an animal brain. Each perceptron is a simple processing element that generates a scalar output based on the data from a large number of inputs. ANNs are mainly used to recognise patterns, classify inputs and adapt themselves to dynamic environments by learning [13]. Neural Networks can work together with Fuzzy Logic in order to overcome the disadvantages of each method. The ANN classifies and learns rules for fuzzy logic and fuzzy logic infers from unclear neural network parameters.

**Genetic Algorithms** (GAs) [14] are optimisation techniques based on the concepts of natural selection and genetics. GAs operates over a
group of candidate solutions (population) that evolves toward better candidate solutions by selection operation and genetic operators such as crossover and mutation. GAs are particularly useful for finding optimum solutions in processes that are non-linear, convoluted, and dependent on several parameters simultaneously. The application of GAs tends to be computationally expensive.

Finite State Machines (FSMs) are used in conventional expert systems to manage complex sequential patterns. In each machine, only one state is true at a time. The subsumption architecture proposed by Brooks is based on independent agents built with FSMs. Fuzzy logic can be used in FSMs in order that all states can be true, but with different degrees of fuzzy truth. Each state is a function of fuzzy facts and previous states.

2.2. Intelligent Machines – Examples

Intelligent machines will have strong social and economical impacts in a broad number of areas like the following ones (only to mention a few of them):

Automated Highways and Intelligent Transportation The US National Automated Highway System Consortium (NAHSC) is carrying out the design of an automated highway system (AHS) capable of substantially improving vehicle throughput, safety and air quality while, reducing the driver stress [15,16]. The most important element of an AHS is the vehicle longitudinal control system. This system can operate in three different modes: fully autonomous behaviour, cooperative driving and platooning. This means that the vehicle should be able to integrate inputs from the driver, infrastructure, other vehicles in the vicinity as well as from its own sensors.

Autonomous Underwater Vehicles (AUVs) Environmental surveying and oceanographic data acquisition in coastal waters by autonomous underwater vehicles. A research example in this area is the MARIUS Project [17] in which the main practical purpose is to develop reliable navigation, guidance and control systems for AUVs.

Telesurgery Laparoscopic and other minimally invasive techniques are a revolutionary approach in surgery which contains components of intelligence like 3D reconstruction devices, haptic perception and very accurate tele-operated dexterity manipulation [18,19].

Assistance to the Elderly and Handicapped Unfortunately, "there is a significant growth in the absolute and relative number of older people in all Member States (European Community) such that by the year 2020 it is estimated that one fourth of the European population will be over 60 years of age" [20]. Regarding this situation, there is a clear need to develop robotic assistive systems, which will increase the independence of disabled people and reduce the costs with health care. Particularly work has been done in several research centers' concerning the development of powered wheelchairs with navigation capabilities and friendly human-machine interface aiming to assist the disabled people (see for example [21–23]).

3. LEARNING REFLEXIVE ROBOT MANIPULATOR SKILLS

The development, improvement, and application of learning techniques taking advantage of sensory information would enable the acquisition of new robot skills and avoid some of the difficulties of explicit programming, and would constitute a useful step for achieving flexibility in robotics. This section discusses a reinforcement learning approach that has been studied [24,25], for on-line self-learning of robot manipulator skills. The structure of the controller (Fig. 1)
includes two map functions, both implemented by neural networks having the state of the environment and possibly previous control commands input. The action map function has the purpose of generating command actions for the system under control, in order to accomplish the skill. The evaluation-prediction map function must learn to predict the future value of a function that evaluates the performance of the controller on the skill that is being implemented. Thus the prediction network, is mainly evaluating the quality of how the action network in executing the skill, and its outputs serves to control the amount of exploration of a Guided Random Search module that performs a random exploration transformation around the mean action generated by the action map function. An external reinforcement signal is provided to the learning system as an external evaluation of the controller. This signal is taken into account to estimate the output gradients in both the action and the prediction networks. Learning in both networks is performed by error backpropagation, using this output gradient information.

Simulation experiments were made [25], for learning a “force control skill”, in which the robot manipulator tool-tip must be moved from a free space situation, to a contact state with a spring-like compliant surface (Fig. 2a) and having a constant interaction force, $f_c$. The motion of the robot tool-tip is performed along one Cartesian degree of freedom (the world Z direction). In order to perform the skill, the system must learn to generate a unidimensional “change of position” command to the robot. Due to the compliance of the environment, this action will generate a change in the force state. Figure 2b presents the force response in a trial, after some other previous learning trials ($f_c = -200$ dN). As can be seen, the controller has accumulated some learned experience enabling, to some extent, the control of the force.

4. MOBILE ROBOT NAVIGATION USING FUZZY LOGIC

It is important for an autonomous mobile robot to be able to navigate on unknown environments, where the location, shape and size of obstacles is unknown, and where there is no map or model of the
world initially available. An interesting possibility for implementing a navigation system is based on a behaviour-based architecture [7]. This section discusses an example of such an architecture for navigating a mobile robot. The architecture, depicted in Figure 3, and includes three behaviours: goal seeking, obstacle avoidance, and wall following. All behaviours have system state information as input, and produce an output command to the robot, composed of a linear velocity, $v$, and an incremental steering angle, $\Delta \theta$ (Fig. 3). System state information is collected with both external sensors (e.g., distance sensors like sonars, and infrared range sensors) and internal sensors (e.g., encoders of the robot wheels). The goal seeking, and obstacle avoidance behaviours in Figure 3 have been implemented by fuzzy logic controllers [26].

The fuzzy logic system that we have used in the fuzzy controllers is composed of Fuzzification, Rule-base, Inference, and Defuzzification modules. The fuzzification module maps crisp numbers into fuzzy sets. This is required to activate rules which are in terms of linguistic variables, which have fuzzy sets associated. The rule-bases for the behaviours consist of a set of rules taking the form of IF-THEN statements:

$$\text{IF}(s_1 = S_{11}) \text{ AND } \ldots \text{ AND } (s_N = S_{1N}) \text{ THEN } (v = V_1, \Delta \theta = \Delta \Theta_1),$$

In these rules $s_i$ represents input linguistic variables, and $S_{ij}$ are associated fuzzy linguistic values. Likewise, $v$, and $\Delta \theta$ represent output linguistic variables, and $V_1$, and $\Delta \Theta_1$ are linguistic values associated to these variables. In our implementation, the set of rules was directly tuned using designer knowledge. Alternately, learning approaches can be employed to generate the fuzzy behaviours (e.g. [27]). The inference module applies and integrates the set of rules in order to transform the fuzzified input data, into the fuzzy sets associated with the output variables. The defuzzification module converts the output fuzzy variables into real-valued output commands. The centre of gravity defuzzification method [26] has been used. Triangular and trapezoidal membership functions [26], have been used in association to both input and output linguistic variables.

For the wall-following behaviour, speed was set constant, and the incremental steering angle, $\Delta \theta$, was directly implemented by a function of two variables on-line estimated from sensor readings: the distance to the wall, and the distance between the heading angle and the tangent to wall. The idea is to calculate a $\Delta \theta$ that will contribute to annul the error in the two input variables. This approach is related to the work of Borenstein and Koren [28]. The behaviour selector module is responsible for selecting which behaviour should be active, and send the corresponding commands to the robot. For selecting the behaviour the following information is used: (1) difference between the robot heading, and the heading to the goal, (2) the distance to the goal, and (3) the distance sensor readings.

Some simulation experiments have been carried out with a Nomad 200 mobile robot [29] (Fig. 4a). Figure 4b presents an experimental navigation result obtained with the navigation architecture of

FIGURE 3 Behaviour-based architecture for navigating a mobile robot.

FIGURE 4 (a) The Nomad 200 mobile robot that was used in the simulation experiment. (b) Navigating a mobile robot on an unknown world: simulation experiment.
Figure 3. The goal seeking behaviour used 28 rules for the speed command, and 5 rules for the steering increment. The obstacle avoidance behaviour used 4 rules for the speed, and 128 rules for steering increment command. It can be seen that the robot was able to navigate to the goal after having faced a world cluttered with a set of obstacles. The location shape and size of these obstacles were unknown to the controller. In this experiment the distance to surrounding objects were measured using the robot sonars, and infrared range sensors.

5. ASSISTIVE NAVIGATION OF A POWERED WHEELCHAIR

Many works are being developed in order to enhance the quality of life for the disabled. In the field of wheelchair rehabilitation technology, efforts have been done to develop strategies of indoor and outdoor navigation (e.g. [21–23, 30]). Some projects are concerned with safety requirements and evaluation of risk conditions, other projects are developing local obstacle avoidance and global path planning methods in order to achieve complex manoeuvres. Some other works are concerned with ergonomic aspects and versatile mechanical structures. Prototypes with robotic arms and legs are being developed. And finally, several projects are developing efficient Human-Machine interfaces.

RobChair [23, 30], a project running in our Institute, aims to provide the end user with an easy and safe way to steer a wheelchair equipped with a voice interface. The powered wheelchair is depicted in Figure 5a. It is a conventional powered wheelchair\(^1\) with two motorised rear wheels and casters in front. Twelve infrared sensors (IR), four ultrasonic sensors, a front tactile bumper and optical encoders on wheels compose the sensorial system. The on-board computer system is linked to our Ethernet network. By this facility we can remotely interact with the wheelchair through a 3D Graphical User Interface (GUI) and simulator, and a voice interface.

The RobChair control system follows a hybrid model composed by a reactive control level and a decision-making level supported by a knowledge-based perceptual system, as depicted in Figure 5b.

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\(^1\)Kiss Institute for Practical Robotics.

FIGURE 5 (a) Wheelchair picture. (b) RobChair control architecture.

The RobChair system has two different modes: an approaching mode and a navigation mode. In the navigation mode we can discern two different approaches: semi-autonomous navigation and fully autonomous navigation. In semi-autonomous mode the control of the wheelchair is shared between the user and the machine. In this case, the wheelchair exhibits obstacle avoidance behaviour capable to assist the user, making wheelchair manoeuvres easier. Thus far, we concerning the fully autonomous mode did little work. Semi-autonomous navigation follows a behaviour-based approach similar to that described in Section 4. It consists of three behaviours as shown in Figure 5b: obstacle avoidance, collision detection and contour following behaviour. Each one of these behaviours result from a goal driven behaviour, which represents the input command from the user through a joystick and/or voice, and sensory information of the environment. Fuzzy logic was used in the implementation of the behaviours in a similar way to that described in Section 4.

6. LEARNING TO NAVIGATE A MOBILE ROBOT

Comparing with the method of Section 4, an approach capable of learning a navigation path and a world model, stands at a higher conceptual level. A learning approach has also been implemented for
learning to navigate a mobile robot on an unknown world [31]. The core of the navigation architecture is based on the parti-game learning approach [32]. With the method, the robot can simultaneously learn a kind of map of its environment, and learn to navigate to a goal region on an unknown world, having the predefined abilities of doing straight-line motion to a specified position in the world, and obstacle detection (not avoidance). The learning approach is based on a selective and iterative multiresolution partitioning of the state-space. The path to the goal is planned as a sequence of cells using a minimax approach, and model information that has been previously learned from experience.

A new method for learning a map of the world [31], based on the Fuzzy ART neural architecture [33, 34], was integrated in our navigation architecture for improving its world model, by making better use of the received sensor information. The method is self-organising and multifunctional, has small data requirements and low computational complexity, has the significant advantage of being capable of incremental on-line operation according to the flow of sensor data reception, and is easy to extend to higher dimensions. With the approach the system incrementally extracts and updates a collection of rectangular geometric primitives, whose union represents occupied space, where sensor data points associated with objects have been perceived - a kind of unsupervised clustering.

The learning approach was extended by the introduction of a method for Predictive On-line Trajectory Filtering. With this approach, taking advantage of the learned Fuzzy ART world model the system is able to significantly reduce the time expended with real-robot exploration effort, by giving priority to predictive exploration.

7. CONCLUSIONS

This chapter reviewed some topics concerning intelligent machines. Firstly theories and techniques for machine intelligence were examined. Intelligent agents operating in dynamic and uncertain environments have to be reactive and adaptive to cope with changing conditions. Current efforts are being done to combine reactive behaviours and cognitive models to make up agent's intelligence. Next the chapter addressed some experiments on the following topics: learning for skills acquisition, learning for mobile robot navigation and reactive navigation. RobChair, an assistive navigation system of a powered wheelchair, was also reported. Concerning this project and as future work, we plan to improve the navigation system namely by incorporating learning and planning capabilities. Since there is a human being involved, the wheelchair movements must be coherent and inspire confidence to the user. We can expect that the intelligent wheelchair will become more acceptable by users if equipped with a more humanised interface (including robust and friendly voice interface).

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References


