



AN OVERVIEW OF ARTIFICIAL INTELLIGENCE AND ROBOTICS

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ABSTRACT

A robot is a machine able to extract information from its environment and use knowledge about its world to move safely in a meaningful and purposive manner. We will focus primarily on autonomous robots, robots that can operate on their own without a human directly controlling them. Robots are physical agents that perform tasks by manipulating the physical world. They are equipped with sensors to perceive their environment and effectors to assert physical forces on it. The first industrial robot using these principles was installed in 1961. These are the robots one knows from industrial facilities like car construction plants. Autonomous robot applications are couriers in hospitals, security guards and lawn mowers. Probably the most important application is the use of autonomous mobile robots in hazardous environments like minefields or the inside of nuclear plants. For the purpose of this overview, we found it clarifying to distinguish these functions with respect to their main role and computational requirements: the perceiving, goal reasoning, planning, acting and monitoring functions.

Keywords: Autonomous robots, History, APT, Artificial intelligence, Applications

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INTRODUCTION

The Robot Institute of America defines a robot as "a programmable, multi-function manipulator designed to move material, parts, tools or specific devices through variable programmed motions for the performance of a variety of tasks" [1-3]. Another definition describes robots as "the intelligent connection of perception to action" [4]. Both definitions are not very precise. The first does not include mobile robots and the second includes humans. However, the second definition points out two very important aspects in robotic systems: perception and action. In this study we will use the following definition.

A robot is a machine able to extract information from its environment and use knowledge about its world to move safely in a meaningful and purposive manner. We will focus primarily on autonomous robots, robots that can operate on their own without a human directly controlling them. Robots are physical agents that perform tasks by manipulating the physical world. They are equipped with sensors to perceive their environment and effectors to assert physical forces on it (covered in more detail in next section). As mentioned before Robots can be put into three main categories: manipulators, mobile robots and humanoid robots [3-6].

Capek and his Robots: The term "Robot" can be traced back to Karel Capek's play "R.U.R. Rossum's universal robots" (in 1921) that comes from the Czech word for "corvee" [4-8].

A brief History of Robots

Robotics is based on two enabling technologies: Tele-manipulators and the ability of numerical control of machines.

Tele-manipulators are remotely controlled machines which usually consist of an arm and a gripper. The movements of arm and gripper follow the instructions the human gives through his **control device**. First tele-manipulators have been used to deal with radio-active material.

Numeric control allows controlling machines very precisely in relation to a given coordinate system. It was first used in 1952 at the MIT and led to the first programming language for machines (called APT: Automatic Programmed Tools).

The combination of both of these techniques leads to the first programmable tele-manipulator. The first industrial robot using these principles was installed in 1961. These are the robots one knows from industrial facilities like car construction plants. The development of mobile robots was driven by the desire to automate transportation in production processes and autonomous transport systems. Since a few years wheel-driven robots are commercially marketed and used for services like "Get and Bring" (for example in hospitals). Humanoid robots are being developed since 1975 when Wabot-I was presented in Japan. The current Wabot-III already has some minor cognitive capabilities [9-14].

Another humanoid robot is "Cog", developed in the MIT-AI-Lab since 1994. Honda's humanoid robot became well known in the public when presented back in 1999. Although it is remote controlled by humans it can walk autonomously (on the floor and stairs). In science fiction robots are already human's best friend but in reality we will only see robots for specific jobs as universal programmable machine slave in the near future [12].

Robotics and AI

Artificial intelligence is a theory. The base object is the agent who is the "actor". It is realized in software. Robots are manufactured as hardware. The connection between those two is that the control of the robot is a software agent that reads data from the sensors decides what to do next and then directs the effectors to act in the physical world [6-9].

Tasks

The first industrial robots [7-12], developed in the late 1950s by George Engelberger and George Devol, were used to automate repetitive tasks in manufacturing and material handling. These industrial robots were very simple and even today most manufacturing robots are not very intelligent. Tasks for robots that are used nowadays vary from transporting containers on and off ships to shaving sheep and milking cows.

Although autonomous robots were already invented in the 1960s, it is not until recently that robots are used for practical purposes. Autonomous robot applications are couriers in hospitals, security guards and lawn mowers. Probably the most important application is the use of autonomous mobile robots in hazardous environments like minefields or the inside of nuclear plants. During the cleanup of the Chernobyl disaster, several Russian lunar explorer robots were used as cleaning vehicles and in 1997 the mobile robot Sojourner landed on Mars to explore the surface.

Deliberation refers to purposeful, chosen or planned actions, carried out in order to achieve some objectives. Many robotics applications do not require deliberation capabilities, e.g., xed robots in manufacturing and other well-modeled environments; vacuum cleaning and other devices limited to a single task; surgical and other tele-operated robots. Deliberation is a critical functionality for an autonomous robot facing a variety of environments and a diversity of tasks [7-12].

- **Planning:**

It combines prediction and search to synthesize a trajectory in an abstract action space, using predictive models of feasible actions and of the environment.

- **Acting:**

It implements on-line close-loop feedback functions that process streams of sensors stimulus to actuators commands in order to rene and control the achievement of planned actions.

- **Perceiving:**

It extracts environment features to identify states, events, and situations relevant for the task. It combines bottom-up sensing, from sensors to meaningful data, with top-down focus mechanisms, sensing actions and planning for information gathering.

- **Monitoring:**

It compares and detects discrepancies between predictions and observations, performs diagnosis and triggers recovery actions.

- **Goal reasoning:**

It keeps current commitments and goals into perspective, assessing their relevance given observed evolutions, opportunities, constraints or failures, deciding about commitments to be abandoned, and goals to be updated.

Parts

Robots are distinguished from each other by the effectors and sensors with which they are equipped. For example, a mobile robot requires legs or wheels, and a tele-operated robot needs a camera. We will assume that a robot has some sort of rigid body, with rigid **links** that can move about. Links meet each other at **joints**, which allow motion. Examples of links are the arms or wheels of a robot.

Attached to the final links are **end effectors**, used by the robot to interact with the world. End effectors can be squeeze grippers, screwdrivers, welding guns, paint sprayers, etc.

Effectors

An effector [8-11] is any device under the control of the robot that affects the environment. Effectors are used in two ways: to change the position of the robot within its environment (locomotion) and to move other objects in the environment (manipulation). To have an impact on the physical world, effectors must be equipped with an **actuator** that converts software commands into physical motion.

The actuators themselves are electric motors or hydraulic or pneumatic cylinders. The correspondence between the actuator motions in a mechanism and the resulting motion in its various parts can be described with kinematics, the study of motion.

For simplicity, we will assume that each actuator determines one single motion or **degree of freedom**. The number of degrees of freedom that a robot possesses is the number of independent position variables that would have to be specified in order to locate all parts of the robot. For example a car-like robot has three degrees of freedom, two for its x, y-position, and one for the direction it is facing. However, there are only two actuators, namely driving and steering. Because the number of controllable degrees of freedom (two) is less than the total degrees of freedom (three), this is a **non-holonomic** robot. In general, a non-holonomic robot is limited in its movement, in this case sideways. Robots that are not non-holonomic are **holonomic** robots, i.e. the number of total and controllable degrees of freedom is the same. A truly holonomic robot can be treated as a mass less point and is capable of moving in any direction instantaneously. Obviously, it is very difficult, if not impossible, to build a robot that behaves like a true holonomic robot.

Sensors

One of the most important parts of a robot is its sensors. Sensors provide feedback to the robot about its current condition and allow a robot to reason about the environment. Many different types of sensors have been developed [9-12].

Proprioception

Like humans, robots have proprioceptive sense that tells them where their joints are. **Encoders** fitted to the joints provide very accurate data about joint angles. Wheel encoders measure the revolution of the robot's wheels. Based on their measurement, odometry can provide an estimate of the robot's location that is very accurate when expressed relative to the robot's previous location. This localization technique is called **dead reckoning**. Unfortunately, because of slippage as the robot moves, the position error from wheel motion increases. Other proprioceptive sensors are accelerometers to detect changes in velocity and a magnetic compass or gyroscope system to measure orientation [10-13].

Force sensing

Force can be regulated to some extent by controlling electric motor current, but accurate control requires a force sensor. Force sensors are usually placed between the manipulator and end effector and can sense forces and torques in different directions [8-10].

Tactile sensing

Tactile sensing is the robotic version of the human sense of touch. A robot's tactile sensor uses an elastic material and sensing scheme that measures the distortion of the material under contact. By understanding the physics of the deformation process, it is possible to derive algorithms that can compute position information for the objects that the sensor touches. Most tactile sensors can also sense vibration [9-11].

Sonar

Sonar stands for sound navigation and Ranging. Sonar sensors measure approximate echo distances to nearby obstacles. Sonar provides useful information about objects very close to the robot and is often used for fast emergency collision avoidance. It can also be used to map the robot's environment over a larger area. In the latter case, an array of a dozen or more sonar sensors is fitted around the perimeter of the robot, each pointing in a different direction. This array is called a sonar ring [10-12].

Sonar works by measuring the time of flight of a sound pulse generated by the sensor that reflects on an object. The pulse is typically about 50 kHz. The speed of sound is about 330 m/s, so the round-trip time delay for an object 1 meter away is about 6×10^{-3} seconds. Although it is possible to measure the time delay very accurately, it is very hard to produce reliable and precise data for mapping [11-14]. The first problem is beam width. Rather than a narrow beam of sound, a typical sensor produces a conical beam with a spread of 10 degrees or more. The second problem comes from the relatively long wavelength (7 mm) of the sonar sound. Objects that are very smooth relative to this wavelength look shiny or specular to the sensor. Sound will only be received back from surfaces of objects that are at straight angles to the beam. Objects with flat surfaces and sharp edges reflect very little sound in

most directions and will probably not be noticed. This is the way stealth aircraft work. Third, after being reflected back from a surface, the sound may strike another surface and be reflected back to the sensor. The time delay will not correspond to a physical object, but to a 'ghost' object [14-17].

Vision

To supplement sonar information, a real-time vision or obstacle detection system is often used. As yet, no robot performs complete scene recognition. Instead vision is used selectively and customized to a specific task or problem [16-18].

Intelligence in robots

Most Artificial intelligence researchers that study robotics are working on mobile robots. Mobile robots pose a unique challenge to the Artificial intelligence community, since they are inherently autonomous and force the researcher to deal with issues such as uncertainty in sensing and action, planning, learning, reliability, and real-time response. By improving and expanding the knowledge of how to successfully integrate these issues into one single system, fundamental contributions can be made to Artificial intelligence research [18-22].

The development of autonomous robots

One of the first mobile robots, Shakey, was constructed in the late 1960s at the Stanford Research Institute [20-23]. The robot used the STRIPS planning system, two independently controlled stepper motors and had a television camera and optical range finder mounted at the top. Shakey demonstrated that general-purpose planning systems were not very efficient and much too slow for practical use. Further research focused on faster processing and higher efficiency.

In the mid 1980s many researchers began to question the 'classical' planning view of intelligent agent and robot design and started working on **situated automata**, finite-state-machines whose inputs are directly linked to the outputs (reflex agent). The robot Flakey that was based on the situated automata theory performed well and even won second place in the First American Association for Artificial Intelligence (AAAI) robot competition and exhibition held in San Jose in 1992 [20-25].

In 1986, Rodney Brooks published his paper [Brooks 1986] on the **subsumption** architecture, a robot control system based on finite-state-machines, which led to the development of a new approach in robotics called **behavior-based robotics** [20-26].

Learning

The goal of learning in a robot is to prepare it to deal with unforeseen situations and circumstances in its environment. The fact that even the simplest of animals seem to be adaptable suggests that learning must be important for survival in the animal world [20-22].

When is learning useful?

There are two main benefits [22-25] of learning in biological systems. First, learning lets the animal adapt to different circumstances in the world, giving it a wider range of environmental conditions in which it can operate effectively. Second, learning reduces the amount of genetic material and intermediate structures required for building the complete functioning adult animal. In some circumstances, it is simpler to build a small structure capable of constructing a larger one, than to specify the larger structure directly.

The first aspect of learning in animals directly applies to robots as well. We would like our robots to adapt to changing external circumstances (e.g. changes in terrain), adapt to changing internal circumstances (e.g. drift in sensors and actuators, loss of power), and perform new tasks when appropriate. The second aspect does not transfer directly to robot control, unless they are programmed using genetic techniques.

We can distinguish three types of knowledge that would be useful for a robot to acquire [24-26]:

1. Hard to program knowledge: information that is very difficult to program by hand may be obtained by showing examples or guiding the robot.
2. Unknown information: the information necessary to program the robot is simply not available. For example, a map of the terrain the robot will be working in.
3. Changing environments: the world is a dynamic place. Even if we had a complete model of the environment to begin with, this knowledge could quickly become obsolete in a dynamic environment. Also slower changes may occur, such as the calibration of the robot's own sensors and effectors.

Integration and Architectures

Beyond the integration of various devices (mechanical, electrical, electronical, etc), robots are complex systems including multiple sensors, actuators and information processing modules. They embed online processing, with various real time requirements, from low-level servo loops up to deliberation functions which confer the necessary autonomy and robustness for the robot to face the variability of tasks and environment. The software integration of all these components must rely on architecture and supporting tools which specify how these components communicate, share resources and CPUs, and how they are implemented on the host computer(s) and operating systems [25-29].

Various architectures have been proposed to tackle this task, among which the following:

Reactive architectures, e.g. the reactive architecture [10], are composed of modules which close the loop between inputs (e.g. sensors) and outputs (e.g. effectors) with internal automata. These modules can be hierarchically organized and can inhibit other modules or weight on their activity. They do not rely on any particular model of the world or plans to achieve and do not support any explicit deliberative activities. Nevertheless, there are a number of works, e.g. [29], which rely on them to implement deliberative functions.

Hierarchical architectures are probably the most widely used in robotics [23, 26, 29]. They propose an organization of the software along layers (two or three) with different temporal requirements and abstraction levels. Often, there is a functional layer containing the low-level sensors effectors processing modules, and a decision layer containing some of the deliberation functions presented here (e.g. planning, acting, monitoring, etc).

Teleo-reactive architectures [26] are more recent. They propose an integrated planning acting paradigm which is implemented at different levels, from deliberation down to reactive functions, using different planning acting horizons and time quantum. Each planner actor is responsible for ensuring the consistency of a constraint network (temporal and atemporal) whose state variables can be shared with other planner's actors to provide a communication mechanism.

Beyond architecture paradigms, it is interesting to note that some robotics systems have achieved an impressive level of integration of numerous deliberation functions on real platforms. The Linkoping UAV project [20] provides planning, acting, perception, monitoring with formal representations all over these components. The NMRA on the DS1 probe [24] also proposed planning, acting, and FDIR onboard. IDEA and T-ReX, providing planning and acting have been used respectively on a robot [26] and an AUV [28].

CONCLUSION

Autonomous robots facing a variety of open environments and a diversity of tasks cannot rely on the decision making capabilities of a human designer or tele-operator. To achieve their missions, they have to exhibit complex reasoning capabilities required to understand their environment and current context, and to act deliberately, in a purposeful, intentional manner. In this paper, we have referred to these reasoning capabilities as deliberation functions, closely interconnected within a complex architecture. We have presented an overview of the state of the art for some of them.

For the purpose of this overview, we found it clarifying to distinguish these functions with respect to their main role and computational requirements: the perceiving, goal reasoning, planning, acting and monitoring functions. But let us insist again: the border line between them is not crisp; the rationale for their implementation within an operational architecture has to take into account numerous requirements, in particular a hierarchy of closed loops, from the most dynamic inner loop, closest to the sensory-motor signals and commands, to the most online" outer loop. Consider for example the relationship between planning and acting. We argued that acting cannot be reduced to execution control", that is the triggering of commands mapped to planned actions. There is a need for significant deliberation to take place between what is planned and the commands achieving it. This acting deliberation may even rely on the same or on different planning techniques as those of the planner, but it has to take into account different state spaces, action spaces and event spaces than those of the planner.

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