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Perception and Situation Assessment for Behavior-Based Robot Control

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Abstract

An approach to robot control is proposed. It replaces numerical models and quantitative measurements by largely qualitative situation assessment and perception, and it all but eliminates the need for world coordinate systems and for calibrations. The approach has been inspired by nature and, specifically, by the fact that organisms are extremely robust and skillful in their interaction with the real world, although (or because?) they do not measure and use neither numerical models nor world coordinate systems for their motion control.

The approach has been implemented with mobile robots and a manipulator arm, and has been tested with encouraging results. In fact, our experience indicates that the robustness of a robot increases in direct relation to the extent to which models and measurements are replaced by situation assessment and perception.

Keywords: robotics, artificial intelligence, calibration-free robots

Introduction

Traditionally, robot control has been based on a careful modeling of the robot and its environment, and on accurate measurements. This approach has severe limitations, most importantly it tends to fail when reality does not conform to the models, or when it is difficult to obtain accurate measurements of all relevant parameters in real time. Moreover, creating and updating the models requires repeated calibrations and is often difficult and expensive. In consideration of these limitations we propose a different approach that substitutes perception and situation assessment for measurements and the evaluation of quantitative models. Moreover, it largely avoids all calibrations and world coordinate systems.

The final goal of our efforts is the intelligent robot. Although the term “intelligence” is difficult to define it is clear that an intelligent robot should have certain characteristics inherent to “intelligent beings”. An example would be a mobile robot that is able to operate in an unmodified natural environment and to perform a variety of tasks without ever needing detailed instructions; moreover, it should be able to adapt to unexpected changes. In other words, it should almost resemble an animal. Of course, such machines do not exist yet, but they would certainly be very useful, and developing them is a fascinating challenge.

It is known that there are many different kinds of intelligence. There is the intelligence that human experts possess; for instance, the intelligence that enables a mathematician to prove theorems, or the intelligence that lets a chess player win a game. We are not interested in this kind of intelligence here. We mean a different kind of intelligence that may be observed in small children or in animals, and which enables them, for instance, to orientate themselves in an environment and to control their motions in an effective and goal-directed way. If robots could be endowed with such a practical intelligence they would, in their respective domains, display a similar adaptability as living beings. They could be robust, user-friendly and useful.

Models and Situations

According to the classical approach, robot control is model-based. Numerical models of the kinematics and dynamics of the robot and of the external objects that the robot should interact with, as well as quantitative sensor models, are the basis for controlling the robot’s motions. The main advantage of model-based control is that it lends itself to the application of classical control theory and, thus, may be considered a straight-forward approach. The weak point of the approach is that it breaks down when there is no accurate quantitative agreement between reality and the models. Differences between models and reality may come about easily; an error in one of the many coefficients that are part of the numerical models suffices. Among the many possible causes for discrepancies are initial calibration errors, aging of components, changes of environmental conditions, such as temperature, humidity, electromagnetic fields or illumination, maintenance work and replacement of components, to mention only a few. Consequently, most robots work only in carefully controlled environments and need frequent recalibrations, in addition to a cumbersome and expensive initial calibration.

Organisms, on the other hand, are robust and adapt easily to changes of their own conditions and of the environment. They never need any calibration, and they normally do not know the values of any parameters related to the characteristics of their “sensors” or “actuators”. Obviously, they do not suffer from the shortcomings of model-based control which leads us to the assumption that they use something other than numerical models for controlling their motions. Perhaps their motion control is based on a holistic assessment of situations and the selection of behaviors to be executed on that basis, and perhaps robotics could benefit from following a similar approach.

According to Webster’s Dictionary [Babcock 1976] The term “situation” describes among others “the way in which something is placed in relation to its surroundings”, a “state”, a “relative position or combination of circumstances at a given moment” or “the sum of total internal and external stimuli that act upon an organism within a given time interval”. A similar, but more operational definition to be used in the context of robotics will be proposed later.

Measurement and Perception

Model-based robot control depends on a continuous flow of numerical values describing the current state of the robot and its environment. These values are derived from measurements performed by the robot’s sensors. One problem here is that the quantities that are needed for updating the numerical models may be difficult to measure, e.g., the distance, mass and velocity of some external object that is posing a collision danger. Also, there are certain important decisions that cannot be made on the basis of measurements alone; the hypothetical decision whether in a particular situation a collision with a parked car should be brought about in order to avoid a collision with a pedestrian is an example.

Humans and other organisms, on the other hand, do not depend on measurements for controlling their motions. If, for instance, we want to sit down on a chair or pass through an open door, we do not first measure the size of the chair, the door, or our body; rather, we make a qualitative judgement whether the chair is high or low, or whether the door is wide or narrow, and then execute a sequence of motions that is adequate for the situation. In short, we substitute perception for measurement.

According to Webster's Third New International Dictionary “perception” is

- a result of perceiving;
- reaction to sensory stimulus;
- direct or intuitive recognition;
- the integration of sensory impressions of events in the external world by a conscious organism;
- awareness of the elements of the environment.

“To perceive” means, according to the same source,

- to become aware of something through the senses;
- to become conscious of something;
- to create a mental image;
- to recognize or identify something, especially as a basis for, or as recognized by, action.

Typical questions to be answered by perception are:

- Which objects exist?
- What is the relationship between objects?
- Is it necessary to react? How?

Perception, rather than measurement, is thus a prerequisite for, and a complement of, situation assessment. Vision is the ideal sensing modality for perception because it is capable of supplying very rich information on the environment.

Situation-Oriented Robot Control

We define the term “situation” in a similar way as quoted above [Babcock 1976], but with a more operational aim, as the set of all decisive factors that should ideally be considered by the robot in selecting the correct behavior pattern at a given moment. These decisive factors are:

- perceivable objects in the environment of the robot and their suspected or recognized states;

- the state of the robot (state of motion, presently executed behavior pattern, ...);

- the goals of the robot, i.e. permanent goals (survival, obstacle avoidance) and transient goals emerging from the actual mission description (destination, corridor to be used, ...);

- the static characteristics of the environment, even if they cannot be perceived by the robot’s sensors at the given moment;

- the repertoire of available behaviors and knowledge of the robot’s abilities to change the present situation in a desired way by executing appropriate behavior patterns.

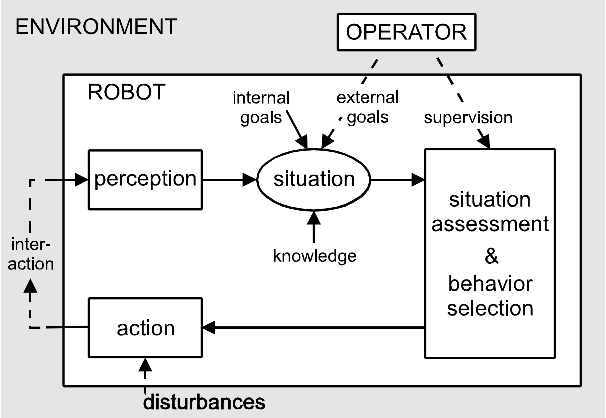

Figure 1:
The role of "situation" as a key concept in the perception-action loop of a situation-oriented behavior-based robot

Figure 1 illustrates the definition of the term "situation" by embedding it in the action-perception loop of a situation-oriented behavior-based robot. The actions of the robot change the state of the environment, and some of these changes are perceived by the robot's sensors. After assessing the situation an appropriate behavior is selected and executed, thus closing the loop. The role of a human operator is to define external goals via a man machine interface and to control behavior selection, e.g., during supervised learning.

Although situation-oriented robot control has proven much more robust and flexible under real-world conditions than classical model-based control it is not perfect. One reason is that, obviously, the robot cannot base its behavior selection on a "true" or "real" situation, but only on an internal image of the situation as created by the robot according to its sensor information and its – always imperfect – knowledge of the world and of its own characteristics. Also, disturbances during the behavior execution can lead to non-expected situations. Although the disturbances may be corrected by either adjusting behavior-immanent parameters or selecting a different behavior, they will usually cause the robot to move in a non-ideal way.

Realized System Architecture

Figure 2 gives an overview of the system architecture that has been realized for our behavior-based mobile robot. In this section we give only a short introduction to the different modules and their interaction (see [Wershofen 1996] for details):

- a situation module taking into account all the decisive factors explained in the last section to the greatest extent that is practically possible, and basing thereupon the dynamic selection of behaviors;
- a sensor module comprising an object-oriented vision system as the main sensor and a proprioceptor system that provides auxiliary information needed by certain behavior patterns;
- an actuator module executing commanded behaviors by activating a sequence of control laws for the motor system;
- an extendable knowledge base providing information about the static characteristics of the environment and the actual mission and goals;

- a man machine interface for operator intervention and status display.

The analysis of the current situation is realized within the situation module which interacts with the sensors, the actuators, the data base management, and the man machine interface in a bidirectional way. Fusing the data and information from the different modules makes situation assessment and behavior selection possible. Acting as the core of the whole system this module is responsible for system management and behavior coordination.

Each cooperation between actuators and sensors is supervised by a specific coordination process within the situation module. By activating and deactivating these coordination processes the management process realizes the situation-dependent concatenation of elementary behavior patterns to complex and elaborate action.

Discussion

The described concepts for controlling a mobile robot by situation-oriented and behavior-based navigation were implemented and tested on the mobile robot *ATHENE II* (Figure 3). Figure 4 shows the test environment, a section of our university's laboratory building with a network of corridors.

The robot uses an attributed topological map that reflects the topology of the network correctly, however, the geometric information it contains needs to be only approximately correct with a large margin for errors. By using such a map the robot is able to locate itself by looking for characteristic landmarks, and to navigate in the network of corridors. When navigating, the robot knows exactly which corridor it is in, but it knows only approximately how far away it is from each end of the corridor. This is sufficient for navigation; in fact, it is similar to the situation experienced by a car driver traveling along a highway.

Because the map knowledge required by a situation-oriented behavior-based robot is of a semi-qualitative nature it is easy for a human user to generate the map, which is a great practical advantage. Moreover, it has been demonstrated that such a robot can even acquire its map knowledge by learning [Wershofen 1996].

The concept of situation-oriented behavior-based navigation has evolved as a consequence of experiences gained with other approaches. In our first attempt at robot navigation we had tried

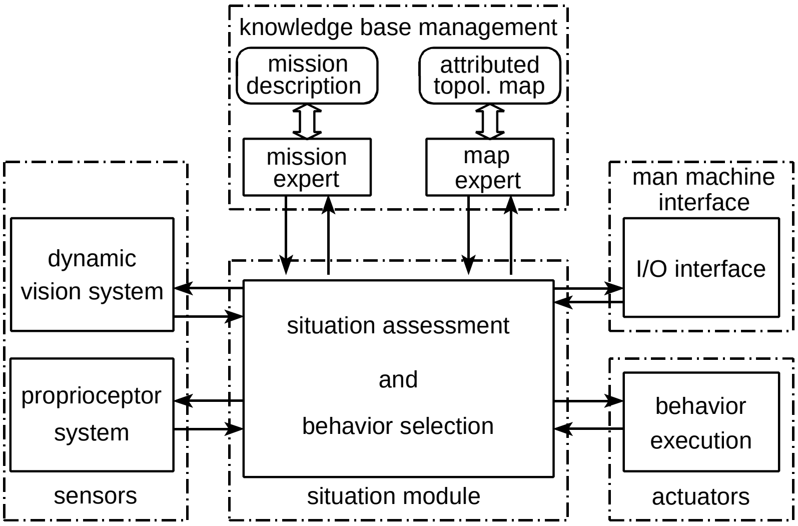

Figure 2
System architecture of a situation-oriented behavior-based robot

Figure 3
The mobile robot *ATHENE II*

to provide the robot with an accurate map and to navigate by dead reckoning and on the basis of a world coordinate system; a vision system was supposed to update the dead reckoning navigator once in a while by observing certain objects, such as pillars, that were used as landmarks. This approach failed, mainly because the errors of the dead reckoning system built up so fast that the robot bumped into a wall before a suitable landmark for correcting the errors had been located.

Our second approach was behavior-based and somewhat perception-oriented. It used a topological map and no global coordinate system, and it was successful in allowing the robot to navigate in the corridors. Now the vision system was the main sensor, and dead reckoning was only used for interpolation and as part of a specific method of motion stereo that does not require a camera calibration [Huber, Graefe 1991]. A disadvantage of the approach was, however, that we did need artificial landmarks at each intersection to support the visual motion control.

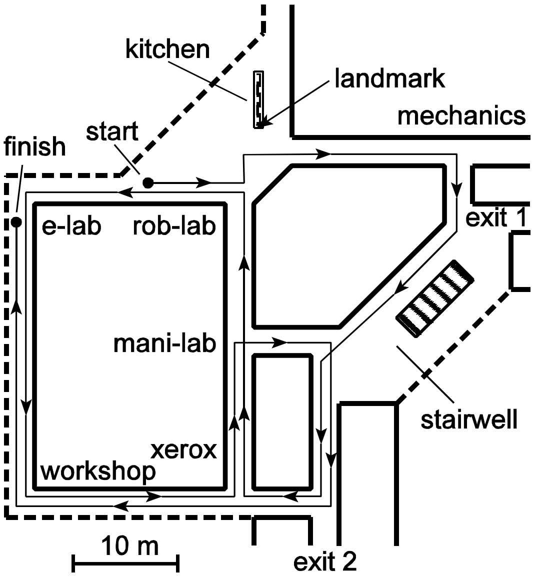

Figure 4
Ground plan of laboratory. Dotted lines: window walls. Arrow lines show the course chosen for a specific experiment.

The third approach, described above and based on situation assessment and largely on perception, proved to be much more robust and flexible. Artificial landmarks were not needed any more, and the robot was now able to acquire map knowledge by supervised, and to an extent even unsupervised, learning. The repertoire of different situations is still rather limited in this simple navigation task, since situations here depend mainly on the location and orientation of the robot and on its mission. Nevertheless, the achieved success shows, however, the power of the concept.

A Second Application: Object Manipulation

The idea of substituting perception for measurement is not limited to robot navigation. Object manipulation by vision-guided arms is another application. According to the concept of object- and behavior-oriented stereo vision [Graefe 1995] a completely uncalibrated manipulator arm controlled by a vision system using a pair of completely uncalibrated cameras is able to manipulate objects. The key point here is that the robot learns to correlate arbitrary motion commands that it sends to its motors with the resulting changes in the images produced by the two cameras. On this basis it computes a sequence of control commands that bring the images closer and closer to their desired final state. When finally both images indicate that the world appears to be in its desired state the world really is in that state, characterized, for instance, by the gripper touching an object to be grasped.

No measurements, no world coordinates and no calibrations are involved. Instead, there is a direct transition from arbitrary image coordinates to motion control commands. The goal of image interpretation is, again, not the construction of a model of the 3-D world, but the derivation of control commands that will bring about a desired situation.

Grasping experiments performed with a manipulator arm (Figure 5) have shown that this approach performs well in the real world [Vollmann, Nguyen 1996], and that it is a basis for studying machine learning [Graefe et al. 1997]. A robot based on this approach has been shown to tolerate, for instance, large arbitrary misadjustments of the cameras without any degradation of its performance. This robustness is in sharp contrast to the dependence on a

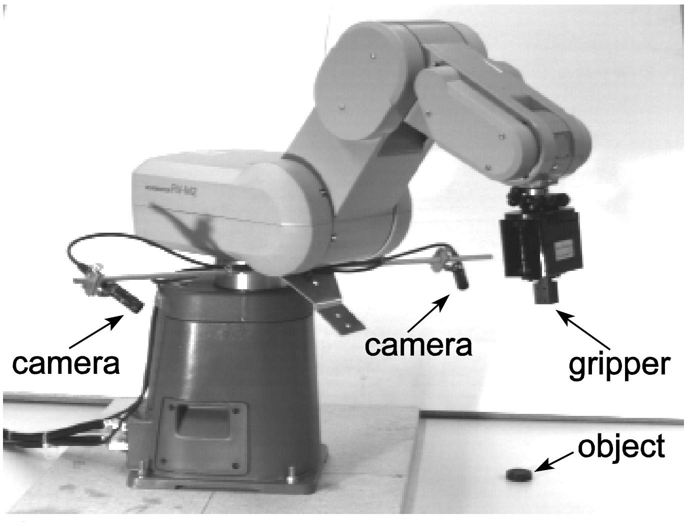

Figure 5
The manipulator arm used for grasping experiments. Two cameras attached to the arm are the only sensors used. The entire system is completely uncalibrated.

careful calibration that is normally characteristic for stereo vision systems.

Conclusions

In contrast to the classical approach that emphasizes measurement and numerical models, the control of intelligent robots may instead be based on perception and situation assessment. Such a control strategy has been implemented on different robots and tested in real-world experiments. The results indicate that the utilization of perception and situation assessment has the potential of greatly improving the adaptability and robustness of future robots. Moreover, robots designed according to this concept need very little calibration, if any, which greatly simplifies their initial deployment and later maintenance in practical applications.

References

Babcock, P. (1976): Webster's Third New International Dictionary of the English Language. G. & C. Merriam Company, Springfield, MA, U.S.A.

Graefe, V. (1995): Object- and Behavior-oriented Stereo Vision for Robust and Adaptive Robot Control. International Symposium on Microsystems, Intelligent Materials, and Robots, Sendai. pp 560-563.

Graefe, V.; Xie, Q.; Vollmann, K. (1997): Using a Knowledge Base in Manipulator Control by Calibration-Free Stereo Vision. IEEE International Conference on Intelligent Processing System, Beijing, Oct. 1997

Huber, J.; Graefe, V. (1991): Quantitative Interpretation of Image Velocities in Real Time. IEEE Workshop on Visual Motion. Princeton, pp 211-216.

Vollmann, K.; Nguyen, M.-C. (1996): Manipulator Control by Calibration-Free Stereo Vision. In D. Casasent (ed.): Intelligent Robots and Computer Vision XV, Proceedings of the SPIE, Vol. 2904. Boston, pp. 218-226.

Wershofen, K. P. (1996): Zur Navigation sehender mobiler Roboter in Wegenetzen von Gebäuden – Ein objektorientierter verhaltensbasierter Ansatz. Dissertation, Fakultät. für Luft- und Raumfahrttechnik der Universität der Bundeswehr München.