Some didactic aspects of teaching robotics

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Abstract—**The contemporary robotics is an excellent tool for teaching science and engineering and an attractive topic for students of all ages. Problems of robotics are fundamentally about the couple sensing – action, the two parallel activities bounded by the robot's dynamics. It is just the robot's dynamics that makes the relation "sense – act" difficult to control and calls for the advanced study. The fist part surveys the authors' experience as teachers and researchers in the field of robotics at the electrical and mechanical engineering faculties. The second part points out some issues of robot control and navigation as we teach them at the university level.**

Keywords-didactic aspects; mobile robotics; stationary robotics

I. Introduction

There is much more to robotics education than just teaching about robots. Robots are finding their way into the classroom so as to help teaching science, math, mechanics, teamwork and even management skills. Many enterprises rely on *off-the-job training* (formal learning) without considering its suitability for the learning tasks at hand. *On-the-job training* (informal learning) has a substantial advantage: it is more close to the problems to be solved. On other hand *on-the-job training* is often unplanned and therefore mostly ineffective. For this reason, bridging formal and informal learning, theory and practice, the abstract and concrete in robotics is the best way to convince the students at all grade levels that the robotic subjects are interesting and useful. The educators have found that teaching with and about robots provide a new and exciting way to interest and motivate their students.

At the Institute of Control and Industrial informatics in Bratislava was established the Office of Robotics Education as a way to help educators, students and parents with interests in robotic. We hope this webpage will serve as a helpful launching point.

From the perspective of teaching robotics may be useful to look at the relation between robotics and mechatronics. Some time ago I found on the Internet a scheme of mechatronic system. It revealed that the same is also true for a robotic system. The robotic system (robot) is also a purposeful connection of mechanical and electrical systems (electromechanical system) equipped with actuators through which the system acquires moving abilities. Its motion is controlled in real time by a digital controller which acts on the electromechanical system through a set of D/A and A/D converters Judging by the scheme its author probably supposed that the control program together with control data (e.g. desired motion trajectory) is loaded into the computer memory at the beginning of the working task. This may be the case of a grinding, milling or other numerically controlled manufacturing machines, which repeatedly do the same operations. Except for some force, torque or temperature sensors such simple "mechatronic" system does need any feedback from its (possibly changing) environment. Thus the scheme represented at most a classical "low level" controlled system without learning.

Complexity of current fixed or mobile robots goes much further. They are required to do tasks which go far beyond the capabilities of the classical industrial manipulators. Letting alone the sophisticated nonlinear robust and adaptive control, the primary requirement laid on modern "mechatronic" systems, which the contemporary robot undoubtedly belongs to, is ability to grasp a "mental image" of both its own state and the state its environment. Having this image (context) in mind the robot should be to improve its knowledge through learning from interactions with the environment.

From what have been said follows that the subjects of robotic cover a wide range of sophisticated problems, which require the university study. Therefore in what follows some problems of teaching the robotics at the university level will be briefly mentioned.

II. Some experience from teaching the robot modeling and control

To understand moving operation of a robot, the student must be familiar with robot kinematics, in particular the homogenous transformations, Denavit –Hartenberg parameters, problems related to the direct and inverse kinematic, manipulator's Jacobian matrix and the like. These problems are relatively easy grasped by all students regardless their previous education. Mastering the problems of robot kinematics is a basic prerequisite for understanding issues of robot dynamic.

The problems of robot dynamic are much more difficult to teach. Primary reason is that the students of electrical engineering are not sufficiently good in mechanics. So as to teach them the notions and mathematical means like the Euler-Lagrange equations, inertia matrix, expressions of kinetic and potential energy etc., the lecturer is forced to remind the basic principles of the mechanics. After doing this he/she can continue with explanation of the robot dynamics. The undergraduates of mechanical engineering are facing the opposite difficulties. They need some preliminary introduction to more sophisticated control issues.

After understanding the robot kinematics and dynamics the subject of robotics becomes much more interesting and attracts a great deal of the students' attention. The essential knowledge the students must comprehend consists in understanding the theoretic reasons why the robot manipulator (except for special configurations, e.g. SCARA robot) being controlled by linear PID controllers cannot reach an acceptable tracking performance. This knowledge is a stepping stone for presentation the philosophy of autonomous control, namely that of named as the computed torques methods.

Grasping the problems of multivariable control is again a rather demanding task. Here the most difficult is to explain principles of co-called inverse dynamics and subsequent synthesis of a robust and/or adaptive controller.

In relation to the design of a robust controller the special attention is given to the robot control based on the theory of variable structure systems (VSS). Though rather difficult, due to step by step explanations the students understand the basic principles of VSS control relatively easily and become fascinated with the possibilities the VSS control offers. In the end the strength of the VSS control is demonstrated by some results obtained with the VVS control of a flexible joint robot. They are acquainted with undesirable effects of the joint flexibility.

The syllabus ends by brief presentation of hybrid position-force control and control of mechanical impedance. It can be concluded that the subject provides students with a good overlook over the field of advanced control industrial robots.

III. Teaching mobile robotics – intelligent navigation and data fusion

A. *Intelligent navigation*

The robot navigation is another aspect of teaching robotics. An autonomously operating mobile robot must respond to instantaneous incentives coming from its own "body" and surrounding environment. To this end the robot needs to handle a wide range of unexpected events, detect and distinguish between normal and faulty states, classify them and finally, if the fault cannot be compensated by a nominal control it should switch to an appropriate fault-tolerating regime. To manage these tasks, the robot functionality must be organized into an appropriate architecture, i.e. a set of organizing principles and core components that create a system basis.

The control community is familiar with the term of "intelligent control", denoting the abilities the conventional control system cannot attain. Leaving alone various meanings of the "intelligent" system, some basic features characterizing an intelligent system will be mentioned here. To mention a few, it is making decisions, adapting to new and uncertain media, self-organizing, planning, and the more. [1, 2] Intelligent systems should not be restricted to those that are based on a particular constituents of so-called soft computing techniques (fuzzy logic, neural networks, genetic algorithms and probabilistic reasoning), as it is frequently done. Soft computing techniques should be considered as mere building blocks or even "bricks" used for building up a "large house" of an intelligent system. What makes a system intelligent is just a synergic use of the softcomputing techniques, which in time and space invoke, optimize and fuse elementary behaviors into an overall system behavior. For instance, fuzzy inference is a computing framework based on the fuzzy reasoning. But the fuzzy system is not able to learn and must be combined with neural networks which add the learning ability. To this end, the fuzzy rule-set is commonly arranged into a special neural architecture like ANFIS and NEFCON with Takagi-Sugeno-Kang and Mamdani inference respectively. [3] Intelligence of such system springs from successive generalization of information chunks (granules) - singular, crisp, and finally fuzzy granular information. [4, 5] Due to the information granularization a system becomes robust with respect to imprecision, uncertainties, and partial truths. Thus, the system's intelligence comes from its architecture i.e. from the inner organization of the system elements and functionalities. To demonstrate this, the *subsumption architecture* (developed in 1986 by Brooks [6, 7]) and used in the synthesis of navigation algorithms of a mobile robot developed at the authors' workplace will be briefly described.

The subsumption architecture was inspired by the behavior of living creatures and heralded a fundamentally new approach to achieving more intelligent robots. The robot behaviour is typically broken down into a set of simpler behaviours which are loosely co-ordinated towards a final goal. Behaviours having higher priority are subsumed under those with lower priorities (running at the background), thus a layered structure is developed. Contrary to the classical hierarchical architecture, in which a particular behaviour assumes control if a given set of logical conditions is fulfilled, the behaviours which are organized into subsumption architecture can appear concurrently and asynchronously and with different intensities. For example, if a robot is navigated in an unknown environment cluttered with obstacles, it is natural to assign the highest priority to the obstacle-avoidance behaviour, and lower priorities to the behaviours which are to be initialised e.g. if the robot finds itself trapped in a deadlock. Using such priority management, the robot being in a deadlock inhibits all obstacle-avoidance related behaviours. Instead, the behaviour being typical for escaping from the deadlock assumes control. In other words, the obstacle avoidance behaviour is normally "subsumed" by the deadlock-resolving behaviour. If the robot finds itself in a deadlock (e.g. in a partly closed space), the obstacle-avoidance behaviour is to some extent suppressed by the deadlock-resolving behaviour. Similarly, a striving-towards–a-goal behaviour subsumes both of them and therefore it possesses the lowest priority. An example of subsumption architecture that was used in the navigation of our experimental robot [8] is depicted in Fig 1. One reason why the highest priority is assigned to the obstacle-avoidance behaviour is that one can reasonably expect that the robot will encounter an obstacle when moving in a terrain. The deadlock-resolving behaviour (lower priority) subsumes the previous one because it is less probable that the robot will be trapped in a deadlock. These two behaviours are subsumed by the goal-striving

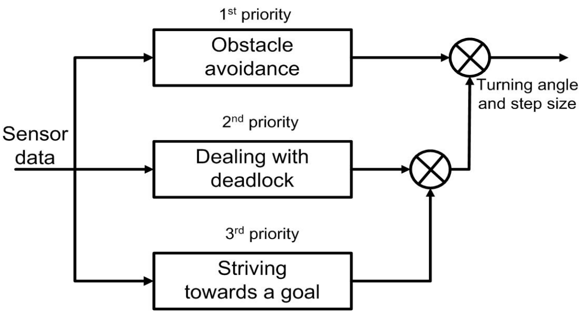

Figure 1. Subsumption architecture

behaviour (the lowest priority), because the probability that an obstacle-free landscape will appear in front of the robot is relatively low. If it happens, the goal-striving behaviour would inhibit or even suppressed both of them. The subsumption architecture is a kind of behaviour-based architectures [9].

Great advantage of the described architecture is that if implemented through fuzzy IF-THEN rules, the transition between behaviours is very smooth. In case that a transition is controlled exclusively by current sensor information, the system is called *reactive.* The reactive systems typify a majority of the autonomous robots operating in distant and unknown environments, like sea beds, battlefields, areas hit by disasters etc. The robot navigation based on the subsumption architecture is has find great popularity among students.

B. Data fusion

When teaching robot navigation the issues of data fusion cannot be avoided, because an autonomously navigated robot is a particular realization of an intelligent system. In this view the teaching the data fusion naturally precedes issues of robot navigation. The thing is that the robot functionality relies on numerous disparate sensors through which it grasps a consistent image of what is going on. An underlying idea of the sensor integration rests on a synergic use of the overlapping information delivered by the sensors of different types. An aim is to obtain aggregated information that would be more complex then that of received from a single sensor. The aggregated (or blended) information is beneficial at least from aspects of noise reduction and novelty extraction, which makes the data patterns hidden in raw signals more obvious.

It is stressed that a single sensor cannot provide a required amount of information. For instance, the ultrasonic range sensor used for identification of an obstacle is uncertain about the exact location of the obstacle to which the distance is measured. This is because of the wide angle of the ultrasound wave cone. Therefore there is a need to install an additional sensor, let us a laser one, which adds additional information about the obstacle direction. Another reason that necessitates the fusion, stems from the fact that mobile robot operates in changing environment; therefore the fusion must take place not only in space but also in time. Besides, the use of a set of (distributed) sensors of different modalities allows fusion of high-level information (e.g. statements) and even to grasp a context. This is to some extent, tantamount to mimicking human-like reasoning. For instance, the fact of finding a personal mine implis higher likelihood of finding other mines or even a whole battlefield (i.e. context).

The number of sensors needed for robot navigation and fault detection is relatively large. Examples include the GPS sensors, proximity sensors, odometers, accelerometers, gyroscopes, inclinometers, velocity, temperature, light and darkness sensors and many others. In order to know “what to fuse“, multimodal information must be fused into a common format, and what is very important, the uncertainty of sensed and fused signals must be taken into account.

Special attention is devoted to the heretical structure of the data fusion. It is explained that at the lowest level is performed a pixel fusion of single signals or pixels. Features (mean value, variance, kurtosis, covariance, power spectrumetc.) are fused at the second level. As to the signals are of random nature, the fusion is usually based on the Bayesian statistics with Kalman filter [10, 11] as a typical representative. The aim of so called *complementary* fusion is to obtain not only accurate but also more complete information. For instance, images from two cameras looking in different directions are fused to obtain a more complex image. Another possibility is that more sensors sense the same quantity, e.g. sonar and laser range sensors. In this case the sensors "compete" in a sense, therefore one can speak about *competitive fusion.* The third kind is *cooperative fusion,* where one sensor relies on the others, (e.g. the battery state can be observed by simultaneous measuring the electric current and time).

The situation is illustrated in Fig. 2. As seen, at low levels run cooperative and competitive fusion while at high levels runs complementary fusion. Results of high level fusion are statements (declarations) about instantaneous state of the robot, saying for instance that "in the azimuthal angle “α” at the distance “d” is seen a small pond" or "the battery is discharged to 50% of its initial capacity". In general, at the lower level runs the signal fusion and at higher level runs the symbolic fusion. While a typical means for signal fusion is Kalman

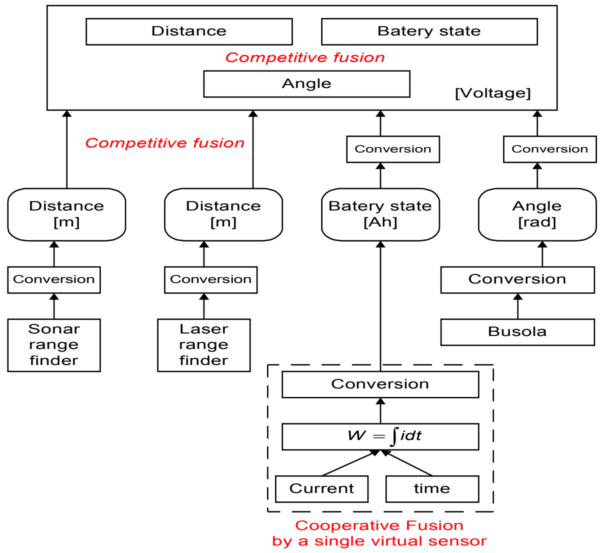

Figure 2. Types and hierarchy of data fusion

filtering, a typical means used at higher levels is either Dempster –Shafer theory of evidence [12-14] or fuzzy logic [15].

The students must become aware that results of the fusion process (at all levels) are not only estimated values (numeric or symbolic) but also corresponding *certainty values*. In case of Kalman filter the result is an estimate of the mean value and by way of the certainty value is used signal variance. Contrary to this, in case of Dempster-Shafer evidence theory the output is a symbolic value, supplemented by its *belief value*. Finally, in the case of fuzzy fusion, the output is the consequent of the fuzzy rule, supplemented by corresponding *degree of fulfillment* (firing strength). In the end of semester some means of data fusion are explained.

1) Example of low level fusion

Let us suppose that the random signal x with normal distribution is directly measured by two different sensors S_1 and S_2. The estimates are x_1, x_2, and their certainty values are given by the standard deviations σ_1 and σ_2. An optimal estimate X is then obtained by fusing the measurements in accordance with the rule

$$X = x_2 + \left[\frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}\right](x_1 - x_2) \tag{1}$$

Variance σ^2 of the fused estimate X is given by the expression

$$\frac{1}{\sigma^2} = \frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2} \tag{2}$$

The fusion process can continue repeatedly in such a way that the estimate X is considered as if it would be a new reading of the sensor S_1, that is x_1. The sensor S_2 performs the next measurement with the reading x_2, which is again fused with x_1. In this way the variance σ^2 gradually decreases while the preciseness of the estimate X is gradually improved.

2) Example of high level fusion

The high levels are occupied with more sophisticated procedures of notion identification, i.e. "what was observed" and "what it means to have observed that". The higher level is a domain for application of *possibilistic approaches*, which can directly handle symbolic quantities, e.g. propositions. Every proposition is accompanied by its certainty value (score), which expresses how certain the sensor is about its estimation of the measurand. Examples of fused propositions:

$z_{i,e}$ = there is a cube "i" in the robot's environment "e"

$z_{i,c}$ = object "i" belongs to cluster "c"

$z_{d,\alpha}$= at angle "α" there as an obstacle at the distance "d"

Higher-level fusion is based either on *Bayesian statistics* (not mentioned here) or possibilistic means, like Dempster-Shafer evidence theory and fuzzy set theory but even a short recapitulation goes beyond this paper.

IV. CONCLUSIONS

Some didactic issues with a brief indication of syllabuses of stationary and mobile robotics taught at the university level were presented. Both the syllabuses and teaching experience as described here cannot be generalized. Every teacher can appropriately modify of them so as to reach the best educational results. The practical laboratory activities were not described. In general, the computer simulations of robot dynamics, control and navigation are supplemented with experimental measurements and control of both industrial manipulators and mobile robots.

The students' understanding of the robotic problems presented during the lectures and within laboratory activities can be considered as very acceptable. The graduates can easily join the robotic and related companies.

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