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IMBEDDING INTELLIGENCE INTO MECHATRONIC SYSTEMS

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An autonomously operating mechatronic system is an instantiation of an intelligent system. Its functionality relies on numerous disparate sensors through which the system grasps a consistent image of what is going on inside and around it. The paper describes the ways of embedding intelligence based on the means of information fusion and learning. The process is exemplified by intelligent navigation of a mobile machine. The feasibility of the chosen approach is demonstrated by both the simulation and real experiment.

Key words: mechatronic system, information fusion, imbedded intelligence

Ugrađivanje inteligencije u mehatroničke sustave. Mehatronički sustav autonomnog djelovanja primjer je instantizacije inteligentnog sustava. Njegova funkcionalnost ovisi o brojnim i različitim senzorima pomoću kojih sustav prikuplja konzistentnu sliku o zbivanjima unutar samog sustava i u njegovom okruženju. Ovaj rad prikazuje načine ugrađivanja umjetne inteligencije utemeljene na sredstvima fuzije informacija i učenja na primjeru inteligentne navigacije pokretnog stroja. Primjenjovost odabranog pristupa potvrđena je simulacijom i eksperimentom u realnim uvjetima.

Ključne riječi: mehatronički sustav, fuzija informacija, ugrađena inteligencija

INTRODUCTION

Mechanical and electrical systems are increasingly integrated through hardware and software, resulting in integrated systems called „mechatronic systems". In finding an optimal balance between mechanical structure, sensors, actuators, and automatic control the embedded intelligence play a decisive role. It could be said that the issues of imbedded intelligence lie at the focus of both industrial and academic research. As early as at the beginning of seventies K.S. Fu [1] linked intelligent system with the ability of making decisions and adapting to new and uncertain situations. Contrary to strictly deterministic systems, the intelligent systems may work to a certain extent unreliably when required to process imprecise and incomplete information.

There is much to be done to set today's intelligent systems on a par with even low - ranked leaving beings, like insects, ants' colonies, birds' flocks etc. Anyway, some partial positive and promising results have been reached. The living systems exhibit natural robustness with respect to the unpredictable and omnipresent environment dynamic changes. This is due to the fact that their organization (i.e. the structure of the system information and control channels) exhibit strong functional and structural adaptivity. This is just what is not yet fully fledged in artificial systems.

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The traditional approaches to imbedding intelligence are based on so-called *Good Old-Fashioned Artificial Intelligence* [2], i.e. the off-line, high-level and mostly symbolic perception and reasoning, which is difficult to implement into autonomous mobile machines. Current approaches are mostly based on soft-computing methods and means i.e. fuzzy logic, neural networks, and genetic algorithms. In this regard it is worth mentioning that the intelligent systems cannot be restricted to those that employ particular constituents of the soft computing as it is frequently done. Particular soft computing means should be considered as mere building blocks. What makes the system intelligent is a synergistic use of these techniques, which fuse elementary data, patterns and knowledge into overall intelligent system intelligence. For instance, the fuzzy inference is a computing framework based on the fuzzy reasoning. But the fuzzy system alone is not able to learn; therefore a kind of neural networks should be used to allow imbedding learning abilities. To this end, the fuzzy rule-set is arranged into special neural architectures like ANFIS or NEFCON with Takagi-Sugeno-Kang and Mamdani inference respectively [3, 4, 5]. Intelligence of the learning neuro-fuzzy systems springs from successive generalization of information pieces. The information fusion and inference runs over (overlapping) information pieces. Due to that the system becomes robust with respect to imprecision, uncertainties, and partial truth.

To demonstrate the role of structure in the process of imbedding intelligence, let us look at the *subsumption ar-*

chitecture, developed in 1986 by Brooks [6, 7]. The subsumption architecture heralded a fundamentally new avenue in the development of intelligent machines. In the subsumption philosophy, the desired global behaviour is typically broken down into a set of simple behaviours which are loosely co-ordinated towards reaching a final goal. Contrary to the hierarchical architecture, the behaviours can appear concurrently and with different intensities. The distant goal activities subsume higher priority activities (e.g. obstacle avoidance); hence a layered structure is developed. Particular behaviour layers selectively assume control over all subsumed layers. A layer (set of behaviours) can inhibit or even supersede activities in the subsumed layers. For instance, when navigating a mobile machine in an unknown environment cluttered with obstacles, it is natural to assign the highest priority to the behaviour typical for the obstacle-avoidance since hitting an obstacle is highly expected. Therefore, behaviours typical for obstacle avoidance are subsumed by the less probable behaviours, like those resolving a deadlock situation. If the higher layer observes that the machine is trapped in a deadlock, it inhibits obstacle avoiding behaviours so as to allow the deadlock resolving behaviours assuming a control. When resolving a deadlock, the other behaviours will run at the background. In other word, the obstacle avoidance behaviour is normally "subsumed" by the *deadlock-resolving* behaviour, but if the mobile machine finds that it wanders in a partly closed space the obstacle-avoidance behaviour is overruled by a deadlock-resolving behaviour. Similarly, the *striving-towards-goal* behaviour subsumes both of them. It has the lowest priority since the probability that an obstacle-free landscape appears in front of the moving machine is relatively low. Due to the described priority management the mobile machine behaves let's say like a man striving to the post office across a complex environment cluttered with buildings, cross roads etc. Undoubtedly the behaviour of the man is considered to be intelligent.

The subsumption architecture belongs to a category of so-called behaviour-based architectures [8]. When implemented by a set of the fuzzy IF-THEN rules then transitions between particular layers are very smooth. In case that the transitions are exclusively controlled by the current sensor information the system is called to be *reactive.* The reactive systems typify a majority of autonomous mobile machines which are set to operate in the distant and unknown environments, like sea beds, battlefields, areas hit by disasters etc. The machines having their functionalities organized into the behaviour-based architectures occupy the highest positions in the realm of the current autonomous machines.

As said above, the autonomously operating machine is an instantiation of the intelligent system and its functionality relies on numerous disparate sensors through which the machine grasps a consistent image of what is going on inside and around it. An aim of data fusion is to obtain the aggregated (fused) information that would be more complex then that of received from a single sensor. Fused information is beneficial at least from the aspects of system robustness, noise reduction and novelty extraction. Besides, the fusion makes the patterns hidden in data more obvious.

Because signals are of random nature, the fusion is usually based on Bayesian statistics with Kalman filter Š9Ć as a typical representative. Results of higher-level fusion are declarations about instantaneous contexts. The higher-level fusion is a domain for application of the means which can directly handle symbolic quantities (propositions) like Dempster–Shafer theory of evidence [10] or fuzzy logic. The higher level fusion is related to sophisticated procedures of notion identification, i.e. "what was observed" or "what it means to have observed that". In the fuzzy fusion, which was used in the experiment the fusion runs in two steps. The sensed signals are first fuzzified. The measures of they certainties are given by values of their membership functions. The fuzzy fusion is in essence a decision-making which runs in accordance with law of *modus ponens*:

Proposition x *is* A_1 *and* y *is* B_1

Fusion rule if x *is* A *and* y *is* B *then* z *is* C

Conclusion z *is* C_1

Figure 1. The experimental robot

where A_1, B_1, C_1, A, B, C are fuzzy sets. It is supposed that A1 is close to A, and B_1 is close to B. If w_1, w_2 are degrees of match between A and A1, and B and B_1 respectively, then $w_1 \wedge w_2$ is a degree of fulfilment of the fuzzy rule, by which the "fused" membership function of C_1 is clipped.

EXPERIMENTAL WORK

To verify feasibility of the fuzzy-neural based subsumption architecture, an experiment with a real mobile robot was done.

Current robot position was identified by odometer and the target position was permanently available. All this was supplemented by information about the degree of fulfilment of the conditions preventing the robot from overthrowing.

Based on sensed information the fuzzy inference system was able to navigate the robot towards the goal while keeping both speed and turning angle near to their allowed limits.

The navigation architecture was designed in the spirit of the behaviour – based philosophy. Fuzzy rules were divided into a small number of sets, each describing a particular behaviour. The behaviours were arranged into subsumption architecture and finally converted into a five layers feed-forward neural network similar to the ANFIS [4]. Inputs to that neuro-fuzzy navigator were: obstacle distance, obstacle angle, and target angle. Outputs of the navigator were robot speed (the step size in case of a walking robot) and direction of robot motion. The resulting network learned without a teacher by the algorithm of back-propagation. The following criterion was minimized during learning.

$$E = (r^d - r)^2 = \left(r^d \, \frac{\sqrt{a^2 + c^2 + 2a \cdot c \cdot \cos\alpha}}{2 \sin\alpha} \right), \quad (1)$$

The r, r^d are actual and desired turning angles respectively, a, c are two subsequent robot steps and á is corresponding turning angle.

The criterion secured maximum allowable robot speed while preventing him from overthrowing. This was possible by controlling parameters a, c and α. A typical structure of the fuzzy rules used in th experiment was like the following one:

IF (obstacle is middle) AND (distance is near) AND (target is right) THEN (turn is right).

The antecedent parts were evaluated by the Min and Max composition rule for fuzzy AND and OR operators respectively. Conversion of the fuzzy outputs to the crisp ones was done by the bisector method [2, 3]. The results of the learned navigations are shown in Figure 2. The behaviours were fused by the fuzzy meta-rules. One of them, allowing the robot to escape from U-shaped obstacles, like those shown in the upper left part of Figure 3 has the following structure:

IF (number-of-loops is great) THEN (weight of deadlock-managing-behaviours is great)

This particular meta-rule strengths the wall-following behaviour, if the wandering lasts too long. The resulting motion of the robot shown in Figure 1 is shown in Figure 2. The robot path is represented by the solid path. The crosses represent contours of the obstacles (some tables and a standing rolled carpet) localized by the scanning sonar installed on the robot.

Analogous results were obtained by simulation. The robot starting his motion inside the U-shaped obstacle on the left top cornner of Figure 3 was required to navigate through relatively complex labyrinth and reach the target position denoted by ’T’. The robot managed this task by strengthening the “deadlock-managing” behaviour, which was a blend of the “wandering” and “wall-following” behaviours. The robot path is shown in Figure 3.

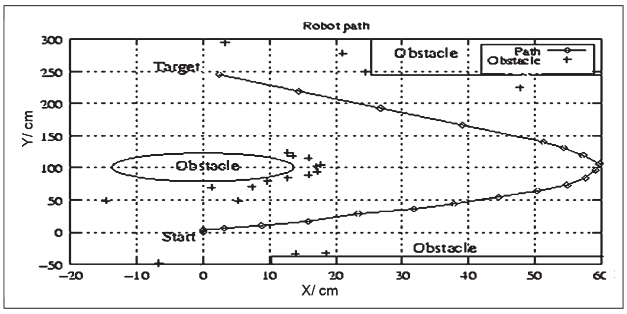

Figure 2. Motion of the robot between detected obstacles (crosses)

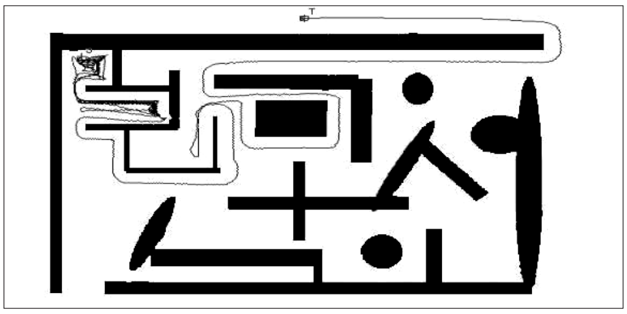

Figure 3. Resolution of U-shaped obstacles

CONCLUSIONS

In parallel with the traditional methods of the symbolic artificial intelligence the means and methods of softcomputing have becoming mature. Intelligence of an artificial system springs from successive generalization of sensor information, starting from single data and ending with knowledge represented by the set of declarations and rules. The logical inference then runs over set of declarations, resulting into the context knowledge based on which the system operates. Due to generalization of the sensor information the system’s behaviour becomes robust with respect to imprecision, uncertainties, and partial truth. Effectiveness of softcomputing-based methods was, in this work, further strengthened by the Brook’s subsumption philosophy demonstrated by the fuzzy-neural navigation of a mobile robot.

In this view the fuzzy-neural methods and means which were further supplemented by behaviour-based philosophy have showed to be one of the means of imbedding intelligence into a mechatronic system, in this case the mobile robot. Process of robot navigation was verified by both the simulation and real experiment. The results obtained clearly demonstrate that in spite of the relative simplicity of the sensor system and navigation algorithms a secure and smooth motion of the robot between obstacles was obtained. This is a direct consequence of the learning neuro-fuzzy subsumtion architecture where the transit from one to other behaviours becomes very smooth. Also the synthesized algorithm is clearly structured and the contribution of particular behaviours may be easily evaluated.

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