Embedding Intelligence Into a Mobile Robot

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Abstract
The paper presents the results obtained within the development of an autonomously operating walking robot. It is supposed that no user interaction and/or assistance are available. Therefore, the robot must rely on its own abilities. It learns from the sensed and subsequently fused information and adapts its behaviour accordingly. In particular, a way of how the robot learns to track an object by teaching a neural network is described.

Key words: autonomous mobile robot, intelligent behaviour, neural network, artificial intelligence

Introduction

An intelligent behaviour is commonly related to the abilities the conventional system cannot attain. As early as at the beginning of seventies K.S. Fu [1] linked intelligent behaviour with the ability of making decisions and based on them to adapt to new and uncertain situations.

Imbedded intelligent systems are to a large extent unreliable when required to process imprecise and incomplete information and based on it to operate in general and not sufficiently specified conditions. There is much to be done to set them on a par with even low ranked leaving systems, like insects, ants' colonies, birds' flocks etc. Anyway reaching some partial results is possible. The living systems exhibit natural robustness with respect to the unpredictable and omnipresent environment dynamic changes. This is due to the fact that all their organization levels (i.e. the structure of the system's information and control channels) are imbedded with a strong functional and structural adaptivity that produces emergent intelligent behaviours of the system as a whole. This is just what is absenting in artificial systems.

The traditional approach to develop a system with the imbedded intelligence the methods based on the so called *Good Old-Fashioned Artificial Intelligence* [2] were applied. It is based on the off-line high-level, mostly symbolic perception and reasoning. However an essential problem came to light, that, for instance a robot, in order to move autonomously in an unknown terrain it must integrate the symbolic form of the information with instantaneous, mostly numerically expressed low-level information being delivered by sensors when the robot interacting with the environment. Newer ways of imbedding the intelligent behaviour lead through the approaches that use the soft-computing means. But in this regard it should be stressed that intelligent systems cannot be restricted to those that are based on a particular constituent of the soft computing techniques (like the fuzzy logic, neural networks, genetic algorithms and probabilistic reasoning), as it is frequently done. Particular soft computing techniques should be considered as mere building blocks or even "bricks" used for building a "large house" of an intelligent system. What makes the system being intelligent is just a synergistic use of these techniques, which in time and space invoke, optimize and fuse elementary behaviours into overall system behaviour. For instance, the fuzzy inference is a computing framework based on the fuzzy reasoning. But the fuzzy system is not able to learn; therefore a kind of the neural network is to be used to allow imbedding certain learning abilities. To this end, the fuzzy rule-set is commonly arranged into the special neural architectures like ANFIS and NEFCON with Takagi-Sugeno-Kang and Mamdani inference respectively. [3] In this way, the intelligent behaviour of the neuro-fuzzy systems springs from successive generalization of information chunks (granules), starting from singular ones and going through crisp granular to fuzzy granular information. [4, 5] The inference process then runs over (overlapping) information granules. Due to the granularization the system becomes robust with respect to imprecision, uncertainties, and partial truth. Thus, the system intelligence comes from the system architecture, i.e. an inner organization of the both system elements and functionalities.

To demonstrate the role of structure in the process of imbedding the intelligence, let us look at the *subsumption architecture*, developed in 1986 by Brooks. [6, 7] The subsumption architecture was inspired by the behaviour of living creatures and to a large extent it heralded a fundamentally new avenue in the development of more intelligent machines. When applying the subsumption philosophy, the requested global behaviour is typically broken down into a set of simpler behaviours that are loosely co-ordinated towards a final goal in such a way, that the every behaviour selectively assumes the control of all subsumed behaviours. Contrary to the hierarchical architecture, where a particular behaviour assumes control when a given set of logical conditions is fulfilled while putting little attention to other behaviours, in the subsumption architecture the various behaviours can appear concurrently and with different intensity. The behaviours with higher priorities are subsumed under those with lower priorities; hence a layered structure is developed. The layer (i.e. a set of behaviours of the same priority) that has assigned higher priority can inhibit or even supersede those with lower priorities. For example, navigating a walking machine in an unknown environment cluttered with obstacles, it is natural to assign the highest priority to the behaviour that is typical for the obstacle-avoidance since coming across an obstacle is highly expected. Lower priorities are assigned to the lower probable situations, for instance when the robot finds itself trapped in a deadlock and tries to escape the deadlock. Using such priority management the machine behaves effectively and, in a sense intelligently. When finding itself in a deadlock the machine inhibits the *obstacle-avoidance* behaviour and the one which allows it to escape from the deadlock assumes control. In other words, the obstacle avoidance behaviour is normally "subsumed" under the *deadlock-resolving* behaviour, but if the mobile machine finds that it wanders in the deadlock (for instance in a partly closed space), the obstacle-avoidance behaviour is inhibited and to some extent overruled by a deadlock-resolving behaviour. Similarly, the *striving-towards–a-goal* behaviour subsumes both of them; hence, it possesses the lowest priority since the probability that an obstacle-free landscape appears in front of the robot is relatively low.

The subsumption architecture belongs to the category of the behaviour-based architectures. [6,7,8] When implemented by a set of the fuzzy IF-THEN rules the transition between particular behaviours will be very smooth. If the transitions between behaviours are exclusively controlled by the contents of current sensor information the system is called as the *reactive* one. The reactive systems typify the majority of autonomous robots which are set to operate in distant and unknown environments, like seabed, battlefields, areas hit by disasters etc. It would be reasonable to stress again that the system may be called intelligent mainly due to its inherent architecture. The robots having their functionalities organized into the behaviour-based agent architectures occupy the highest positions in the realm of current autonomous robots.

Need for the sensor fusion

The autonomously operating machine is an instantiation of the intelligent system. Its functionality strongly relies on numerous disparate sensors through which the machine grasps a consistent image of what is going on inside it and around it. An underlying idea of the sensor integration rests on a synergic use of the overlapping information delivered by the sensors of different kinds. An aim is to obtain the aggregated information that would be more complex then that of received from a single sensor. Such blended information is beneficial at least from the aspects of noise reduction and novelty extraction. This blending (fusing) process makes the data patterns which are hidden in raw signals more obvious.

As a rule, a single sensor cannot provide the required amount of information. Besides, fusing a set of sensors of different modalities results into the high-level information (e.g. statements) and even it can grasp a context. For instance, the fact of finding a personal mine implies a somewhat higher likelihood of finding other mines or even a whole battlefield (i.e. the context). In order to know “what to fuse“, the multimodal information must be represented in a common format. A measure of the uncertainties of the sensed and the resulting fused information must be taken into account as well.

The fusion runs at the different hierarchical levels. The lowest one is a signal and/or pixel fusion and can be carried out by Boolean logic. At the second level are fused features, that is the patterns occurring in data sets. The common features are mean value, variance, covariance, power spectrum etc. Because signals are of random nature, the fusion usually uses Bayesian statistics with Kalman filter [9] as a typical representative. Results of higher-level fusion are statements (declarations) about instantaneous contexts. While a typical means used in signal fusion is Kalman filtering, a typical means used at higher levels is either Dempster –Shafer theory of evidence [10] or fuzzy logic.

The higher level fusion is related to 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. In the fuzzy *approach* that was used here, the fusion runs in two steps. The sensed signals are first granulated (fuzzification). The measure of the certainty is given by membership functions. Within the second step runs the true fussion – the decision-making. This is done by the *modus ponens* :

- Declaration: x is A and y is B
- <u>Fusion: if x is A and y is B then z is C</u>
- Conclusion: z is C1

Intelligent navigation

The robot used in the experiment was equipped with a ring of ultrasonic rangers providing information about both the distance and angle of the nearest obstacle. Besides, another input provided information about the target position. Output signals (angle and speed) of the fuzzy inference system controlled the robot left / right turnings and modified its speed. The designed navigation was reactive without any environmental map.

In order to keep the motion sufficiently smooth, free of sharp turnings and transversal swings when moving between close obstacles, parameters of fuzzy rules were updated within the process of navigation. It was done periodically in two steps for each period. Within the first step the membership functions tuning took place. The fuzzy sets describing particular behaviours were arranged into a layered feed-forward neural network were updated by the unsupervised learning. The minimal value a cost function protected the robot from possible overthrowing due to high speed when moving along a small turning radius. This allowed changing the turning radius, and thus accounted for instantaneous dynamic conditions. The structure of the neural network used is shown in Fig. 1.

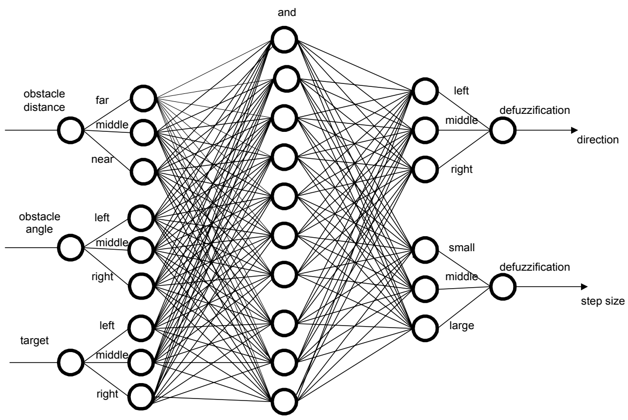

Fig. 1 Neural network for learning navigation

Within the second step the fine tuning took place, namely, the straight walls of trapezoidal output functions of the neuron output functions were curved with the aim to reach yet smaller value of the cost function.

The decision process that imitated an experienced human operator run over 24 fuzzy rules. Typical structure of the fuzzy rules used is demonstrated in the following examples:

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

The antecedent parts were evaluated by the Min-Max composition rule for fuzzy AND and OR operators respectively. For conversion of the fuzzy outputs to the crisp one was done by used the bisector method [2,3]. The results of the learned navigations are shown in Fig. 2.

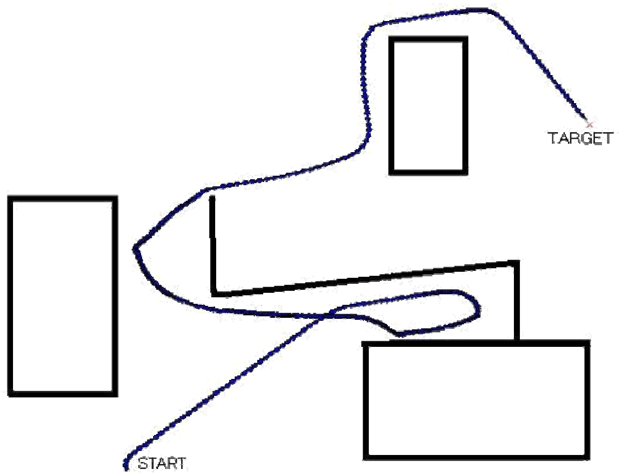

Fig 2. Navigation in the cluttered environment

Conclusion

The secret behind the intelligence of artificial systems springs from successive generalization of sensor information into information chunks or "granules", and the inference running over (overlapping) information granules. Due to granulation the system becomes robust with respect to imprecision, uncertainties, and partial truth. In parallel with the traditional methods of the symbolic artificial intelligence the means and methods offered by the softcomputing are effectively used in the design of intelligent machines. The strength of this approach, which was further supplemented by the Brook's subsumption philosophy, was demonstrated by the robot navigation. Those, together with the paradigms of the unsupervised learning showed to be powerful means of imbedding intelligence into a mobile robot. In this view, the machine that is able to operate autonomously in an unknown environment may be considered as an instantiation of the intelligent system.

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