USING DRIVING BEHAVIOR MODELS FOR AUTONOMOUS MOBILE ROBOT NAVIGATION

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Abstract

The paper explores the possibilities of learning steering control behaviors for navigation from a human operator. Behaviors allow the development of structured navigation control in the face of uncertain environment models. However, their design is rendered difficult by the nature of real sensor readings, which are non-linear, uncertain and even contradictory. Hence, learning strategies are interesting in that they incorporate actual sensor information from human-driven real-world experiments. In this sense, a modelling method is presented that efficiently generates fuzzy behavior rules from a set of input-output data. Yet, the application of these techniques poses particular problems due to user-vehicle interaction issues, which are discussed in the paper. Experimental results illustrate the whole procedure applied to a real mobile robot outfitted with ultrasonic sensors.

Keywords: Fuzzy Modelling, Autonomous Navigation, Mobile Robots, Reactive Behaviors

1 INTRODUCTION

Performing purposeful tasks with autonomous mobile robots implies tackling numerous problems. In the first place, a realistic approach cannot rely strictly on rigid models of the environment. This is why many researchers pursue behavior based navigation, with behaviors serving as reactive controllers that adapt their output to execution-time environmental information. Behaviors are specialized functional modules that tend to be simple and independent, thus improving the navigator's design.

Nevertheless, behaviors perceive environment information via real sensors, such as sonars, which originate many erroneous readings and non-linear data. Introducing these non-linearities in the design is not always intuitive for a human designer, and usually involves intensive trial-and-error experiments in order to adjust control parameters.

On the other hand, learning methods can provide an efficient way to moderate design effort. In this manner, independent behaviors can be produced from a set of human-driven experiments in which pairs of input sensor data and steering control data are measured. Furthermore, this data already incorporates uncertainty and non-linearities of the real sensor readings that can be thus assimilated into the model.

The paper first reviews previous work in Section 2, and then introduces the basics of navigation behaviors (Section 3). Section 4 states the problems associated with learning methods applied to robot navigation. An efficient fuzzy modelling approach is introduced in section 5. Application results are discussed in section 6. Finally, section 7 is devoted to conclusions.

2 PREVIOUS WORK

In general, learning for a system model is to determine or upgrade the parameters describing the relations between the system inputs and outputs. Typically, in control applications, fuzzy controllers and neural controllers can be obtained by means of different learning approaches. This allows the development of control systems without mathematical models, reaching good robust and adaptive behavior.

Learning can be divided into the categories of supervised and unsupervised learning [14]. Supervised learning approximates the functional relations between the environmental system inputs and outputs by establishing an associative memory. Either a neural network or a fuzzy model can be formed by using supervised learning. Unsupervised learning stands for self-organized learning without a learning feedback signal.

In general, learning in fuzzy systems may involve parameter learning and structure learning, corresponding to the update of the fuzzy model parameters (e.g., membership functions) [5] and the fuzzy model structure (e.g., fuzzy rules) [15], respectively. Both parameter and structure learning are considered in [8].

In mobile robot applications, several authors make use of reinforcement learning by means of neural networks in order to identify rules and to adjust fuzzy controller parameters [7][3][2][6]. In these applications the robot learns the motion behavior during execution, while some or all of its actions receive positive or negative reinforcement.

The major drawbacks of these methods are usually their slow convergence, which increases development cost due to long training sessions, as well as the selection of appropriate performance evaluation criteria.

Other methods are based on genetic algorithms [10], either to refine and even redesign an existing rulebase or to generate a set of rules. In general, this is also a slow process because it is necessary to assess performance of all possible variations under the same initial conditions.

Fuzzy identification methods have also been applied to obtain fuzzy controllers for mobile robotic from measured input-output data obtained from actual operator control [12]. In this way, in [11] a wall-following controller is obtained by applying several methods for the decision of the number of rules, the identification of parameters and membership functions, and the generation of fuzzy rules. Another modelling method is applied to the backing-up truck problem in [13].

3 BEHAVIOR BASED NAVIGATION

Although behaviors were first introduced to achieve safe robot navigation in the absence of world models [4], the need to carry out deliberate plans has contributed to extended use of task-oriented behaviors. Thus, tasks can be made up by appropriately sequencing behaviors such as “wall following”, “turning round corners” and so on. In particular, indoor and other naturally structured environments can usually be navigated by means of two generic behaviors:

- *Wall following*, in which the robot maintains a distance to perceived contours, like walls.
- *Advance*, in which the vehicle navigates from a contour to another belonging to a different object.

In order to concatenate instances of these basic behaviors it can be necessary to consider “turning behaviors, depending on vehicle kinematics and sensor configuration, such as *Inside* (or concave) turn, *Outside* (or convex) turn, or *Align* to wall turn.

The use of behaviors is illustrated in Fig. 1, where a sequential task is used to guide a vehicle from point A to point B on a bidimensional map of an indoor environment.

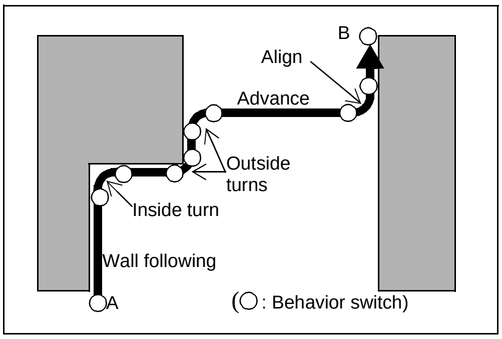


Fig. 1. A path as a sequence of behaviors.

Switching behaviors occurs when a particular task-dependent sensor context is detected.

4 THE DILEMMA OF DRIVING KNOWLEDGE ACQUISITION

Modelling human knowledge for automatic control of complex dynamic systems has given rise to a number of different approaches [9]. There are cases in which experience and proficiency in control cannot be easily expressed in terms of if-then rules by a human operator. Guiding a vehicle is one of those cases, since its ability usually involves complex human perception mechanisms.

In these cases, the controller has to be obtained from actual measurements of system variables, in which operator reactions under different situations are recorded. In order to guarantee that the model considers the same amount of information as the human operator (and not less), the general approach consists in limiting the operator’s perception to only those measurable variables that will be inputs of the automatic controller.

Furthermore, the performance of the resulting controller is determined by how close the “learning environment” is to the actual working environment. However, in practice, the controller is often learned from a simulated model of the system. This is especially true when learning methods are time-consuming or demand performance evaluation for engineered initial conditions and exhaustive system states.

In view of this reasoning, the problem of learning operator control for automatically guiding a vehicle poses a dilemma. If the operator is to interact with a model of the vehicle-environment system, simulation parameters (mainly time) can be engineered so that operator responses can be conscientiously derived from a set of measurable sensor data.

On the other hand, training data can be obtained from actual vehicle guidance. In this case, real time urgency makes it difficult for the operator to analyse complex sensor data, so control actions have to be based on his or her own personal perception capabilities.

The adoption of either two approaches is an open question. Nevertheless, some facts can be pointed out. The model-based method guarantees that control can be achieved in terms of the considered input variables, but the resulting controller’s performance over the real system will depend on the model’s accuracy. Besides, the operator requires special training to govern the system, since driving knowledge is usually based on human perception. That is, the driver has to learn anew how to drive like an automatic controller.

The second approach appears to be more pragmatic. Sensor data is recorded while the operator naturally controls the vehicle. The problem is that a set of input variables has to be empirically chosen that captures the essence of human perception of the problem. The key might be on the modelling technique. If the controller can be achieved with not much cost of time and training effort, the second approach becomes feasible since it becomes possible to test performance of different alternative controllers. Moreover, such a learning method could be combined with simulation in order to assess the development of the sensor system in the first place.

5 FUZZY MODEL APPROACH

This section proposes the use of a particular fuzzy modelling approach for learning navigation control from a human operator [8]. The main features of the method can be summarized in the following points:

* Least squares parameter identification.
* Design flexibility.
* Self-generation of rules.
* Independence of measured data distribution.
* Efficient antecendent partition.

Least squares has been chosen for the identification of rule consequents because of its demonstrated efficiency and its easiness for implementation in hardware platforms. This approach allows optimizing the number of rules with a relatively low computational cost.

This efficient technique can be combined with fuzzy modelling so that it can be indistinctly used to produce fuzzy rulebases with a variety of fuzzy operators, defuzzification techniques, and shapes of membership functions. Moreover, the parameters of the method are independent of the inference technique.

Finally, the fuzzy modelling scheme is completed with an automatic rule generation algorithm in order to minimize design effort. Particularly, a self-generating method [1] has been adapted to the least squares approach and has been improved to deal more efficiently with complex systems and uneven distributions of measured input-output data. The modelling algorithm iteratively refines the rulebase by adding rules until the inference error is reduced to a predetermined value.

6 EXPERIMENTAL RESULTS

The fuzzy modelling method has been used to implement individual fuzzy behaviors on the AURORA mobile robot (see Fig. 2), a four wheeled robot equipped with two ultrasonic sensors at the front and another one at each side, with a ranging distance of about 1.3 meters (see Fig. 3). This robot is 1.4 meters long by 0.8 meters wide.

Basically, a plan, generated either by a user or an automatic planner, is a sequence of behaviors and their switching conditions. A supervisor module is in charge of activating and deactivating the behaviors, as the conditions are

Fig. 2. The AURORA mobile robot.

detected through the sensing system.

Fuzzy modelling has been considered to model some steering behaviors needed to make up purposeful tasks in indoor environments: following walls, following corridors, aligning to walls, and inside corners.

In general, a number of teaching experiments (ranging from 15 to 40) where performed for each of the behaviors. The input-output data was collected at each control interval (every 0.15 s). Only the sensors directly involved in the behavior were considered (the corresponding side sensor in the case of walls, both sides for the corridor, and the two front sensors together with the inner side sensor for wall alignment and inside corners). In any case, it is important to consider for the model the least possible number of input variables, because of the size and complexity of the resulting rulebase.

During the measurement experiments, the vehicle was driven by the operator through a joystick connected

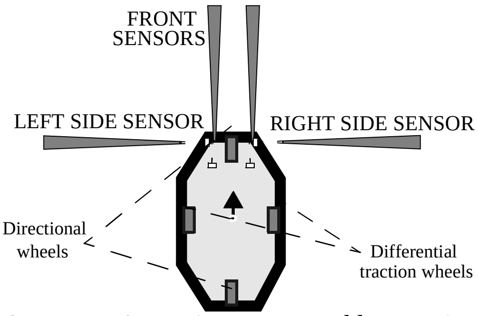
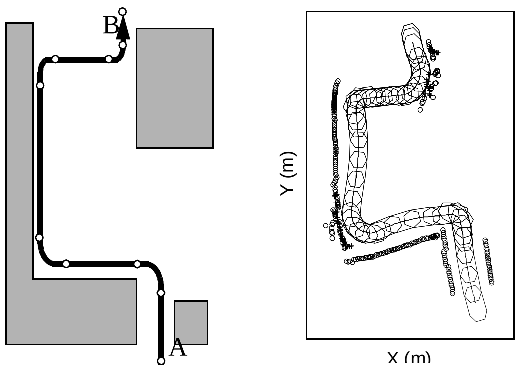


Fig. 3. AURORA's sensing ranges and locomotion.



a) b)

Fig. 4. Results from a real experiment from A to B with learned navigation behaviors a) Task. b) Results.

directly to it. The driver's experience and ability to guide the vehicle rests on first-hand visual perception of the operation rather than the interpretation a flow of sensor readings, even if these are presented graphically. In cases when results were not as good as expected, the efficiency of the modelling algorithm allowed for easily learning a new controller from a different set of input variables, by using the same original experiments.

Results form a real navigation experiment are shown in Fig. 4. The path is achieved as a sequence of learned behaviors based on sensor data, in which odometry is used just as a possible context switching conditions. It must be noticed how sensor readings along the path (represented by o) are sometimes erroneous due to sensor non-linearities. Individual behaviors successfully cope with this source of uncertainty.

7 CONCLUSIONS

Fuzzy logic provides a way to design non-linear controllers as a set of knowledge rules. However, there are cases in which experience and proficiency in control cannot be easily expressed in terms of if-then rules by a human operator. Guiding a vehicle is one of those cases, since its ability involves complex human perception mechanisms. Moreover, once an adequate rulebase has been stated, it usually requires numerous trial-and-error tests in order to fine tune the fuzzy parameters.

Modelling methods based on learning from input-output data can be useful to capture operator knowledge. However, a dilemma stems from the difficulty in measuring human perception of the problem. As an alternative to the somewhat artificial solution of learning from a simulator, the availability of efficient modelling algorithms allows for empirical choice of input variables from a set of original input-output data.

A particular fuzzy modelling method has been applied to the problem. Results from a real robot equipped with a simple sensor system show that a good solution can be achieved with low development cost.

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