Mobile Robot Localization with an Artificial Neural Network

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Abstract. This paper presents a neural network based approach to a mobile robot positioning in front of a certain local object. The robot is equipped with ultrasonic range sensors mounted round the platform. We employ the Fuzzy-ARTMAP network for supervised learning of associations between vectors of sensors readouts and the robot's pose coordinates. In this approach, a world model in a form of a map, as well as its updating routine, become superflous for the considered problem solution. The system, trained on a real world data of a door neighborhood region reveals satisfactory performance, sufficient for a door passing task purposes. The proposed method of a mobile robot positioning may be efficiently applied in environments containing natural, geometrical beacons.

1 Introduction

Mobile robot navigation problem can be stated into three fundamental sub-problems: estimation of the current position with respect to the goal and surrounding objects, finding an obstacle-free path between some distinguished locations and execution of the preplanned trajectory [12]. In this paper we are principally concerned with the first task - the localization - and maintain, that finding a robust and reliable solution to this problem is an essential premise to answering the remaining questions.

The location of a mobile robot is usually described by the estimates of the vehicle's position and orientation (the pose) expressed in some coordinate system, coupled with certain statistical measures of the estimation errors [7].

A typical approach is to reduce the position estimation problem to that of matching a perceived configuration of the robot's environment with an a priori known model of it, usually given as a map. Published methods differ mainly in the principles of the world modeling and the matching evaluation routines.

The occupancy grid based methods have been found as unreliable and complex in the context of direct applications to the positioning task [15]. But the offered conveniency in filtering sensory inputs and multisensory data integration keeps them attractive since the first attempts described in [13]. Recently published localization techniques, based upon a grid model of the environment, use for the matching some detected features of the raster images [6] or extracted line segments [15], rather than the grids directly. This brings them close to the classical approaches based upon vectorial description of the world (as in [5]). The matching evaluation techniques range from geometrical methods for obtaining relative displacements and rotations neccesary to transform the perceived scene description into the pre-defined one [5, 13], to those employing Kalman fiter formalism for tracking some environmental features to update the estimated robot's pose [16, 12, 18, 15].

Even robust matching routines may fail when facing real world and inherent problem of noise, which is strongly dependend on types and quality of sensors. The testbed used for experiments described here was a vehicle equipped with the ultrasonic range sensors, mounted round the platform. Sonar transducers often fail to see an object or alternatively misjudge an indicated distance, thus localization descriptions computed from the readings obtained from such sensors are bound to be inaccurate. However, claiming that for some typical local environment configurations sensory noise features are typical too, we employ an artificial neural network to teach the robot to retrieve its local pose (i.e. position and orientation) from ultrasonic range measurements.

While in the most of the related work it is assumed that an explicit model of the environment is available, in the approach proposed in this paper we try to solve the problem of positioning by the way of learning the direct mapping between sensory readouts and robot's poses relative to a certain local object. This way a model of the local environment is not neccesary, as replaced by a knowledge hidden in adaptive connection strength values of the neural net, thus the map, as well as its updating routine, may be both omitted. We define a multidimensional space of the immediate ultrasonic range readouts (initially preprocessed) as the local environment space, and we introduce the space of vehicle's topological locations obtained from metric coordinates of the robot's pose. The learning problem is then formulated as a clustering of two spaces and teaching associative links among the clusters belonging to these spaces.

The particular object we focus on in this paper is an opened door, and the illustrative application of the investigated localization method is fine positioning for a door passing task purposes. The tool we implemented is the Fuzzy-ARTMAP neural network, described in the following section.

2 Fuzzy-ARTMAP for learning localization associations

ART is a class of neural network structures, based on the Adaptive Resonance Theory [2], which perform nonlinear, incremental, unsupervised categorization of a set of input data. The fundamental ART algorithm divides input vectors into a number of clusters, in such a way that the data belonging to each cluster are all similar within a specified tolerance.

The basic ART module is composed of two layers of neuronlike nodes (F_1 and F_2 in Fig.1). The input signal excites the nodes of F_2 through links of adaptive strength ($[w]$ in Fig. 1.). According to the competitive activation and learning rules, just one F_2 node, which excitation level is the largest among the others, is activated. If such a winner fulfills a condition of resemblance, in regard to the chosen similarity tolerance, the input pattern is classified as an instance of the winning category, and the connection strengths of the activated node are adjusted to make them more sensitive to the input vector in the future. Otherwise, another search for the best matching class is performed, or a new category is created by adding a new node in F_2. Thus new patterns may fit in and modify shapes of existing categories, if they match closely, or require establishing new categories when neccesary.

The Fuzzy-ART network [3] is one of the ART family. It accepts real-valued components of input vectors, and treats data as patterns of fuzzy membership values. The procedure extends to representing to which degree subsequent features are present in an input vector or in a certain recognition category. Actually, the absence of a feature, and even the extent to which the feature is absent in the data vector, may also be taken into account by the Fuzzy-ART module, when it is implemented in a complementary coding form [3].

The ARTMAP system [4] is composed of the two ART networks, interconnected by the layer of neuronlike nodes called a *map field*. This layer is used to form predictive associations between categories established in ART_a and ART_b structures (Fig.2). During learning, subsequent couples of incoming patterns (training pairs) create or modify categories respectively in ART_a and ART_b modules, while the *map field* adaptive links code forced associations between categories representing vectors belonging to the training pairs. Thus the resulting map does not directly associate exemplars from training pairs, but rather their symbolic representations in the form of categories.

After the ARTMAP has been trained, it can be used to predict an association between an input vector and a related category of the ART_b module. As long as the learning was performed on a representative set of data, one may claim that the predictions are reasonably correct. In our case we use the Fuzzy-ARTMAP system, which is an ARTMAP built with use of Fuzzy-ART classifiers.

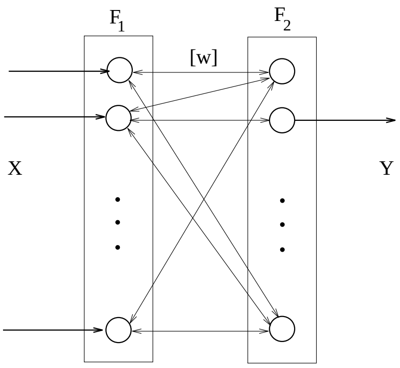

Figure 1.: The ART basic module architecture.

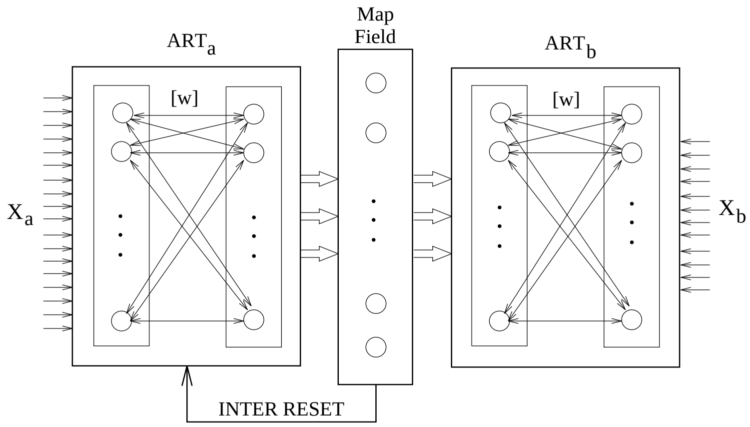

Figure 2.: The ARTMAP system architecture.

In order to enter a door a human does not need to know the exact coordinates of his location with respect to the doorway. It is enough to evaluate a qualitative aspect of the relative position as *"I am far from the front, on the left side of the normal axis, heading directly to the door"*. A natural reaction is to turn right and evaluate a new position. A number of robotic control systems emboding human reactive behavior have been described so far, including those employing a range of neural network modules (as Back-Prop in [14], Kohonen in [17, 11] and Fuzzy-ART in [10]). In our research, at the moment, we do not deal with a control feedback loop, focusing on a static localization problem.

In the considered case, the quantitive metric information on robot's position and orientation with respect to the door is pre-categorized into a set of coordinate intervals, as shown in Fig. 3. We distinct 35 predefined clusters of the position within a so-called door neighborhood region (Fig.3b), and 7 categories coding the relative orientation angle (Fig.3c). Each term describes the topological meaning of the robot's location in front of the door and is assigned to the value, which forces establishing different categories of the ART_b Fuzzy-ARTMAP module, for diferent combinations of X, Y and Θ clusters (see Fig.4).

The environment data space, built upon 11 real valued components obtained by preprocessing raw readings of the ultrasonic range sensors mounted on the front edge of the robot, is the input space to the Fuzzy-ARTMAP system (Fig.4). This space is clustered autonomously by the Fuzzy-ART algorithm of the ART_a module (ref. Fig.2). During training, the network learns to associate links between given points of the environment space and the appropriate categories of the topological location, as they are supplied as training pairs (Fig.4a).

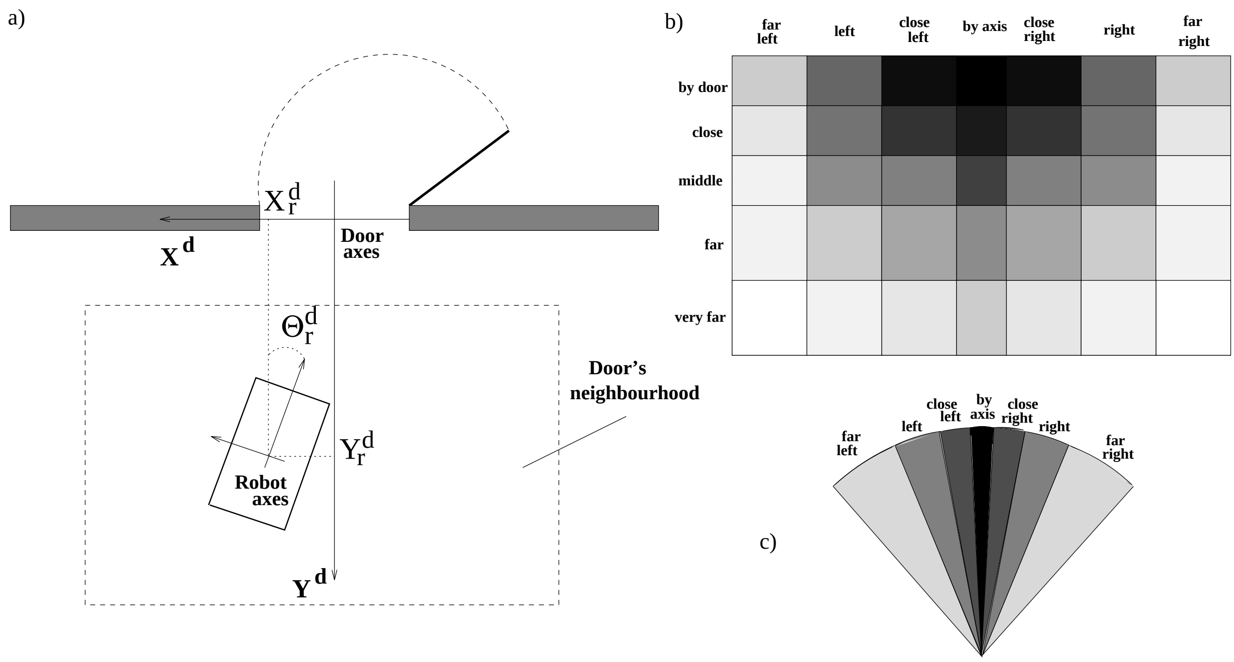

Figure 3. Robot in front of the door: a) metric description; b) topological categorization of the position coordinates; c) topological categorization of the orientation angle.

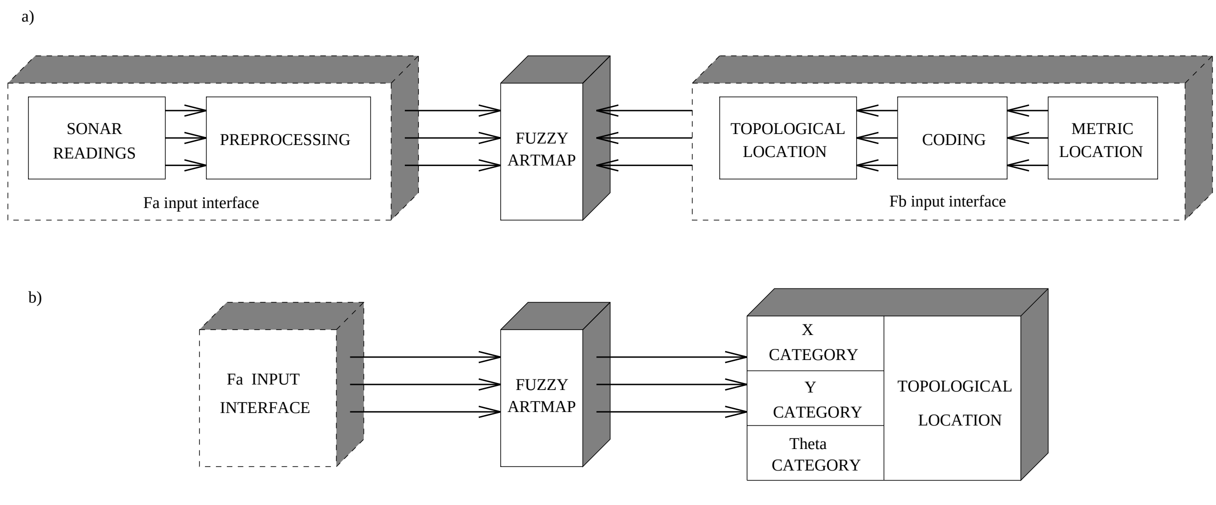

Figure 4. Localization association process: a) supervised learning of the mapping between the environment space and the topological location space; b) performance mode: the system predicts relative location, processing a set of the selected ultrasonic range sensors readouts.

Then, during the performance mode, the network is able to retrieve the location of the robot within a frame of the door neighborhood region, as long as the robot is actually placed somewhere in this predefined region. The retrieved data has rather a qualitative meaning, due to the topological categorization of the position and orientation coordinates. It bears however enough information to be useful for a door passing locomotion task.

3 Experiment

The aim of the conducted experiment was to investigate correctness and robustness of the learning process, in order to determine an efficient structure and parameters of the described localization system.

For the tests we used data produced with the *Robuter* mobile platform software simulator (developed at LIFIA, INP Grenoble, France [8, 9]) and also the data collected on the real vehicle.

Simulated trials allowed us to develop appropriate structures of the input and output spaces of the Fuzzy-ARTMAP system, as well as to adjust the network's parameters. In particular we noticed that by the way of splitting the topological location space into subspaces related to the robot's position and orientation separately, the correctness of the obtained mapping estimation considerably increased. All the aspects presented in the remaining part of this paper concern however measurements performed on the real vehicle.

During the data collection phase the robot has been wandering along the entire door's neighborhood area, collecting ultrasonic range sensors readouts, together with the respective pose coordinates obtained with use of odometry. In such a way the set containing 4669 training pairs of type {*vector-of-raw-readouts-of-sonars, vector-of-metric-location-coordinates*} has been collected.

Then the raw sonary readings have been preprocessed by limiting their values up to 3 meters, and by scaling these distances linearly into the range [0.0, 1.0]. The respective metric pose coordinates readouts have been also preprocessed, according to the rules described in the previous section (see Fig.3 and Fig.4).

In order to evaluate the performance of the learning process, we use the *hold-out* method of handling training data for learning systems [19]. From the entire set of 4669 pairs we have selected the *training* and the *testing* sets randomly. The learning trials were conducted in five separate stages, in which the training sets contained respectively 200, 500, 1000, 1500 and 2000 randomly chosen pairs, while the testing sets of 1000 pairs were randomly composed using the remaining data. For each training stage three sequences of testing, with use of different testing sets, were performed.

Three empirical error rates were calculated for each learning trial [19, 1]. The *overall error rate* E_{ov} experesses a total number of wrong associations made by the taught system among the training set. The *ommision error rate* E_{om} characterizes the number of cases when an example belonging to a given class was not recognized as an instance of this class, whereas the *commision error rate* E_{co} expresses the number of examples categorized improperly as the instances of a given class. Detailed formulas are given below:

$$E_{ov} = \frac{N_e}{N_t}, \qquad E_{om} = \frac{\sum_{i=1}^{N_c} E_{om}^i}{N_t}, \qquad E_{co} = \frac{\sum_{i=1}^{N_c} E_{co}^i}{N_t}$$

$$E_{om}^i = \frac{N_{om}^i}{N_p^i}, \qquad E_{co}^i = \frac{N_{co}^i}{N_n^i}$$

where:

N_e - total number of misclassifications among the testing set;
N_t - size of the testing set;
N_{om}^i - number of examples, belonging to the class i, recognized as the instances of different classes;
N_p^i - total number of instances of class i in the testing set;
N_{co}^i - number of examples recognized as the instances of class i, actually belonging to another class;
N_n^i - total number of examples belonging to the other classes than the class i among the testing set.

The numerical results of tests given in Table 1. show the convergence of the localization associations learning process. It may be noticed that the empirical error rates decrease while the number of the training data vectors increases.

By all appearances the achieved quality of prediction (about 16% of overall error of topological position estimation for 2000 training pairs) seems to be nonsatisfactory. However, as it is depicted in Fig. 5a, majority of errors (ca. 80%) occured within narrow regions by the border lines between adjacent topological categories. Consequently, most of the door neighborhood area is free of misclasifications.

test sequence	position					orientation				
	OVERALL ERROR									
	stage 1	stage 2	stage 3	stage 4	stage 5	stage 1	stage 2	stage 3	stage 4	stage 5
1	0.381	0.321	0.211	0.181	0.167	0.381	0.291	0.183	0.162	0.134
2	0.391	0.311	0.325	0.195	0.151	0.341	0.260	0.191	0.183	0.123
3	0.345	0.332	0.211	0.141	0.159	0.351	0.192	0.211	0.121	0.132
average	0.372	0.321	0.249	0.172	0.159	0.358	0.247	0.195	0.155	0.129
	OMISSION ERROR									
1	0.412	0.292	0.272	0.223	0.212	0.381	0.263	0.211	0.211	0.212
2	0.343	0.311	0.210	0.213	0.172	0.342	0.192	0.182	0.199	0.192
3	0.311	0.321	0.253	0.187	0.192	0.412	0.220	0.193	0.181	0.205
average	0.355	0.308	0.245	0.208	0.192	0.378	0.225	0.195	0.197	0.203
	COMISSION ERROR									
1	0.141	0.035	0.030	0.008	0.005	0.108	0.092	0.016	0.068	0.010
2	0.139	0.087	0.027	0.009	0.004	0.128	0.082	0.101	0.098	0.031
3	0.118	0.054	0.022	0.019	0.009	0.178	0.072	0.072	0.081	0.041
average	0.132	0.058	0.026	0.012	0.006	0.138	0.082	0.063	0.082	0.027

Table 1. Empirical error rates obtained for hold-out sampling of the entire data set. The testing sets sizes equal 1000 for all the trials, while the learning sets sizes were 200, 500, 1000, 1500 and 2000 for the stages from 1 to 5 respectively.

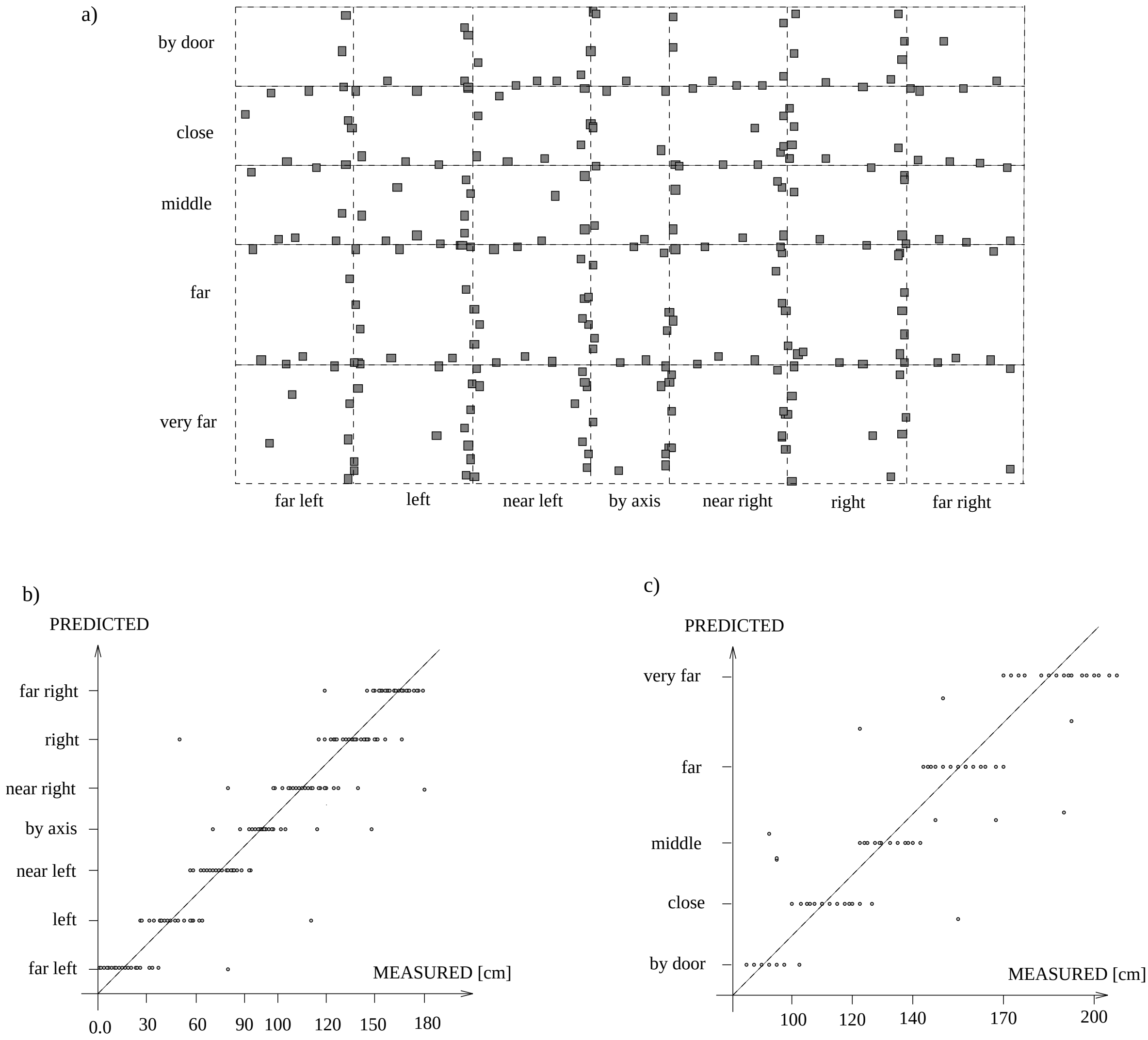

Figure 5. Distribution of prediction errors over door's neighbourhood: a) incorrect predictions (filled squares) are placed most often along the border lines of the topological clusters; b) and c) correspondence of real locations and predictions generated by the trained system for x and y axes of the door's coordinates.

As it was expected, the Fuzzy-ARTMAP system is likely to mismatch neighboring clusters, when it is forced to code similar sets of sonars' readouts as different topological associations. The region of door neighborhood with marked locations of only incorrect predictions is presented in Fig. 5a. In Fig. 5b and 5c the correspondences between the robot's actual position within the door coordinate system and the respective predictions of the network is shown. It may be noticed that the number of significant prediction errors is rather small (not more than 3% of the testing examples), since most of the incorrect predictions actually suit expected step function shapes depicted in Fig. 5b and 5c.

The obtained prediction quality (3% of large errors plus 13% of neighboring clusters mismatches) do not exclude the presented method from a practical application to a door passing control task.

4 Conclusions

In this paper, we have presented a method for determining a mobile robot position and orientation within a local environment. The proposed approach is based upon learning a direct mapping between ultrasonic range sensors' readouts and vehicle's pose coordinates, related to a certain local object. The particular geometrical beacon considered here is an opened door, and a purposive application is a fine positionning of a vehicle for a door passing task. The implemented adaptive tool is the Fuzzy-ARTMAP neural network, capable of incremental, supervised learning of associations between vectors of sensory readouts space and robot's pose coordinates.

Experimental results show the convergence of the learning process, but the overall prediction errror rate is not small enough for fine positioning. However, most of misleading predictions used to occur by boundaries of the topological categories, where mainly just neighboring clusters are confused. Thus the actual rate of large errors reaches only 3% over testing sets, and the proposed method of positioning may be applied to control tasks, such as door passing.

By employing the supervised learning technique, we avoid difficulties of explicit modeling the interactions between the sensory system and the environment. A world model in a form of a map, as well as its updating routine, usually memory and time consuming, are both not neccesary to solve the posed problem. Moreover, the incremental learning capabilities of the Fuzzy-ARTMAP neural network, although not discussed here, make the implementation flexible and capable of dealing with possible non-stationarities of the modeled mapping.

Though only the case of a door-like geometrical beacon is treated in this paper, a proposed method of a mobile robot local positioning should be straightforwardly applicable in environments containing variety of geometrical beacons, such as specific furniture, hallway crossings, corners, etc. A problem of generalization of the learned associations for objects slightly different than the particular one used in the described experiment, remain open for future investigations.

Acknowledgement

The authors would like to express their thanks to Professor James L. Crowley and Mr. Patrick Reignier of Laboratoire d'Informatique Fondamentale et d'Intelligence Artificielle (LIFIA), Grenoble, France, for their kind assistance during the experiments on the LIFIA's robot and for their valuable comments regarding the presented work.

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