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MODEL-BASED NAVIGATION OF INDUSTRIAL MOBILE ROBOTS

Abstract : In this article the world modelling and self-localization methods for mobile robots operating in an industrial environment are discussed. By maintaining the up-to-date world model and position estimate, the mobile robot does not rely on wires or paint-stripes to navigate. The architecture of the a priori world-model has been described. Two different representations of the dynamic-maps are considered, namely vector-based and raster-based. The method for robot localization in the a priori known structured environment is described. The results of experiments in map building and localization, with using of the low-cost optical scanner (as the source of data) are presented.

1. INTRODUCTION

Environment modelling is an important issue for the navigation of the autonomous mobile robots. The form of the model is specific to the application domain. Typically, the mobile robot needs the ability to construct maps from sensed data. In the case of robots operating in a well-structured environment the map could be provided in advance. However, even in the industrial environment, whose model is *a priori* known, the robot has to update its knowledge, in order to perform properly such tasks as path planning or collision avoidance. In this article, we propose two categories of the environment models. First category represents a priori known aspects of the environment such as the layout of the work cells, shape and position of static obstacles etc. They originate from preliminary measurements of dimensions of the scene. Such a model is treated as reference system for the localization of robots, and the source of reliable information used for task planning and map maintenance. Second class of models is supposed to reflect dynamic changes of the scene. These maps are based on sensory data, and are permanently updated.

An important requirement for a mobile robot is also to locate itself in the environment. Since accuracy of odometry decreases over the covered distance [6], the robot has to correct its position using measurements from external sensors. If the map of the working field is known *a priori*, the self-localization can be accomplished by establishing the correspondence between current sensory input and the set of known landmarks.

Perception system is one of the fundamental elements of an autonomous mobile robot. For industrial applications, this system has to be simple and low cost. There are many different sensor systems used with mobile robots. One of the most appropriate sensors for industrial robots are optical/laser range finders and scanners [8]. The infrared-LED based scanner has been used as the principal on-board sensor on our experimental mobile robot [8, 12]. This is a device developed at our department, especially for mobile robots. Fields of application for this inexpensive scanner could be first of all cost critical systems (e.g. industrial applications). The commercial IR range finder (manufactured by

Pepperl+Fuchs GmbH) has been used in this sensor system as the linear distance measurement head. During the tests performed in our laboratory [9], it has been found, that the parameters of this head are worse than those declared by the manufacturer (Fig. 1A). The results of these tests motivated us to develop the method for eliminating of some systematic errors in range measurements [9]. Thanks to this correction the error in distance measurement does not exceed 5cm for actual distances up to 4m, regardless of the beam incidence angle ϕ (Fig. 1B), This performance is acceptable for most of the mobile robot navigation purposes. The correction procedure has been used in the map building and localization methods for the mobile robot described in the next sections.

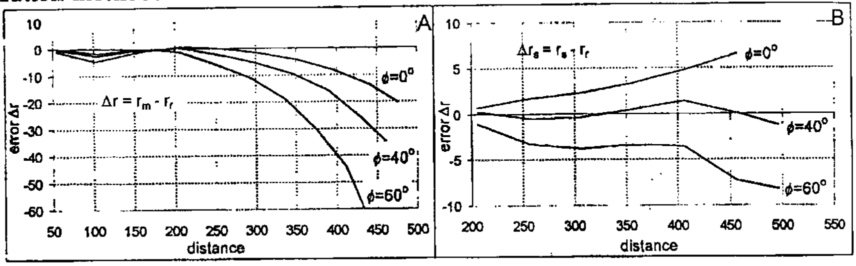

Figure 1: The correction of range measurements

2. REPRESENTING THE A PRIORI KNOWLEDGE

Target application for the model-based navigation concepts which are discussed here are the industrial systems. In that case, the environment usually consists of simple form objects and the location of the principal objects is fixed at least for some period of time. In particular, the major part of the scene can be represented by polyhedral models. Such a simplified geometrical representation is used in order to reduce computational complexity problems. On the other hand, this representation can be sufficient for navigation tasks. Polyhedral scene model is compact and easily defined, it fits the natural properties of industrial scenes, and it can be supported by the available sensors (e.g. scanner).

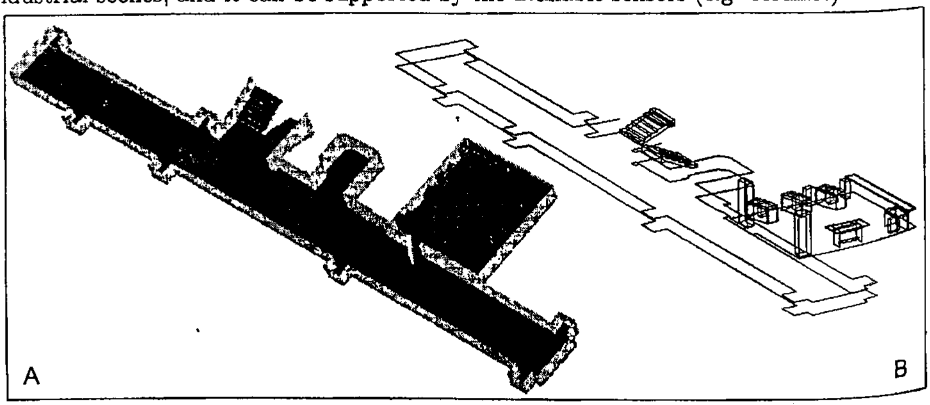

Figure 2: Predefined model of the indoor environment

The Geometrical Data Base (GDB) has been defined to incorporate and handle static elements of the scene model. It contains all available *a priori* geometrical knowledge. The

GDB provides the shape and layout information describing such elements of the scene as walls, doorways, corridors, and some other stationary elements like machine-tools or furniture (Fig. 2A). In this system simple objects are represented with free polyhedrons. Compound objects consisting of multiple primitive solids are also allowed. Some objects are placed in the library as generic prototypes. The abstraction of the GDB into 2.5D/2D-vector (Fig. 2B) or into raster-map is possible. This allows the fusion of the acquired sensor data with the *a priori* model.

3. ENVIRONMENT MODELLING

3.1. Vector-based maps

In the industrial systems, the major part of the scene can be represented by 2D polygon models. Such vector-based maps are concise data structures which can be efficiently used for path planning, robot positioning and object recognition. Moreover, these maps fit well to the natural data acquisition scheme associated with optical/laser scanners.

In this section, we describe techniques for building of the 2D vector map from scanner data. The map is built in terms of geometric primitives that are represented by the vectors of parameters and their covariance matrices modelling spatial uncertainty. In addition, each object in the map includes quality parameter and keeps track of the number of times it has been observed and updated. Unlike some other methods known from literature [7], the here proposed method defines the map with three different kinds of primitives : polygons, poly-lines, and clusters (the last ones represent distance measurements which cannot be assigned to lines). The above primitives are represented by their coordinates in the global frame. Clusters are sets of points enveloped by convex hulls, that represent them [12].

The initial data processing step is the correction of scanner measurements. Plausibility checks are also applied to refuse some erroneous sensor readings. In the next step, the scanned points are transformed into cartesian coordinates $\mathbf{X}_P = (x, y)$. The uncertainty of location of the measured points depends on the uncertainty of the measurements vector $\mathbf{M} = [\rho, \varphi]^T$ which is represented by the covariance matrix $\mathbf{C}_M$:

$$\mathbf{C}_M = \begin{bmatrix} \sigma_\rho^2 & 0 \\ 0 & \sigma_\varphi^2 \end{bmatrix}, \tag{1}$$

Because the relation between $\mathbf{M}$ and $\mathbf{X}$ is nonlinear, the covariance matrix $\mathbf{C}_P$ representing spatial uncertainty of a point is calculated from the first-order approximation :

$$\mathbf{C}_P = \mathbf{J}_P \mathbf{C}_M \mathbf{J}_P^T. \tag{2}$$

where $\mathbf{J}_P$ is the Jacobian of the transformat to vector $\mathbf{M}$. In the following step the points are grouped together to form individual objects [12]. The *Iterative End Point Fit* algorithm [2] is applied to find single elements of lines from groups of points representing particular objects. The result of the splitting process are the points suitable for line fitting.

The supporting line of a line segment is represented by the equation :

$$x\cos(\phi) + y\sin(\phi) - r = 0 \tag{3}$$

The vector $L = [r, \phi]^T$ of parameters of this equation is computed by using the least squares method. This transformation can be generally expressed as $L = f_L(X_P)$ (see [13] for details). The uncertainty of line parameters depends on the uncertainty of all the measured points and is represented by covariance matrix C_L obtained from following expression :

$$C_L = \sum_{i=1}^{n_p} J_L C_{P_i} J_L^T. \tag{4}$$

where n_p is the number of scanned points, J_L is the Jacobian of the nonlinear transformat f_L with respect to the vector X_P, and C_{P_i} is the covariance matrix of i-th point X_{P_i}. The equation (3) describes an infinite line. To obtain a line segment which describes the possible edge of an obstacle, the coordinates of the starting and end points are determined [13].

The model of the whole environment explored by the mobile robot is obtained by integrating the line segments and clusters from local maps generated during the execution of robot path. Because the low scanning frequency makes it impossible to do measurements during robot motion, the robot stops to scan the surrounding, updates its internal map and continues the trip. The aggregation of line segments from different local maps is performed in two stages : matching and fusion. The matching procedure checks whether or not segments are part of the same edge. If the parameters of the supporting lines do not differ more than assumed and the distances between endpoints of the line segments fall within the tolerance range, then the segments pass the matching test [12, 13]. The fusion procedure approximates the new line segment from two segments which were detected before. For the new line the parameters of equation (3) are computed from the parameters of the supporting lines of the fused segments, by taking into account the uncertainties of both r and ϕ parameters, represented by the covariance matrix C_L. This is done by using a Kalman filter algorithm :

$$K = C_{L_1}(C_{L_1} + C_{L_2})^{-1}, \tag{5}$$

$$L_f = L_1 - K(L_1 - L_2), \tag{6}$$

$$C_{L_f} = (I - K)C_{L_1}. \tag{7}$$

where L_f is the vector of parameters of the fused line, C_{L_f} is its covariance matrix, and K is the Kalman gain.

Next, the new end points of the fused line segment are determined [13]. Fused line segments put in the global map include also a parameter q_n that depends on the number of times it has been observed and updated. This parameter is incremented if a line segment in the global map is matched to a segment from the local map. Unmatched line segments in the local map are copied into the global map and have a quality parameter set to $q_n = 1$. The last stage of building the global vector map consists of the reconstruction of complex geometric objects by using the detected line segments and clusters [12]. For path planning purposes, the lines would be more useful if they were grouped together into polygons and poly-lines.

Test runs of the map building system have been performed in the corridors of our laboratory. The global vector map that has been obtained while the robot followed a path and took scans from 9 scanning positions is shown in Figure 3.

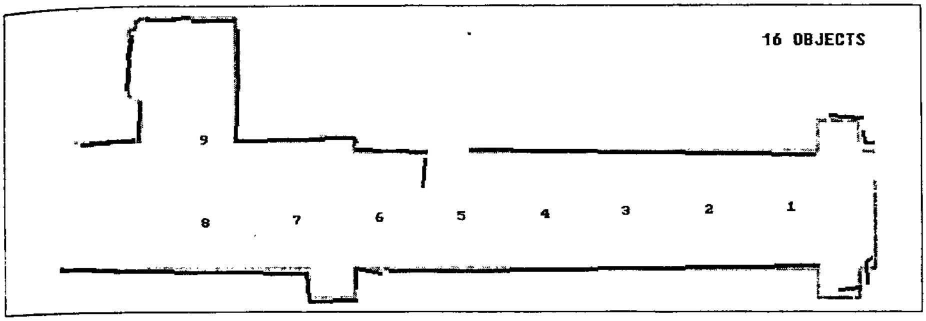

Figure 3: Vector map of the hallway built from scanner data

3.2. Raster-based maps

The problems in vector map building are mainly related to the difficulties in the interpretation of sensory data. The uncertainties associated with the sensor noise can be handled by statistical methods (e.g. Kalman filtering), but it is rather difficult to cope with the uncertainty associated with the validity of sensory readings. Vector-based map builder (as described in the previous section) needs accurate and dense-sampled measurements to produce an usable map. Because the industrial mobile robots have to be low-cost, they are widely equipped with the simple and cheap ultrasonic range finders (sonars). A credible vector map can not be based solely on sonar data, because sonars suffer from wide-beam problems and specular reflections which results in many spurious readings [8]..

A very convenient tool for dealing with spurious sensory data is the occupancy grid based approach [5]. Occupancy grids represent space as an array of cells, each one holding an estimate of the confidence that it is empty/occupied. Raster maps tolerate data uncertainty and ambiguity, even when weakly-structured environments have to be described. They however require large amount of memory, whenever large floor areas have to be covered with dense raster. Their further disadvantage is the rough raster-discretisation of obstacles on the scene.

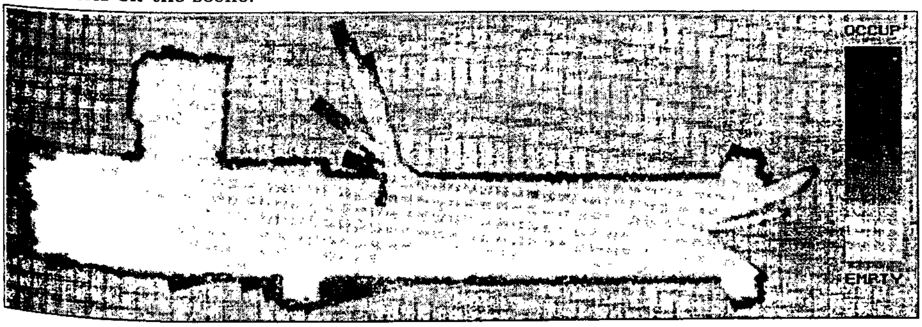

Figure 4: Raster map of the hallway built from scanner data

The raster-maps presented in this article have been tested especially in the context of the multi-robot navigation in an industrial environment [10]. So far raster maps have been proposed to let the robots with limited perceptual competence (e.g. equipped only with simple sonars) to build the updated map. Robot equipped with both sonars and scanner can build raster maps by using both sources of data, because these maps in natural way can fuse data from various types of sensors.

Raster maps are updated by using Bayesian integration scheme [11]. Occupancy probability density function is updated for each distance measurement, by using the Gaussian distribution pattern and the current variance of the measurement. Moreover, plausibility checks are applied to exclude some spurious sensor readings from the map updating process. The raster map can be initialized with the content of the GDB, and in such case the sensory data are used only to up-date this map. Figure 4 shows the raster map of the laboratory hallway built from scanner data. The same data as for the vector map presented above were used.

4. MODEL-BASED LOCALIZATION OF THE ROBOT

In this section a global localization system is described, that allows the mobile robot to estimate its position and orientation in a structured indoor environment. The availability of the *a priori* model of the environment is assumed. Because the system will be used in office/factory buildings this assumption is justified. Unfortunately, the optical scanner does not have intensity channel available, so it is not able to identify retroreflective landmarks. For this reason a method based on naturally occurring geometrical structures has been proposed. These features are extracted from the scanner data, and are used as reference points, so the system is independent of any artificial landmarks. Considering a typical indoor environment, the vertices, corners and doorways have been chosen as *natural landmarks*. Methods for natural landmarks extraction are based on scanner data processing algorithms which have been described in the previous sections. The disadvantage of the scanner is its low data acquisition rate. This causes the robôt to stop while the measurement are taken. The robot moves under odometric control for a period of time, then stops to locate landmarks, updates its position and continues the trip. Due to this fact and the poor performance of odometry of the *LabMate* platform, it is not possible to use localization algorithm assuming that the displacement between the sensed data and the reference model is small [1].

In our approach the matching algorithm establishes the correspondence between these natural landmarks extracted from current sensory input (local map) and the reference points in the global map. The localization method is feature-based, so only the most distinctive structures from the GDB content (such as wall junctions) are used. The 2D-coordinates of such points are calculated, and for each landmark the distances between it and all other possible landmarks are computed. The list of landmarks and distances serves as the environment representation during the matching stage [3]. To establish a correspondence between extracted features and the known landmarks a matching algorithm that compares not single landmarks but structures created from all the extracted features has been employed [14]. This approach is very useful in a cluttered environment with many "spurious" landmarks. If three or more landmarks are matched with the corresponding reference points in the global map, then it is possible to calculate the position and orientation of the vehicle by using triangulation.

As the triangulation method is sensitive to errors [6], natural landmarks are located randomly, the accuracy of some landmarks location is poor, and spurious features due to not modelled obstacles are possible, the landmark selection method has been developed, which makes possible to choose the best landmarks among all extracted features. Because there is no single measure relevant to all the aspects of landmarks "goodness" a fuzzy inference approach has been proposed merging the measures for particular attributes of a landmark [14].

The localization experiment has been performed in a well structured environment, but cluttered with several unknown obstacles (white cylinders on Fig. 5A). The length of the preplanned path was 15 meters. Due to the odometry errors the robot was not able to execute this path without performing the relocalization. With the self-localization performed at 9 preplanned points the position errors Δx and Δy were kept below 12cm. The natural landmarks extracted from sensory data at one of the scanning positions are shown in Fig. 5B.

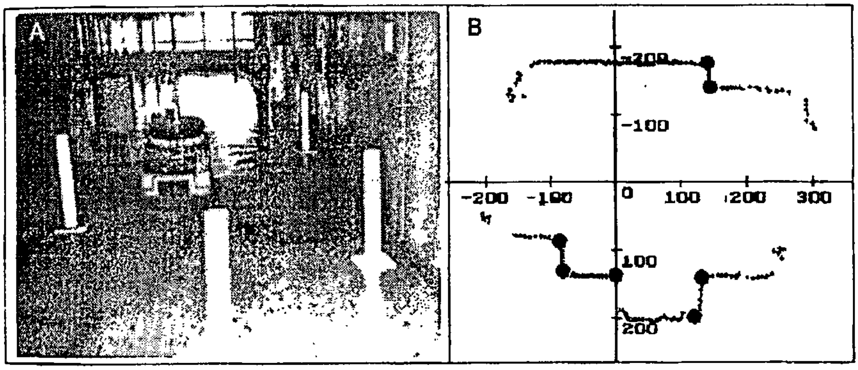

Figure 5: The robot while experiment (A) and the extracted landmarks (B)

5. CONCLUSIONS

The aim of the research presented here was to develop and preliminarily verify subsystems which are essential to the operation of the mobile robots in typical industrial environment. These subsystems are : environment model based on the *a priori* knowledge, two different (and in some sense complementary) map-builders, and the self-localization subsystem. By maintaining the up-to-date world model and position estimate, the industrial mobile robots are not forced to rely on wires or paint-stripes to navigate. The environment models are aimed at supporting robot navigation. Input data used for map building are provided by sensors or are derived from the GDB, so the maps can contain both the *a priori* and the *accumulated* knowledge about the scene. We let the coexistence of different forms of the environment model to promote the more flexible use of sensors having different operational characteristics. Moreover, this approach supports the multi-robot navigation schemes because the robots with different perceptual competence can build the updated world model and share the acquired knowledge [10]. The selection which map is used depends widely on the task. If the high accuracy of path planning and self-localization is needed, the exact vector map seems to be most appropriate. Raster-based maps are especially useful as the solution enabling direct sensor fusion. Though this representation is more expensive than the vector one, the small requirements regarding sensor equipment is its unique advantage in the context of low-cost applications.

The possibility of using the low-cost optical scanner as the primary sensor for mobile robots has been demonstrated. This sensor has been used as the principal source of data in all the subsystems presented here. From experiments performed in a real environment it could be seen that all the systems demonstrate a satisfying performance to cost ratio.

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