Robust Mapping and Path Planning for Indoor Robots based on Sensor Integration of Sonar and a 2D Laser Range Finder

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Abstract - In this study a sensor integration scheme to improve the capabilities of an indoor robot, has been developed such as mapping, collision avoidance and path planning. This integration has been carried out using a sonar ranging system and a 2D laser scanner, with participation of other sensors. The main goal of the integration is to reinforce the robustness of the overall system and overcome the sensors' disadvantages. This system inherits the advantages of these sensors and enables the robot to navigate safely in the working environment. The 2D laser scanner has been used to develop a mapping technique called the vector mapping algorithm to get consistent high precision maps with low memory requirements. The generated maps have been used as a base for an autonomous path planning algorithm depending on straight line navigation (SLN algorithm). The vector mapping algorithm has been implemented on an RWI B21 robot, one of the available robot platforms at the University of Tübingen.

Introduction

Over the last two decades intensive research has been carried out about sensor integration of indoor robots. These efforts were mainly divided in two fields: the first is the development of high precision ranging sensors (in general, environmental odometric data acquisition systems), the second is the development of an intelligent scheme to integrate these sensors. This integration exhibits different strengths and weaknesses. If the sensor integration is successful, the system will inherit the advantages of the different sensors, which means that the robustness and safety of the system is reinforced and also the consistency of the mapping is enhanced. On the other side, sensor integration is fraught with difficulties: the mismatch of different features and properties of sensors may lead to complexity and instability, problems of synchronization and different sensor locations increase the difficulty of implementation and the accumulation of noise could decrease the precision [1].

The sensor integration supports many robotic research topics such as map building, self-localization, path planning, robot control, object recognition, man-robot-interface and navigation [2]. In this paper the main goals of the sensor integration are map building required for path planning algorithms and collision avoidance in stationary and dynamic environments. According to the map building, the laser scanner and the sonar ranging system have been used to acquire an odometric vector map. This mapping paradigm has several advantages compared with other types of maps, like occupancy grids, topological graphs and combinations thereof [3], [4], [5]. The generated maps have been manipulated and used as base for the SLN algorithm. For the navigation, the laser scanner, the sonar ranging system, tactile sensors, the digital compass, the button server and the local panel have been integrated to increase the robustness of the overall system and to help in collision avoidance. The laser scanner was the main tool of this system while the sonar ranging system was used to recognize transparent and non-reflecting objects. The other sensors (tactile sensors, panel buttons, compass. etc.) have been used to support the safety and the robustness of the overall system.

In this paper the following topics will be discussed: part I focuses on the sonar sensor characteristics, advantages, disadvantages, mapping capabilities and related works. In part II the mapping using a laser scanner is presented. In part III the vector mapping paradigm is demonstrated. Part IV illustrates the odometric data correction using model reference. Part V presents the SLN algorithm and finally part VI contains the results, comparison and conclusion.

I. The Sonar Ranging System

Sonar sensors are used successfully in a wide variety of applications, such as medical imaging, non-destructive testing and vehicle ranging systems. In robotics the sonar is used mainly as a ranging system. Sonar transducers can be classified into three types i) magnetostrictive, ii) piezoelectric and iii) electrostatic. In this study electrostatic transducers of type Polaroid 6500 have been used, because of their suitable characteristics and because they were already available on all of the robotic platforms operated in our robotics lab, including the RWI B21, "Colin", on which the experiments were performed. Fig. 1 shows a pattern obtained from the transducer as a 3D conic distribution. The characteristic radiation function $I(\theta)$ can be described by the equation of Morse & Ingard (1968):

$$I(\theta)=\left(\frac{2J_1(k\,r_p\sin\theta)}{k\,r_p\sin\theta}\right)^2 \qquad (1)$$

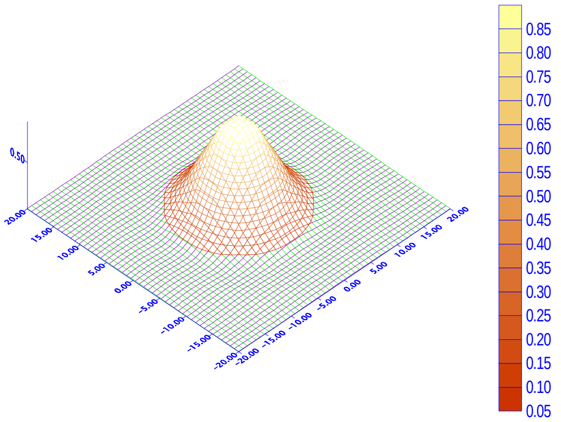


Fig. 1. The 3D distribution of sonar

where J_1 is a Bessel function of the first kind, r_p = 19 mm is the piston radius and θ is the azimuthal angle. The wave number $k = 2\pi f/c_s$ is obtained from the sound wave frequency f and the speed of sound $C_s \approx 340$m/s.

There is also an exponential loss in signal strength, due to attenuation or absorption of sound in the transmission medium (air). Fig. 2 shows the decrement of the sonar's power and certainty, i.e.

$$S_{trans} = \frac{e^{-\alpha d}}{d^2} \quad (2)$$

The precision of mapping using the sonar ranging system alone is not good enough because of the inherent disadvantages of sonar sensors: missing responses due to reflections of the sonar cone, misreadings from multiple reflections, crosstalk of multiple sensors, limited measurement range, effect of the atmospheric conditions (temperature, air pressure, moisture), and relatively slow response time and, consequently, low measurement frequency.

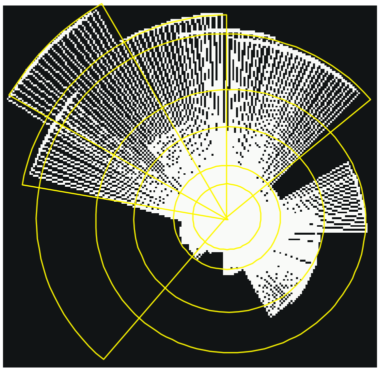


Fig. 2. Decrement of sonar's power and certainty

Despite the mentioned disadvantages, the sonar sensors are widely used in robotics because of their positive features, like low cost, light weight, small size, and low power consumption. Fig. 3 displays a map of part of our working environment using the B21 platform's sonar sensors.

In mobile robot mapping and navigation, there are many examples of research using sonar ranging systems with good results, e.g. Elfes (1989) [4], [5], Leonard & Durrant Whyte (1992) [6], Fox et. al. (1997) [7], Borenstein & Koren (1995) [8], [9]. An improvement of mapping using integration of multiple sonar sensors over the time based on Bayesian rule is also done by Thrun (1996) [10], [11], and Mojaev & Zell (1998) [12]. Another improvement technique using triangulation algorithm has been introduced by Wijk (1998) [13] to get better results using sonar sensors.

In this work the outputs of both laser scanner and sonar sensors have been processed using a conventional digital filter to estimate the odometric data of the environment. The main goal of the sonar was to support the navigation and mapping by detecting the transparent obstacles unidentified by the laser scanner and to detect objects located above the vertical detection level of 30cm of the 2D laser scanner.

II. Mapping Using Laser Scanner

To gather the odometric data of an environment, the laser scanner returns a set of points corresponding to the intersection points of the laser beam with the obstacles. The laser beam rotates in a horizontal plane and emanates from a scanner mounted on the robot. The scan is a 2D slice of the environment. We used a SICK LMS 200 laser scanner mounted on our B21 robot "Colin". A comparison between SICK and AccuRange laser scanners has been introduced by A. Scott et.al. (2000) [18]. The 2D laser scanners have many advantages, like high speed, high precision, high angular resolution and easy data interpretation. The laser scanner has also several disadvantages, like high cost, high weight (4.5 kg), 2D plane scanning limitation, high power consumption and problems with glass doors and very black mat materials.

Fig. 3. Map building using sonar sensors

In fig. 4 we define some special marks (denoted from 1 to 6). The marks 1, 5 and 6 are used to sign the position of the glass doors. The laser scanner failed to detect them due to their transparency. The area marked by 2 is the downward stairs and should not be entered with the B21 platform. The horizontal plane laser scanner is not able to detect downward stairs. The area marked by 3 is a table and the laser scanner was able to identify just the legs of the table but the table itself wasn't recognized. The object marked by 4 is a dynamic object (door) and the presented location is not permanent. Based on the preceding discussion an intelligent integration between the laser scanner and the sonar sensors has been developed to avoid such disadvantages.

III. Vector Mapping Paradigm

Several mapping paradigms have been investigated to model the robot's working environment. The most widely used methods are the occupancy grid, the topological graph and maps integrating both. Each of these methods has its characteristics, advantages and disadvantages.

Throughout this work the vector mapping paradigm has been used. This technique is suitable for robots equipped with a laser scanner. The vector mapping is originally based on the occupancy grid with a reduced map size. The main idea of the vector mapping is to determine an empty space as a region of cells between the laser scanner (robot's position) and the detected obstacles. In other words, these empty cells will be represented by end points of the laser rays (vectors) and the position of the laser scanner. The measurements of the vector mapping are given in a polar coordinate system whose origin is the position of the scanner (robot), while the end of the vectors are the obstacle boundaries. This map reduces both computer power and memory requirements. In this method, it is required to record just the start (once per scan) and the end of the vectors so the region in between is considered free space that will preserve the consistency of the maps. The laser scanner sends out 180 laser rays per scan with 1° angular resolution. The resolution of the vector mapping can be controlled using either hardware or software techniques.

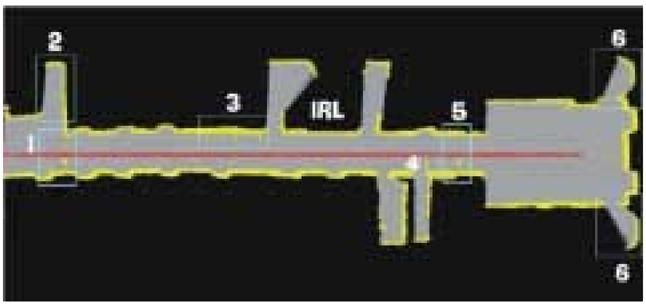


Fig. 4. Mapping using the laser scanner. The marks 1 to 6 are problematic cases for the scanner.

Fig. 5 illustrates the principle of the vector mapping paradigm. In this case the robot can map its environment from three central measurement points covering all the empty area (visible region) [14]. The vector mapping technique can be easily converted to the traditional map paradigms. As example, the occupancy grid can be generated by marking all cells included in the vector region by null (empty) and the remainder cells by one (occupied). Also the topological graph and integrated form can be estimated through the occupancy grid. Based on vector mapping the contour-graph can be generated. This graph includes the contours of the existing obstacles. This graph is used later in the path planning and navigation based on the SLN-algorithm. Enlarging the obstacle's boundaries is used to generate the contour graph. The minimum extension of obstacle boundaries is the sum of the threshold distance and the robot radius. This extension can be enlarged to get a contact in the middle of the free space (Voronoi diagram) if the obstacles are near and can be decreased to the minimum value if the obstacles are far away.

Fig. 6 presents two different models based on vector mapping: the first one has been built using 500 measurement points and the second using only 10 points. The difference in

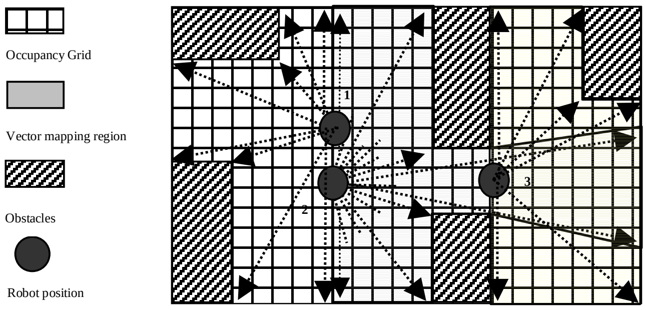
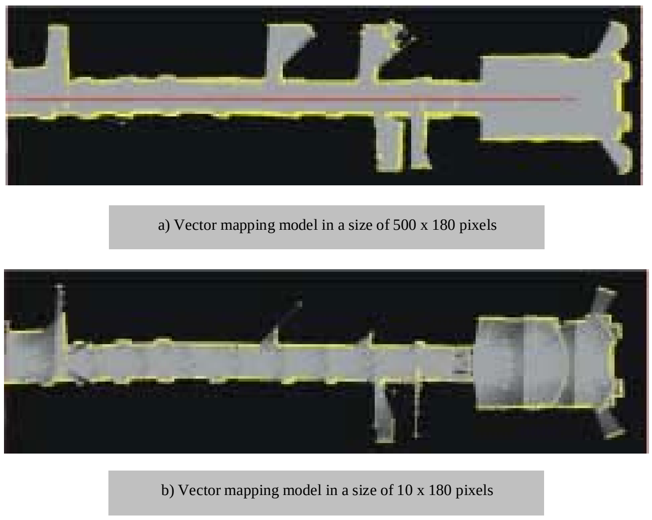


Fig. 5. Principle of the vector-mapping algorithm



a) Vector mapping model in a size of 500 x 180 pixels

b) Vector mapping model in a size of 10 x 180 pixels

Fig. 6. The vector mapping models using 500 vs. only 10 measurement points.

precision between the two models seems not too much although the map size difference is clearly large: the second map (6b) size is about 2% of the first map size (6a). This sort of mapping has a flexible resolution format depending on the required precision and the computational power of the system. Adjusting the number of the central measurement points can control the resolution of the map. The vector mapping has the advantages of the traditional mapping techniques: precision, consistency and efficiency with a low storage size.

IV. Model Reference

The acquisition of the odometric data is associated with different types of noise e.g. non-linear noise (backlash hysteresis, toggle, threshold, saturation, damping and friction), time based noise (accumulation effect) and white noise. Another form of odometric errors is generated by the mechanical system from rotation or due to slippage and drifting, see fig. 7.

In outdoor applications the global positioning system (GPS) is widely used as a localization system with a certain (large) tolerance. In indoor application similar global positioning systems are not widely used or available, so various algorithms have been developed to correct the maps and to attain precise models of the environment. The model reference method is considered as a plausible solution to correct these erroneous maps. This method is easy to be implemented and generates high precision maps. The overall map is an assembly of segments arranged corresponding to a model of nodes and paths (reference model), see fig. 8.

The model reference method presents an accurate solution for the correction of odometric data errors based on direct learning. That means a model of nodes and paths is used to correct the maps. Another technique has been used by Thrun et. al. 1997, which depends on the training (indirect learning) of neural networks.

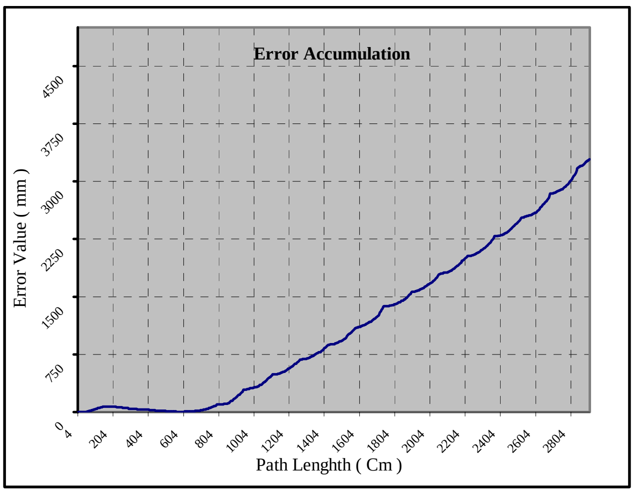


Fig. 7. Accumulation of odometric errors

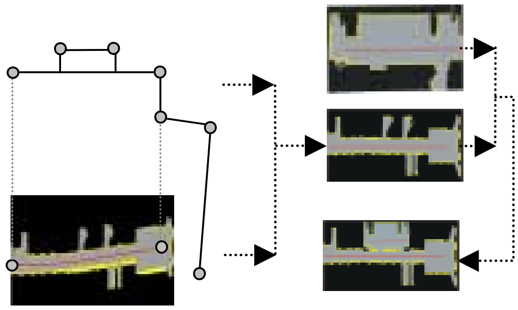


Fig. 8. Odometry correction using model reference

V. The SLN Algorithm

We now present the SLN path-planning algorithm used to estimate the shortest path of robots autonomously. The idea of using the straight line as a base in estimating of a path is used in several algorithms such as Bug or ALG [15], [16], [17]. In contrast to these online algorithms the SLN algorithm operates on a previously computed full or partial map of the environment. The primitive definition of the straight line is "the shortest path between two points". We try to benefit from this idea in estimating the shortest path autonomously. The complete solution presented in this paper starts with a map using the vector mapping paradigm. These maps are converted into a contour graph by enlarging the obstacle's boundaries. This graph is used as a base to develop the SLN-algorithm. This algorithm can be implemented in 5 phases, see fig. 9:

• ***Initialisation phase***: In this phase the parameters of the contour graph are defined, such as the set O of obstacles o_i, the start position S_0 and the goal position of the robot $T_{x,y}$. Each of these obstacles is defined by a set of properties: type, location and contour.

• ***Segmentation phase***: The contours of the obstacles are intersected with a straight line linking the start with the goal position. Hence, the contour of each obstacle will be split into two segments and one of them is shorter than the other or equal. If we have n obstacles and we start with point S_0 then the obstacles divide the line in $n+1$ line segments and $2n+1$ points S_0, S_1, …, S_{2n+1} and line segments $line_i = \overline{S_{2i}, S_{2i+1}}$ for $0 \le i \le n$, and object contour segments $cont_i$ connecting point S_{2i-1} with point S_{2i} over a series of unnamed intermediate points on the shorter side of the object contour, with $1 \le i \le n$. Line segments $line_{i-1}$ and $line_i$ are connected by an object contour segment $cont_i$. See fig. 10.

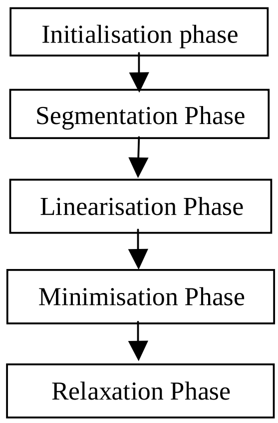


Fig. 9. The SLN algorithm phases

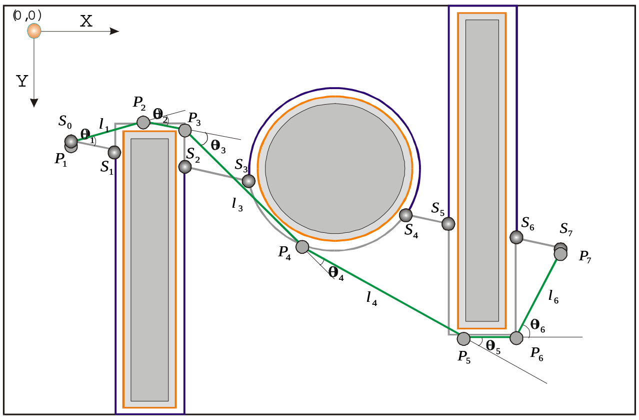


Fig. 10. The SLN-simulator (path designer).

• ***Linearisation phase***: In this phase the second path is generated by linearising the sections of the first path. We successively try to combine two path segments to a larger path segment by vector addition of their vectors. We keep the new combined path segment if it does not intersect one of the obstacles (except on the contour only). The points on this second path are denoted by P_0, …, P_m, where $P_0 = S_0$ is the original robot starting position, $P_m = S_{2n+1}$ is the target position, and the other P_i are points on the contour of an object, mostly not identical to any S_j.

The second path may then be described as a sequence of rotations θ_i and translations l_i of the robot at the control points $P_i = (x_i, y_i)$ with $1 \le i \le m$.

$$\|l_i\| = \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} \qquad (3)$$

$$\theta_i = \operatorname{asin}\left(\frac{y_i - y_{i-1}}{l_{i-1}}\right) - \operatorname{asin}\left(\frac{y_{i+1} - y_i}{l_i}\right) \qquad (4)$$

• ***Minimisation phase***: The maximum number of possible paths between the start and goal position is 2^n, where n is the number of obstacles along the line connecting the start to the goal position. In real world scenarios n is usually very small. Minimising the length of the path can be obtained by selection of the minimum set of segments. The resulting path is the shortest one.

• ***Relaxation phase***: In this phase the final path is relaxed to enhance the performance of the robot. The smoothing and relaxation of the final path minimize the execution time and save the required power.

The SLN simulator is a unit of the robot software kit (RSK) that has been developed to implement this algorithm. This simulator has a map designer and also accepts the contour graph format of the working environment. This algorithm provides the autonomous path planning and minimizes the path length. Fig. 11 presents a screen shot of the SLN simulator (path designer). The map can be generated easily using the map designer or can be introduced as contour format files.

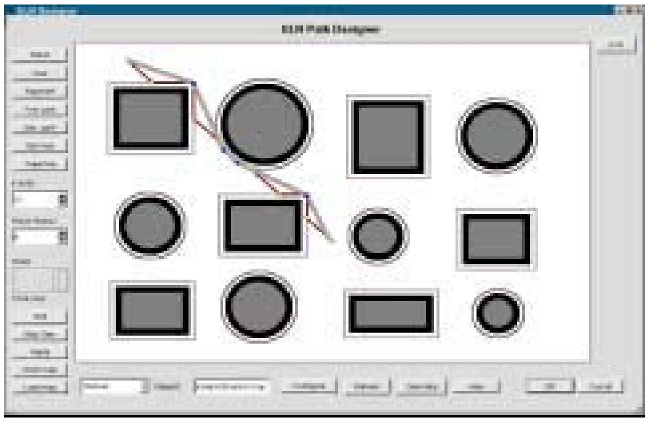


Fig. 11. A screen shot of the SLN simulator (path designer).

The elapsed time needed for the algorithm depends on many factors: number of obstacles, complexity, obstacle distribution, type of obstacles and size of obstacles. Table 1 indicates the elapsed time of 7 different cases of study. In general the elapsed time for 5 obstacles is approximately 35 ms, and we must take into consideration that the processing time has no linear relationship with the map construction. But in general the results encourage the implementation of the SLN algorithm online.

Compared with the currently popular path planners based on generalized Voronoi diagrams the SLN algorithm has the following advantages and disadvantages:

• Using a Voronoi diagram, the robot must follow a path centred between the obstacles during navigation. This minimises the probability of a collision, but makes the path longer than necessary. Using the SLN algorithm, the robot does not need to follow such a path, which can be considerably shorter, if the space among obstacles is large.

• The path generated by the SLN algorithm is not subject to the following problem of the generalized Voronoi algorithm: following corridors with open sideway doors or over hallways, the generalized Voronoi diagram path planner usually trigger some unexpected sideway robot motion.

• The SLN algorithm might be a bit more complicated to implement than the generalized Voronoi diagram algorithm.

No. of intersected objects	Total no. of objects	Elapsed time [ms]
1	3	7
2	6	18
3	8	38
4	8	49
4	15	27
2	4	32
4	12	29

Table 1. The elapsed time during processing of SLN-Algorithm in 7 different cases of study.

• Its theoretical time complexity is exponential in the number of obstacles along the straight line from start to goal, but not in the number of obstacles present in the map.

VI. Conclusion

In this paper a robot mapping and path planning algorithm based on sensor fusion of sonar and laser range data has been presented. We first discussed the most important characteristics, advantages and disadvantages of these sensors. The vector mapping paradigm has been applied to generate a suitable map types that can be used as a starting point of an autonomous path-planning algorithm. This method has a small storage size and high precision compared with the traditional mapping algorithms. The SLN algorithm has been developed to determine the path in environments with multiple obstacles. The sensor integration supported the robustness and the consistency of the generated maps. It also improved the performance of the overall system.

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