Sensor Fusion for Localizing a Mobile Robot Outside of Buildings

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Abstract. In this paper we show that it is possible to extend a mobile indoor service robot, making it capable of performing autonomous transportation tasks in outdoor environments. While the higher-level software (like planners, schedulers and collision avoidance) is no different than that used in indoor vehicles and therefore both well known and reliable, the sensor fusion layer is the challenging part due to the extreme ambiguity of sensor data outside most buildings. Therefore we focus on the self-localization aspect of the system, showing that it is possible to predict the robot's position with such low uncertainty that a typical transportation task in an industrial outdoor environment can be performed quickly, safely and robustly. We rely only on low cost off-the-shelf sensors (optical encoder, fiber-optical gyroscope and a laser range finder), without adjusting the robot's environment (e.g. by way of addition of artificial landmarks), making the system affordable and easy to maintain. We prove the usability of our approach through extensive tests with a real robot around our institute campus. Test drives totalling over 20km show that it is possible to find and traverse a target door in over 99% of all cases.

1 Introduction

In contrast to the many systems that exist for localizing a robot in indoor environments, few systems deal with this problem in outdoor environments. In most cases, like in autonomous street vehicles [DG88, TLR99], the localization capabilities do not need to be so precise as is needed by an autonomous service robot, which requires the ability to navigate reliably with a maximum positioning error of a few centimeters, or at least recognize when its uncertainty exceeds an upper bound. The existing systems that meet the aforementioned requirements fail to meet the requirements of an industry-related market, like being affordable and functional even in non-optimal environments that can be dirty, with uneven or slippery surfaces or with suboptimal sight caused by fog, rain, bright lights or darkness. In many cases the use of artificial landmarks provide a higher accuracy, but they are often impractical, costly to install and maintain, unflexible and hard to extend.

In this paper summarizes the main results from [Has00]. It presents an approach that proposes to fill this gap, using a set of off-the-shelf sensors (optical encoders, fiber-optical gyroscope and a laser scanner) and a vectorized map of the environment like those that are often available in most facility administrations or that can be bought from the local survey office (in Germany: "ALK", *allgemeine Liegenschaftskarten*).

The general conditions for this approach are given by typical industrial transportation tasks: a robot leaves a building at a given point (a door), travels on a user-defined "virtual" track, which is not necessarily visible, to its target destination, and then enters a building through a predefined door. This re-entry door can be the same door through which the robot left, or a different one. On this path, the inaccuracy of the robot's position must remain below a given upper bound. If the inaccuracy exceeds the bound, the robot must detect the failure and react accordingly, such as stopping immediately.

The approach can be divided roughly into two steps, the first being fusion of the inertial sensors, the encoders and the fiber-optical gyroscope, with a Kalman filter. This provides a first position estimate together with a measure of its uncertainty. A second stage then tries to minimize this uncertainty using the data delivered by a feature extraction stage operating on the laser scanner data and the map.

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This paper is organised as follows. After introducing the robot platform and area used for testing the presented algorithm, we will present the localization algorithm in detail, followed by empirical results that prove its efficiency and usability. Finally, we summarize our results.

2 The Robot Platform and Test Area

The robot used for testing our algorithm (fig. 1) is a prototype manufactured by *Daum and Partner*, Germany. It is a 200kg rear-wheel driven vehicle with ackerman steering, equipped with incremental encoders on the passive front wheels and an absolute encoder providing the steering angle. The front laser scanner provides 180° scans with a resolution of 0.5° and is required to satisfy the safety regulation of the German *Technischen Überwachungsverein, TÜV*. A fiberoptical gyroskope and a DGPS receiver complete the sensor set.

The data are processed by a PC/104 size Pentium 166MHZ computer equipped with digital, analog and canbus io-cards for acessing the robots hardware and sensors. A netlink for sending status information was provided by a wireless ethernet.

The test drives were run on our institute campus (fig. 2). We used three different tracks of 50m, 250m and 520m. They includes different kind of surfaces, like pave, sand, mud, bumps and acclivities and different kinds of environmental structures, including non-regular surfaces like bushes, trees and parked cars.

The map seen in fig. 2 is part of a ALK,*allgemeine Liegenschaftskarten*, which can be bought from the local survey office. These maps can directly be used by the system to define virtual tracks for the robot.

Fig. 1. Robot used: The prototype “Handycart“, manufactured by *Daum and Partner*, Germany.

3 The Localization Algorithm

The algorithm consists of two main steps, which will now explained in detail. In the first step, the data from the inertial sensors (the encoders, and the optical gyroscope) is merged in a preprocessing step and then fed into a Kalman filter.

The resulting position estimate is then improved by a second step, where a feature extraction on the laser scanner data is performed. The obtained features (namely, the position of doors and the main orientation of walls) are then compared to a map and used to reduce the uncertainty of the first step.

Fig. 2. Part of our campus with virtual tracks used for testing our approach. Track lenghts are 50m, 250m and 520m

Both steps are now explained in detail:

3.1 Fusing the Inertial Sensors

Of course, all the inertial sensor data could be merged by simply putting them into a Kalman filter [GBF98], but our experiments show that a deterministic approach can do better. Because of the high weight of the robot and the positioning of the encoders on the passive front wheels it is impossible that both steering wheels are affected by slippage. This assumption is proven by our experiments. In the case of no measurement error, the measured change of the robot's orientation vector will be the same using the gyroscope as that of the encoder values. In the case of wheel slippage or bumps, where the odometric data imply a wrong change of orientation, these values differ significantly (fig. 3), because the gyroscope is unaffected by mechanical shocks.

This effect allows not only to detect odometric measurement errors, but also the sign of the difference indicates which wheel is affected by slippage and therefore produced the wrong measurements. We then use an alternative calculation of the new position, getting the change in orientation from the gyroscope and the distance information from the one correct wheel encoder.

This is possible because, as our experiments show, the weight of the robot and the wheel encoders mounted on the passive wheels prevent the slippage of both wheels at once. Therefore using this technique, we eliminate the disadvantages of both the gyroscope (the high drift) and the wheel encoders (sensitivity to slipperage), resulting in a significant increase in position accuracy in comparison to the Kalman filter-only solution (fig. 4).

Borenstein and Feng [BF96] have called such fusion of gyroscopic and odometric data *gyrodometry.* They have reported a similar increase in robustness for pose estimation from this fusion like we have found. In particular, they have also reported the ability of gyrodometric position estimation to recover from non-systematic errors induced by slippage and bumps.

We also tried using a differential GPS, merging its data at this point with preprocessed data from the first step described above, but it turned out that there is no noticeable increase in positioning accuracy. The DGPS data turned out to have a too high variation for improving the uncertainty of any estimation. The main reason for this lies most likely in the multiple reflexion of the satelite signals against the walls of the surrounding buildings.

3.2 Reducing the Uncertainty

To improve the position estimate, we now extract the position of potentially existing doors and of the main wall orientation out of the laser scan data.

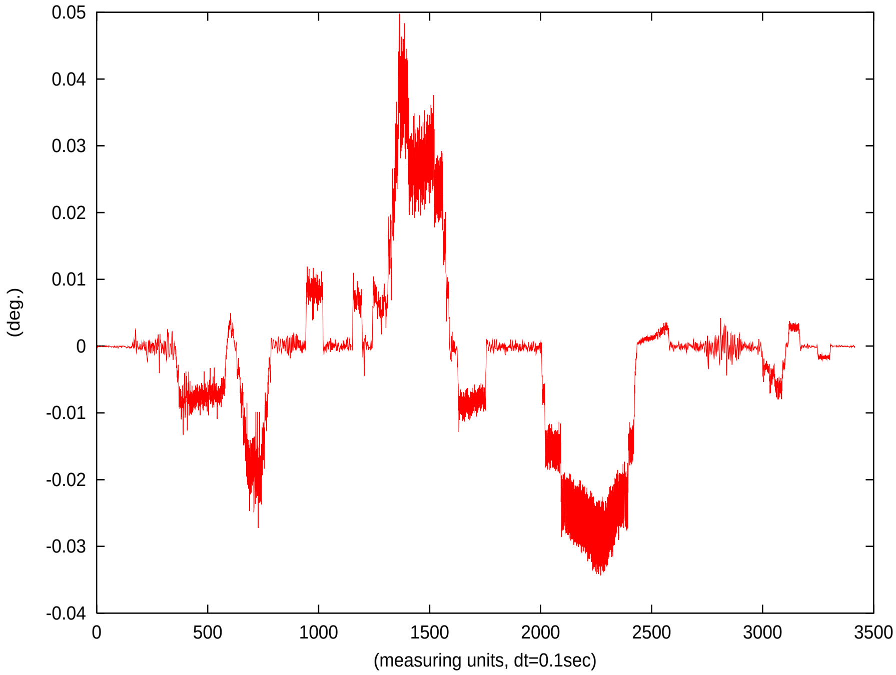

Fig. 3. Difference between the change of the orientation vector provided by the gyroscope and the wheel encoders. (At dt=600, 1300 and 2050 the robot traversed bumps in the surface!)

The doors are detected using a modified Hough Transformation [Dav90, IK88], which detects "line-breaks" of a certain length rather than line segments. If a door is visible in a scan, it is detected in 98% of all individual scans using this algorithm. The algorithm is capable of processing at least 5 scans per second (of 180° each with 361 dots per scan). Because of this fast processing of scans it is possible to detect every visible door while travelling by.

Using the measured position of the door relative to the robot, its current position estimate and its uncertainty provided by the Kalman filter, it is easy to determine which door in the map corresponds to the detected one. In our scenario we can only allow measurement errors that are much smaller than the distance between two doors, so every door can easily by determined by elementary geometric calculations. Once knowing the relative position of the door to the robot and its exact position from the map now makes it a trivial thing to recalculate the absolute position of the robot and use this information for a position update in the Kalman filter.

The main wall orientation is calculated using angle histograms, which are almost translation-invariant under the assumption of only small positioning errors[WWP94]. Like doors, outside walls are not always visible, and so only those histogram peaks in the list that provide a significant height above the histogram average are taken into account. This indicates that a wall in sight is of a length "worth being considered".

Once we have a main wall orientation, we extract the same value out of the map under the assumption of our current position estimate. We then compare the two values and calculate a correction of the orientation vector.

This of course corrects the orientation error only. The robot has possibly been travelling with this error for a couple of meters, so the system maintains a queue of limited size, storing the position update of the last 10 meters (a value that can be adjusted according to the memory available). After we get the correction, we track this error back and get again a correction of the position.

It turns out that this feature is especially useful in the correction of a priori errors in the orientation vector when leaving the building. Of course, when the robot switches from indoor to outdoor navigation, it has to start with an initial position, which is determined by the door position and the robot's angle relative to the walls. Clearly, these values are never exact. The angle histogram approach turns out to be useful in limiting the error resulting from this source.

Guivant et al. [GNB00] report a similar use of laser range data for outdoor navigation. Their approach is more general than ours in that they make use of the laser intensity data in addition to the range data for

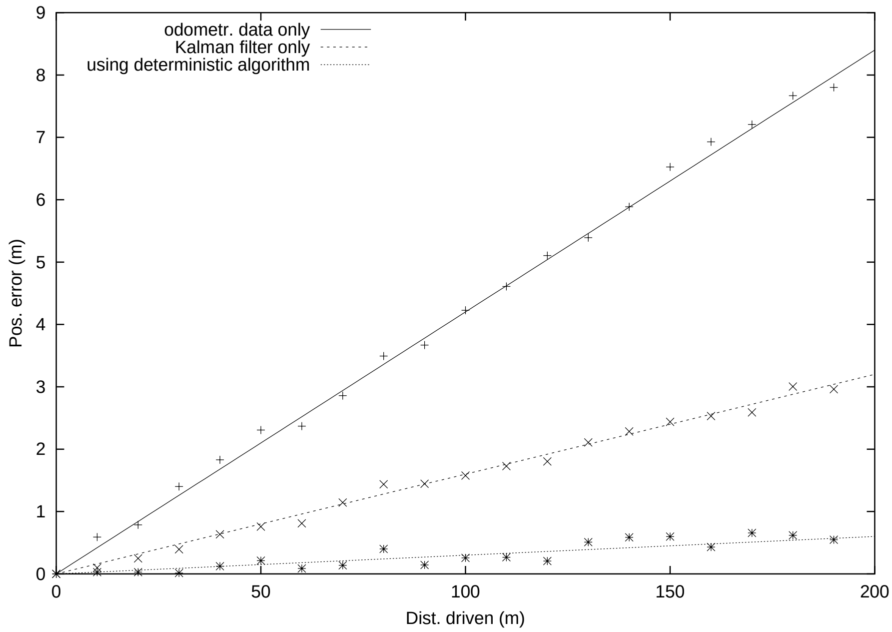

Fig. 4. Positioning error provided from different methods of fusing odometric and gyroscopic data. Measurements are plotted only every 10m for sake of readability

discriminating landmarks (which may include artificial beacons); moreover, their approach is also intended for map building. Yet, it differs from ours in a number of important details that are due to differences in the target applications. We presume to navigate in the vicinity of buildings, like in factory yards or institute campuses. Therefore, we must expect some dynamicity of the environment, like humans or cars or other mobile objects, blocking temporarily landmarks. Using the known geometry of the buildings, including line segments, corners, and doors, for uncertainty reduction in the various ways just presented, proves to be efficient. Together with the gyrometric position estimation, it suffices to perform robust drives, including door-to-door missions, as will be seen in the next section.

4 Experimental Results

We have tested our approach in extensive drives around our institute campus. To accomplish this we choose three different paths (see 2), each of which contained different surfaces (sand, holes, bumps, crushed stone, mud, asphalt) and environmental structures, including non-regular surfaces like bushes, trees and parked cars.

The main tests consisted of measuring how exact a given target point can be reached after travelling a given distance. The results of these tests are shown in tab. 1 and fig. 5. As one can see, a transportation task like described in the first chapter can be performed with such a high reliability that it satisfies most application needs.

The precision of the positioning estimate depends of course on the landmarks detected in the environment. We therefore measured the minimal and average travelling distance until reaching a given quadratic error in the positioning estmate. We chose four error limits of 10cm, 30cm, 50cm and 100cm and performed 40 test drives through environments providing a whide spectrum of different environmental structures (fig. 2). The results can be seen in tab. 2.

The second task was to leave a building through a door and re-enter a building through another door. Again, between the doors there were three diffent paths of 51m, 280m and 520m length (fig. 6). Like described before, the doors allow additional corrections of the positioning error. Because of that, it is possible to find and enter a door even with relativly high positioning errors. The results can be even better if the robot uses a more sophisticated “door-searching-strategy“ which will be implemented shortly.

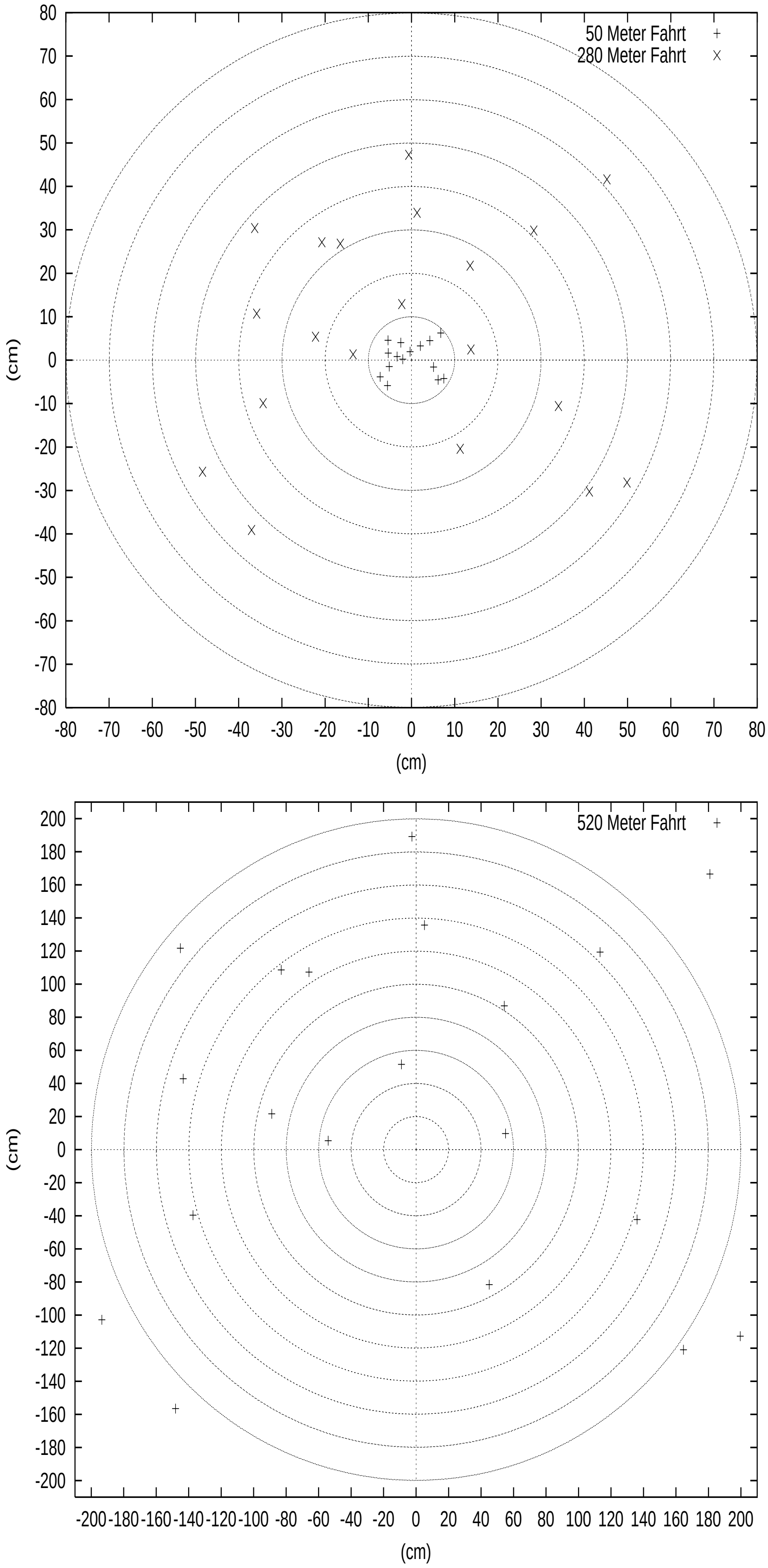

Fig. 5. Distribution of reached endpoints around the real target point

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		travelling distance 50m	250m	520m
Extrema [cm]	min(dx)	-7.3	-48.4	-156.5
	max(dx)	7.5	49.9	189.1
	min(dy)	-5.8	-39.1	-193.5
	max(dy)	6.2	47.2	199.6
Mean [cm]	dx	-0.3	-1.4	-5.9
	dy	0.4	6.4	25.5
	abs(dx)	4.6	25.3	101.2
	abs(dy)	3.2	22.8	91.1
	$\sqrt{(dx^2+dy^2)}$	5.8	36.8	147.0
Standard-deviation [cm]	dx	5.2	30.3	121.5
	dy	3.8	26.5	104.2
	abs(dx)	2.1	15.8	63.3
	abs(dy)	1.9	13.2	52.9
	$\sqrt{(dx^2+dy^2)}$	2.3	15.0	59.9

Table 1. Statistical examination of the positioning errors when travelling to a given target point. 25 drives were carried out over each of 3 different track lengths. The extrema, means and standard-devation of the absolut error and the errors in x/y-direction are provided.

Positioning-error	Distance travelled(m) Min.	Avg.
10cm	45.0	73.2
30cm	119.0	160.0
50cm	210.0	302.3
100cm	389.0	425.1

Table 2. Minimal and average travelling distance until exceeding a given quadratic error in the position estimate

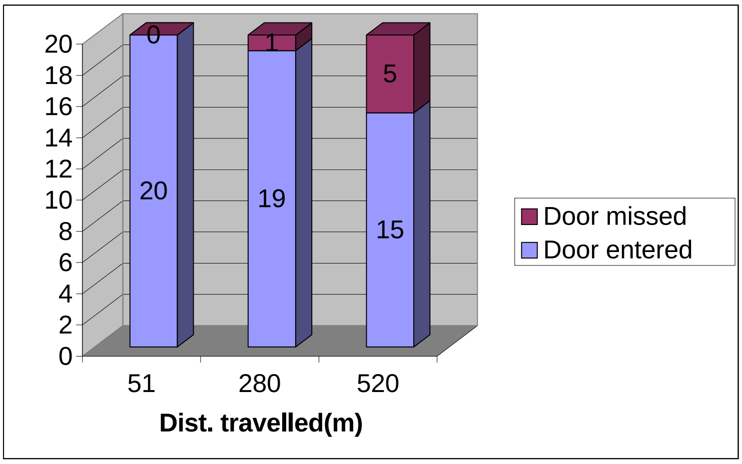

Fig. 6. Results of the door-to-door drives. It is shown how often a target door is successfully entered

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5 Conclusion

We have shown that it is possible to extend an off-the-shelf transportation robot platform with low-cost standard sensors, thereby making it capable of performing transportation tasks indoors as well as outdoors.

The reliability and robustness of the system is very high. It is independent of visual conditions and insensitive to the structure of the surface it is travelling on (as long as the robot is able to travel on them). Even after longer drives, the system is still able to reliably localize and enter a target door. Finally, the system keeps track of its own uncertainty, making it easy for higher level software to act accordingly if the uncertainty of the position knowledge exceeds a given limit.

The system does not require changes in the environment in order to localize itself. It is therefore possible for the user to define a "virtual" path of the robot , making the robot flexible and the system easy to learn and to maintain.

The results shown above can be improved using active-perception approaches, which will be implemented shortly.

6 Acknowledgements

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