Probabilistic Matching for 3D Scan Registration

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Abstract

In this paper we consider the problem of three-dimensional scan registration for autonomous mobile vehicles. The problem of 3D scan matching is of enormous importance for the construction of metric representations of the environment, for localization, and for navigation planning in the three-dimensional space. We present a probabilistic technique that computes a probability density for each pair of scans and then performs the registration using a greedy hill-climbing search in the likelihood space. We compare our approach with the ICP-algorithm which currently is the most popular technique for matching 3D range scans. We present experiments illustrating that the estimation error of the ICP algorithm is significantly higher than the resulting error obtained with our probabilistic approach.

1 Introduction

The topic of learning 3D models of buildings (exterior and interior) and man-made objects has received considerable attention over the past few years. 3D models are useful for a range of applications. For example, architects and building managers may use 3D models for design and utility studies using virtual reality (VR) technology. Emergency crews, such as fire fighters, could utilize 3D models for planning as to how to best operate at a hazardous site. 3D models are also useful for robots operating in urban environments. And finally, accurate 3D models could be a great supplement to the video game industry. In all of these application domains, there is a need for methods that can generate 3D models at low cost, and with minimum human intervention.

In the literature, approaches for 3D mapping can be divided into two categories: Approaches that assume knowledge of the pose of the sensors [1, 2, 3, 5, 14], and approaches that do not [11, 15, 12, 7]. In the present paper, we are interested in using mobile robots for data acquisition; hence our approach falls into the second category due to the inherent uncertainty in robot odometry. A popular approach to deal with possible errors in odometry is the registration of different scans. The technique presented in [11], for example, uses features extracted from camera images for localization. However, they also rely on the supervision by a human operator especially in situations with poor illuminations and spares features. [15] in contrast assumes that the robot operates on a planar space and thus can use 2D scan matching techniques to estimate the position of the vehicle. In [10] we presented an approach to simplify the models resulting from this process. By fitting planes to the range data, we obtained a significant reduction of the

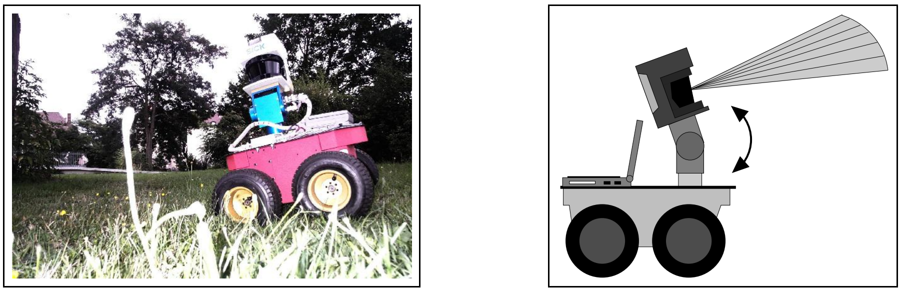

Figure 1: The robot Herbert which is equipped with a SICK LMS laser and an AMTEC wrist unit. The 3D-data are acquired by changing the tilt of the AMTEC module.

complexity of the model. [12] creates planar 3D models using camera images. In this system the registration is carried out using landmarks such as edges extracted from the camera images. Frueh et al. [7] present a technique to eliminate rotational errors of the robot by comparing 3D scans. They extract planes out of the range scans and minimize the distances between different planes.

In this paper we consider the problem of full 3D range scan registration without restrictions on the displacements between two different scans. The data are acquired with the mobile robot Herbert (see Figure 1), which is a Pioneer 2-AT system equipped with a 2D Sick LMS range scanner mounted on an AMTEC PowerCube Wrist Module. Each complete sweep obtained with this system consists results in 146.000 range data.

Currently, the Iterative Closest Point algorithm (ICP), which iteratively tries to minimize the distances between the points on the first scan and the corresponding closest point in the second scan, is one of the most popular techniques for range registration. Whereas this approach is quite efficient, it has the major drawback, that a convergence to the correct position is not guaranteed. To overcome this problem, we propose a probabilistic matching technique that uses an approximative probabilistic and parametric model representing the characteristics of the sensor. Compared to the ICP algorithm, our approach has several desirable advantages. First, the parameters of the model can be adapted to the accuracy of the underlying sensor. Second, our approach considers the complete rays of each laser beam and therefore can correctly handle occlusions. It does not require any heuristics to deal with occlusions, as for example, proposed in [9]. Finally, it can correctly handle maximum range measurements which generally are filtered out in scan matching procedures.

2 The ICP algorithm

The Iterative Closest Point (ICP) Algorithm [4, 8] is a popular method of range data processing. Given two sets of partially overlapping range data and an initial estimate of their relative positions, the ICP approach computes a registration of these two sets in an iterative fashion. In each round, the ICP algorithm determines for each point in the first set the closest point in the second set. It then tries to find a relative position of the two scans such that the mean squared error (MSE) given by the sum of the squared distances between the corresponding points is

Figure 2: Polygonal model obtained after registering two scans using our probabilistic method.

minimized. The process is continued until either the MSE falls below a given threshold or no further improvement can be achieved.

The key properties of the ICP algorithm can be summarized as follows. First, it converges to the nearest local minimum of the sum of squared distances between the closest points. Therefore, the final location is not necessarily equivalent to the optimal position. Furthermore, a good initial estimation of the transformation between point sets is required to ensure convergence to a good position. Finally, the ICP algorithm cannot deal with maximum-range measurements. Accordingly, it throws away a serious amount of information. In our experiments the maximum range measurements form around 35% of the overall data.

3 Probabilistic Scan Registration

At the core of the probabilistic range scan registration is an approximative physical model of the range scanning process. Obviously, an ideal sensor would always measure the correct distance to closest obstacle in the sensing direction. However, sensors and models generated out of range scanners are noisy. Therefore, our current model incorporates measurement noise and random noise in order to deal with errors typically found in 3D range scans. First, we generally have normally distributed measurement errors around the distance “expected” according to the current position of the scanner and the given the model of the environment (e.g. the previous scan). Additionally, we observe randomly distributed measurements because of errors in the model and because of deviations in the angles between corresponding beams in consecutive scans. Therefore, our model consist of a mixture of a Gaussian with a uniform distribution (see Figure 3). The mode of the Gaussian corresponds to the distance expected according to the current state of the robot and the given surface. Please note that this quantity can efficiently be computed using ray-tracing techniques based on a spacial tiling and indexing [13]. In practice, the values of the other two parameters, i.e. the variance of the Gaussian and the height of the uniform have to be adapted to the actual accuracy of the sensor uses (see also [6]). Additionally, to speed-up the computation, we use a piecewise linear approximation of this density.

To compute the likelihood of a beam, we compute the distance d_e to the closest obstacle in the

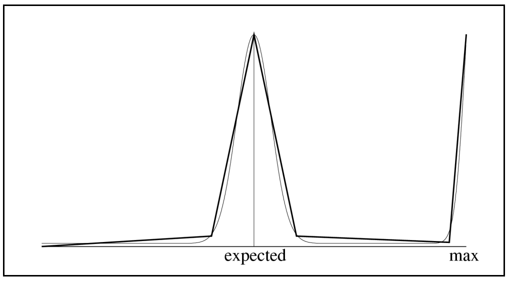

Figure 3: The probabilistic measurement model given as a mixture of a Gaussian and a uniform distribution and its approximation by piecewise linear functions.

measurement direction. Then we compute the probability of the measured distance d_m given the expected distance, i.e. we determine the quantity $P(d_m \mid d_e)$ using the mixture computed for d_e. Under the assumption that all beams in S are independent given the model S', the likelihood of a complete sweep S given S' and a location l is then computed according to

$$p(S \mid S', l) \;=\; \prod_{s \in S} p(s \mid d_e(s, S', l)) \tag{1}$$

Here $d_e(s, S', l)$ is the distance expected according to the beam direction of s, the previous scan S', and the location of the scanner l. To compute this quantity, our current system constructs a surface out of S' by introducing a triangle between adjacent points whose distance does not exceed a certain threshold which itself depends on the length of the beams. To determine the most likely position of the scan S given a reference scan S' we apply a hill-climbing strategy similar to that of ICP. We repeatedly change the position l of the scan S as long as the likelihood $p(S \mid S', l)$ increases.

Compared to the ICP algorithm and other scan-matching techniques, our approach has several advantages. First, it exploits the fact that each laser beam is a ray that does not go through surfaces and therefore does not require special heuristics for dealing with occlusions. Please note that there are variants of the ICP that match a scan to the corresponding closest points on the surface. However, even those approaches cannot correctly deal with occlusions. Second, our approach exploits maximum range readings since beams going through surfaces reduce the likelihood of an alignment.

4 Experiments

The experiments described in this section are designed to analyze the advantages of our probabilistic method over the ICP technique. To acquire the data we moved our mobile robot Herbert (see Figure 1) over our university campus and recorded data by changing the tilt of the AMTEC Wrist Module in a range of 145 degrees. During such a tilt operation the SICK LMS scanner takes 400 scans each consisting of 361 beams at an angular resolution of 0.5 degrees.

Figure 2 shows the final model obtained by registering two 3D scans with our probabilistic method. As can be seen from the figure, important details such as windows and corners are still

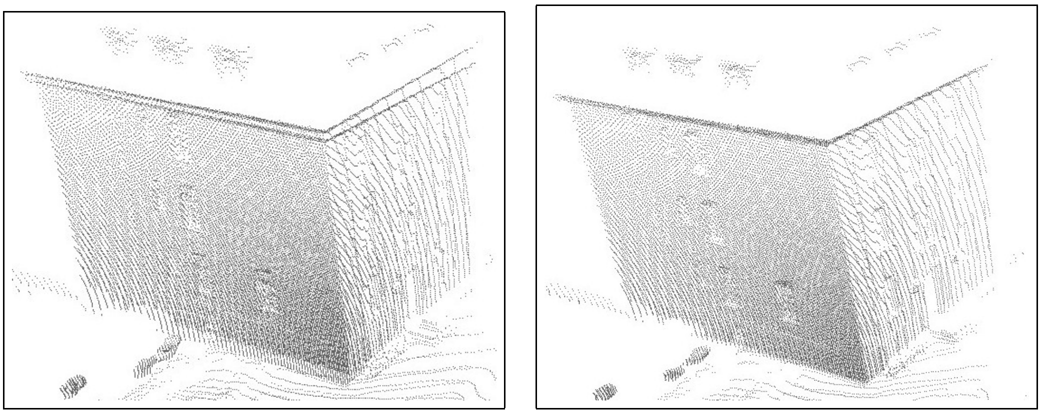

Figure 4: Details of two scans registered with ICP (left) and our probabilistic method (right).

Table 1: Resulting estimation errors.

Displacement	ICP	Ray-Tracing
5 cm	79.8 cm	8.8 cm
10 cm	74.6 cm	8.4 cm
20 cm	81.2 cm	11.6 cm
35 cm	86.3 cm	6.0 cm
50 cm	81.3 cm	10.7 cm
70 cm	85.9 cm	8.6 cm
100 cm	94.5 cm	11.1 cm
average error	83.4 cm (+/-) 5.7	9.3 cm (+/-) 3.7

clearly visible which indicates a small localization error. Figure 4 gives a detailed view of a part of the model obtained after registering the two scans with the ICP algorithm and our technique. As can be seen from the figure the ICP algorithm produces a larger error than our approach.

To quantitatively compare our algorithm to the ICP algorithm we randomly introduced errors in the odometry data and applied both algorithms to register the scans. The correct pose of the second scan relative to the first scan was estimated manually by inspecting different displacements. Table 1 shows the results for different amounts of error introduced. As can be seen from the figure the ICP algorithm never converges to the correct position. This is mainly due to wrong assignments in areas in which the system scanned the ground. In contrast to that, our probabilistic approach converges to the correct position with only a small residual error.

5 Conclusions

In this paper we presented a probabilistic method for full 3D scan registration. Our approach is a dense matching technique that makes no assumptions about features or landmarks in the environment. Additionally, it does not require that the ground is planar or that the range scans contain planar structures. The key advantages of our method are threefold. First, our method includes a ray-tracing operation and therefore can correctly handle occlusions. It does not require special heuristics for dealing with occlusions. Second, our approach is able to exploit maximum range readings which generally is not possible with scan matching procedures. Finally, the basic parameters of the model are sensor-specific and in principle can be adapted according to the accuracy of the sensor.

The technique has been implemented and tested on a mobile robot and in a realistic outdoor scenario. We furthermore analyzed our approach and compared it to the popular ICP algorithm. The experiments demonstrate that our approach can reliably register three-dimensional range scans and that it provides a higher accuracy than the ICP technique.

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