SCAN MATCHING WITHOUT ODOMETRY INFORMATION

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Abstract: We present an algorithm for merging two partial maps obtained with a laser range scanner into a single map. The most unique original aspect of our algorithm is that it does not require any information on the position where the scans were collected but uses only geometrical features of the scans.

1 INTRODUCTION

The increasing use of mobile robots equipped with laser range scanners has stimulated the development of methods for matching and aligning scan data collected by these sensors. Usually these methods align two scans starting from some information about the relative position of the sensors obtained from odometry (Lu and Milios, 1997; Cox, 1991; Röfer, 2001). Some methods (Einsele, 1997; Martignoni III and Smart, 2002) do not use information coming from odometry, but they work well only in rectilinear environments and for small displacements of the robot.

In this paper we present a method for matching two scans that does not require any odometry information and that works for significant displacements of the robot. For the purposes of this paper, a scan is a collection of segments. In our experimental setting each scan is obtained by acquiring with a SICK LMS 200 laser range scanner (mounted on a Robuter mobile platform at a height of approximately 50 cm) a sequence of distance measurements along directions separated by a programmable angle (1°, in our case) sweeping 180°. The result of the sensing operation is thus a set of points expressed in polar coordinates, with the origin of the coordinate frame in the sensor itself. We approximate these points with a set of segments following the method described in (González-Baños and Latombe, 2002). The use of segments instead of points reduces the computational complexity of finding the match between scans. Since the method does not use odometry information, it relies exclusively on the geometry of the scans. In particular, we consider the angles between pairs of segments in the scans as a sort of “geometrical landmarks” on which the matching process is based. We assume that the robot moves on an indoor 2D surface and that walls and vertical objects are at the height of the laser scan.

The method integrates two scans, $S_1$ and $S_2$, into a map $S_{1,2}$. It is composed of three major steps:

1. find the possible transformations of $S_2$ on $S_1$;
2. evaluate the transformations to identify the best transformation $t$ of $S_2$ on $S_1$;
3. apply the best transformation to $S_2$ (obtaining $S'_2$) and fuse the segments of $S_1$ and of $S'_2$ to obtain $S_{1,2}$.

This paper is structured as follows. The next Section describes in detail our method, while in Section 3 we discuss the experimental activity performed to validate it. Section 4 concludes the paper.

2 THE PROPOSED METHOD

In the algorithms, two points are considered to coincide when they are closer than POINTDISTANCE TOLERANCE (in our experiments we set this parameter to 15 mm) and two angles are considered equal when their values differ for less than ANGLEDIFFERENCE TOLERANCE (in our experiments we set this parameter to 0.2 rad).

2.1 Finding Transformations

This step, given the scans $S_1$ and $S_2$, first finds the angles between the segments in $S_1$ and between the seg-
ments in \( S_2 \) and, second, finds the possible transformations (namely, the rotations and translations) that superimpose at least one angle \( \alpha_2 \) of \( S_2 \) to an equal angle \( \alpha_1 \) of \( S_1 \). Angles between pairs of segments in a scan are the geometrical landmarks we adopt. Finding the possible transformations is a difficult combinatorial problem since in principle, without any information about the relative positions of the two scans, there are \( O(n_1^2 n_2^2) \) possible transformations, where \( n_1 \) and \( n_2 \) are the numbers of segments in \( S_1 \) and \( S_2 \), respectively.

We have therefore devised three heuristics for reducing this complexity and finding a set of (hopefully) significant transformations between two scans. They are described in the following.

1. Considering Angles between Consecutive Segments. In each scan, we select the angles between two consecutive segments; let \( A_1^i \) and \( A_2^j \) be the sets of such angles for \( S_1 \) and \( S_2 \), respectively. Two segments are considered consecutive when they have an extreme point in common. Then, we find the set of all the transformations that make an angle in \( A_2^j \) to correspond to an equal angle in \( A_1^i \). The number of possible transformations found by this method is \( O(n_1 n_2) \). We note that finding the sets \( A_1^i \) and \( A_2^j \) is greatly facilitated when the segments in \( S_1 \) and in \( S_2 \) are ordered. This is usually the case with laser range scanners, since the points returned by the sensor are ordered counterclockwise and it is straightforward to maintain the same order in the segments that approximate the points.

Although this method seems to perform well in indoor environments where the angles are usually normal, the errors introduced by the sensor and by the algorithm that approximates points with segments alter the representation of these angles.

2. Considering Angles between Randomly Selected Segments. In each scan, we examine a number of angles between pairs of segments selected randomly. We assign a higher probability to be selected to longer segments, since they provide more precise information about the environment. Let \( A_1^i \) and \( A_2^j \) be the sets of the selected angles for \( S_1 \) and \( S_2 \), respectively. We find the set of all the transformations that brings an angle in \( A_2^j \) to correspond to an equal angle in \( A_1^i \). The number of transformations generated by this method is \( O(a_1 a_2) \), where \( a_1 = |A_1^i| \) and \( a_2 = |A_2^j| \) are the number of selected angles in \( A_1^i \) and \( A_2^j \), respectively.

Instead of assigning directly to each segment the probability of being selected (according to its length) and of selecting the \( a_1 \) (respectively \( a_2 \)) pairs, the following approximate and easy-to-implement technique is employed. Initially only segments longer than \( \text{SEGMENTDIVISIONFACTOR} \) times the length of the longest segment in \( S_1 \) (resp. \( S_2 \)) are considered for selection. All the segments considered have equal probability of being selected. Then, we proceed to it-
segment $s^t_{2p}$ and then we compute the length $l_1$ of the common part of $s_1$ and $s^t_{2p}$, we do the same but projecting $s_1$ on $s^t_{2p}$, obtaining $l_2$. The matching value of $s_1$ and $s^t_{2p}$ is calculated as the average of $l_1$ and $l_2$. When $s_1$ and $s^t_{2p}$ do not intersect, the matching value is multiplied by $0.95d(s_1,s^t_{2p})/\text{POINTDISTANCE TOLERANCE}$ to penalize the match between segments that are far away. Note that 0.95 is an empirical constant whose value has been determined during experimental activities and $d(s_1, s^t_{2p})$ is the distance between two segments, calculated as $d(s_1, s^t_{2p}) = \min(\max(\text{dist}(s_1, \text{start}(s^t_{2p})), \text{dist}(s_1, \text{end}(s^t_{2p}))), \max(\text{dist}(s^t_{2p}, \text{start}(s_1)), \text{dist}(s^t_{2p}, \text{end}(s_1))))$. When the common part of $s_1$ and $s^t_{2p}$ is such that if $l_1 = 0$ and $l_2 = 0$, the matching value is set to 0.

Finally, two special cases can appear during the evaluation of the matching values of $s_1$ and $s^t_{2p}$. The matching value is set to 0 when two segments are too far away, namely when $d(s_1, s^t_{2p}) > \text{SEGMENTDISTANCE TOLERANCE}$. If the two segments are more than $\text{SEGMENTLENGTH TOLERANCE}$ shorter than the acceptable error, then $P_{n-1}$ is the final approximation $P$. For $s$ substitutes $s$ in $P_{n-1}$ and is connected to the two closest segments in $P_{n-1}$ to obtain the new polyline $P_n$.

The above algorithm evaluates a single transformation by considering all the pairs of segments of the two scans that are $O(n^2)$.

### 2.3 Transforming and Fusing Scans

Once the best transformation $t$ has been found, the third and last step of our method transforms the second scan $S_2$ in the reference frame of $S_1$ according to $t$ obtaining $S_2^t$.

The map that constitutes the output of our scan matching method is obtained by fusing the segments of $S_1$ with the segments of $S_2^t$. To this end, we use the idea of matching chains. A matching chain of the pair of scans $S_1$ and $S_2^t$ is a set $C = \{(s_1, s^t_{2p}) | s_1 \in S_1 \text{ and } s^t_{2p} \in S_2^t \}$, have a positive matching value for $t$} algebraically closed under segment belong-to relation. Specifically, a matching chain $C$ is such that if $(s_1, s^t_{2p}) \in C$, then also $(s_1, s^t_{2p}) \in C$ and $(s, s^t_{2p}) \in C$ for all the segments $s$ that have a positive match value (namely, have matched with $s_1$ or with $s^t_{2p}$). We explicitly note that, given an element $(s_1, s^t_{2p})$, the matching chain $C$ that contains (that is generated by) $(s_1, s^t_{2p})$ is uniquely identified. A transformation $t$ generates a set of (disjoint) matching chains. The main idea behind the fusion of segments is that each matching chain (i.e., each set of matching segments) is substituted in the final map by a single polyline. Therefore, the final map is obtained by adding the polylines that represent the matched segments to the unmatched segments of $S_1$ and $S_2^t$. The problem is thus reduced to build a polyline that approximates the segments in a matching chain $C$. With this polyline, it is easy to smoothly connect the different segments inserted in the final map.

The solution to the above problem consists in iteratively building a sequence of approximating polylines $P_0, P_1, \ldots$ that converges to the polyline $P$ that adequately approximates (and substitutes in the resulting map) the matching segments in $C$. The polyline $P_0$ is composed of a single segment connecting the pair of farthest points in $C$. Given the polyline $P_{n-1}$, call $s$ the segment in (a pair belonging to) $C$ that is at maximum distance from its (closest) corresponding segment $s$ in $P_{n-1}$. If the distance $d(s, s)$ is less than the acceptable error, then $P_{n-1}$ is the final approximation $P$. Otherwise, $s$ substitutes $s$ in $P_{n-1}$ and is connected to the two closest segments in $P_{n-1}$ to obtain the new polyline $P_n$.

### 3 EXPERIMENTAL RESULTS

The method presented in this paper has been coded in ANSI C++ employing LEDA libraries 4.2 (LEDA Library, 2004) for two-dimensional geometry and has been run on a 1GHz Pentium III processor with Linux SuSe 8.0. We considered 31 pairs of scans (from $S_1$ to $S_2$ to $S_31$ to $S_32$) that have been acquired by driving the robot manually and without recording any odometric information. The scans have been collected in a laboratory, a very scattered environment, in a narrow hallway with rectilinear walls, and in a department hall, a large open space with long perpendicular walls. The correctness of the scan matches has been determined by visually evaluating the initial scans and the final map with respect to the real environment. For every scan match, we tested the basic method and the three heuristics, sometimes modifying the values of the parameters.

In general, our experimental results demonstrate that our method performs very well: 28 pairs of scans out of 31 have been correctly matched. Unsurprisingly, the histogram-based heuristic worked well with scans containing long and perpendicular segments, as those taken in the hallway and in the hall. The heuristic based on consecutive segments seems to work well in all three kinds of environment, even if sometimes it needs some parameter adjustments.

Table 1 shows the results obtained for three interesting scan matches (see also Fig. 1). $S_4$ and $S_5$ were taken inside the laboratory: they contain a large number of short segments since the environment is highly scattered. $S_{18}$ and $S_{19}$ were taken along the hallway: they contain fewer segments than the previous scans.
and are characterized by long rectilinear segments. $S_{25}$ and $S_{26}$ were taken in the hall: they contain only few segments since the environment is characterized by long rectilinear and perpendicular walls.

Table 1: Some experimental results

<table>
<thead>
<tr>
<th># of segments</th>
<th>$S_4$</th>
<th>$S_5$</th>
<th>$S_{18}$</th>
<th>$S_{19}$</th>
<th>$S_{25}$</th>
<th>$S_{26}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>9.36 (41260)</td>
<td>9.32 (3096)</td>
<td>9.38 (231)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consecutive</td>
<td>1.25 (12)</td>
<td>0.73 (27)</td>
<td>0.65 (4)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random</td>
<td>7.60 (1)</td>
<td>2.51 (1)</td>
<td>0.78 (1)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Histogram</td>
<td>3.39 (154)</td>
<td>1.97 (192)</td>
<td>0.13 (182)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

1 [Number of possible transformations that have been evaluated]
2 Obtained by generating about 200000 angles

4 CONCLUSIONS

We have described a method for scan matching that works without any information about the relative positions of the two scans but relies exclusively on the geometrical features of the scans. This is the major feature which distinguishes our method from most of the scan alignment and matching methods reported in the literature. Extensive experimental results validated the effectiveness of the approach. We are working to apply this method to the integration of $n$ scans.

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