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SCAN MATCHING WITHOUT ODOMETRY INFORMATION

Francesco Amigoni, Simone Gasparini
Dipartimento di Elettronica e Informazione, Politecnico di Milano
Piazza Leonardo da Vinci 32, 20133 Milano, Italy
Email: amigoni@elet.polimi.it, gasparini@airlab.elet.polimi.it

Maria Gini
Dept of Computer Science and Engineering, University of Minnesota
Minneapolis, USA
Email: gini@cs.umn.edu

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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 aspect of our algorithm is that it does not require any information on the position where the scans were collected. The algorithm operates by performing a geometric match of the two scans and returns the best fused map obtained by merging the two partial maps. The algorithm attempts to reduce the number of segments in the fused map, by replacing overlapping segments with a single segment. We present heuristics to speed up the computation, and experimental results obtained with a mobile robot in an indoor environment.

1 INTRODUCTION

The increasing use of mobile robots equipped with laser range scanners has stimulated the development of methods for 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).

In this paper we present a method for matching two scans that does not require any odometry information. 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 laser range scanner (mounted on a mobile robot at a given height) a sequence of distance measurements along directions separated by a programmable angle (one degree, in our case). 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 (Gonzáles-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 a 2D surface and that walls and vertical objects are at the height of the laser scan. The method proposed in this paper can correctly match two scans even when their displacement is significative, provided that they have an overlap containing at least an angle representing the same portion of the environment.

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

1. determine 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 $S_{1,2}$.

The main advantage of our scan matching method is that, since it is independent of any prior knowledge about the relative position of the scans, it is applicable indifferently in situations in which the two scans have been perceived by the same robot at different time instants, as well as in situations in which the two scans have been perceived by two robots in two different locations. In both cases, $S_1$ and $S_2$ are matched only on the basis of the geometrical information they contain. For this reason, our scan matching method is naturally applicable to multirobot map building (Simmons et al., 2000; Burgard et al., 2002). In this context, the map merging problem, namely the problem of building a global map from data collected...
by several robot, is usually solved by extending the SLAM techniques (Burgard et al., 2002; Williams et al., 2002; Stewart et al., 2003; Fenwick et al., 2002), the EM techniques (Simmons et al., 2000; Thrun et al., 2000), or a combination of the two approaches (Thrun, 2001). All these map merging techniques rely on the assumption that the robot positions are known. For example, in (Simmons et al., 2000; Burgard et al., 2002) the positions of the robots are assumed to be known at every time instant; in (Thrun et al., 2000) the robots don’t know their relative start position but it is assumed that each robot starts within sight of a robot, called the team leader. Our scan matching method could be employed to merge overlapping maps of different robots without knowing their positions, since the method is fully independent of the displacement between the maps. In the following, we refer to the single robot case but all the results are applicable to the multirobot case.

This paper is structured as follows. The next Section reviews the state of the art in scan matching methods. In Section 3 we describe in detail our method and in Section 4 we discuss the experimental activity performed to validate it. Section 5 concludes the paper.

2 THE SCAN MATCHING PROBLEM

Scan matching is the process of calculating the translation and rotation of a scan to maximize its overlap with a reference scan. The translation and rotation can be represented by a displacement vector. Most of the scan matching methods discussed in the following employ laser range scanners, since they guarantee more accuracy and reliability than sensors like sonars.

A number of scan matching algorithms have been presented in the last two decades; they differ for the kind of environments in which they perform well (e.g., linear, rectilinear or polygonal environments) and for the required computational effort. For example, the method proposed in (Weiss et al., 1994) adopts cross-correlation to approach the problem. From the actual and previous point scans, angle and distance histograms are extracted and cross-correlated. The maxima of the respective cross-correlation functions give the rotation and the translation between the two scans. The method uses odometry for an initial position estimate, since evaluation of cross-correlation functions might be erroneous for large displacements between scans. The major drawback of this method is that the algorithm performs well only in environments consisting of straight perpendicular walls and it only allows for minor changes of the environment. The improvement in (Röfer, 2001) deals with non-perpendicular walls and segment maps, even if it still assumes straight walls and shows poor performances in scattered environments.

Another well-known technique is the iterative algorithm of (Cox, 1991) for matching range scans to an a priori map of line segments. Since it assumes small displacements between a scan and the map, the algorithm first finds the correspondence between scan points and line segments and then calculates the translation and rotation that minimize the (square of all) point-to-segment distances. The two steps are repeated until the process converges. Each iteration returns a position correction vector and a variance-covariance matrix that evaluates the match. This approach has been extended by (Gutmann and Schlegel, 1996): instead of having an a priori model of the environment, line segments are extracted from the previous scans and used as the reference model for the matching process. Rejection criteria are used for reducing the amount of false point-to-line assignments in order to speed-up the method. These last two methods can be applied only to polygonal environments, a limitation that our method tries to partially overcome.

The IDC (Iterative Dual Correspondence) algorithm (Lu and Milios, 1997) performs well in rectilinear as well as in irregular environments. Like (Cox, 1991), IDC iteratively minimizes an error measure by first finding a correspondence between points in the reference scan and points in the actual scan, and then doing a least square minimization of all point-to-point distances to determine the best translation and rotation. An initial position estimate is provided through odometry to avoid erroneous alignments. The computational cost of IDC is high and the method does not seem to be suited for polygonal environments. Thus, (Gutmann and Schlegel, 1996) proposed a scan matching method that combines (Cox, 1991) (used in polygonal environments) and IDC (used in non-polygonal environments). IDC-S (IDC-Sector) (Bengtsson and Baerveldt, 1999) reduces noise sensitivity of original IDC and copes with dynamic environments. All these methods employ information obtained from odometry.

The method proposed in (Zhang and Ghosh, 2000) extracts line segments from range points and uses a special Center of Gravity representation for describing the uncertainty of line segments. Relying on odometry readings as initial estimate for the displacement vector, it matches pairs of segments and computes the translation by least square minimization, as in (Lu and Milios, 1997).

The method presented by (Einsele, 1997) uses a panoramic range finder to build segment maps. It extracts line segments representing walls or other boundaries of the environment and matches the scans taken from different positions without relying on any additional source of information. This is done by employing dynamic programming algorithms applied to
the vertical lines of the map. It can operate in polygonal or rectilinear environment but it doesn’t work well in scattered environments and it relies on small displacement of the robot.

Finally, the method illustrated in (Martignoni III and Smart, 2002) extracts line segments from laser range readings and matches the actual map and a global map incrementally built during the exploration. It first determines the heading between the two maps by computing the histogram of the angle differences and then adjusts the translation by overlapping the line segments with least square minimization. The method works in linear and static environments and with very small displacements between two maps; the method can also perform a global search, but it becomes slower and prone to errors in environments with many similarities.

3 THE PROPOSED METHOD

This Section details the three main steps of our method for scan matching. In the algorithms, two points are considered to coincide when they are closer than POINTDISTANCETOLERANCE (in our experiments we set this parameter to 15 mm) and two angles are considered equal when their values differ for less than ANGLEDIFFERENCETOLERANCE (in our experiments we set this parameter to 0.2 rad).

3.1 Determining the Possible Transformations

This step, given the scans $S_1$ and $S_2$, first finds the angles between segments in $S_1$ and between segments 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 $S_1$. Recall that 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 $O(n_1^2n_2^2)$ 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. The three heuristics are described in the following.

1. Considering Angles between Consecutive Segments. In each scan, we select the angles between two consecutive segments; let $A_1^S$ and $A_2^S$ 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 $A_1^S$ to correspond to an equal angle in $A_2^S$. The number of possible transformations found by this method is $O(n_1n_2)$.

Although this method seems to perform well in indoor environments where the angles are usually regular, the errors introduced by the sensor and by the algorithm that approximates points with segments alter the representation of these regular angles. For example, Fig. 1 shows the segment representation of a portion of an environment with four right angles. It is evident that the angles between consecutive segments sometimes do not constitute a good model of the environment angles.

![Figure 1: A portion of a scan representing four right angles of the environment](image)

To improve the performance of this heuristic, it is possible to consider angles between consecutive segments without a common extreme point (when an order is defined for the segments of a scan) by setting the parameter NONCONSECUTIVEEDGES to “yes”. Consecutive segments can be considered to form significant angles only if they are longer than a fraction (specified by the parameter SEGMENTLENGTHPERCENTAGE) of the longest segment in the scan. The implicit assumption is that long segments are more reliable than short segments in representing the environment.

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 $A_1^r$ and $A_2^r$ 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 $A_2^r$ to correspond to an equal angle in $A_1^r$. The number of transformations generated by this method is $O(a_1a_2)$, where $a_1 = |A_1^r|$ and
\[ a_2 = |A_2'| \] are the number of selected angles in \( A_1' \) and \( A_2' \), 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 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 iterate with \( k = 1, \ldots, K \). During the \( k \)-th iteration, we use a threshold equal to \( \text{SEGMENTDIVISIONFACTOR} \times \text{length of the longest segment in } S_1 \) (resp. \( S_2 \)). Out of the segments longer than this threshold we select one with equal probability. Thus, the parameter \( \text{SEGMENTDIVISIONFACTOR} \) determines the length of the segments that are considered for selection and, implicitly, the probability of selection. This technique tries first to find transformations based on angles between long segments; then it progressively considers transformations based on angles between shorter and shorter segments. The above technique can be further improved by stopping the generation of transformations when a “good enough” transformation is found. (The evaluation of the quality of a transformation is discussed in Section 3.2.)

3. Considering Angles between Perpendicular Segments. In each scan, we select only angles between perpendicular segments. This heuristic is particularly convenient for indoor environments, where the presence of regular walls usually involves perpendicular segments. The heuristic is based on histograms. The histogram of \( S_1 \) (and, in similar way, that of \( S_2 \)) is an array of \( n \) slots elements, where \( n \) is the number of buckets of the histogram. Each bucket \( L_i \) (\( i = 0, 1, \ldots, n \) slots – 1) contains the segments with orientation comprised between \( \pi \times i/n \) and \( \pi \times (i + 1)/n \) slots, measured with respect to a given reference axis. To each element \( L_i \) of the histogram of \( S_1 \) is associated a value calculated as the sum of the lengths of the segments in \( L_i \). The principal direction of an histogram is the element with maximum value. The normal direction of an histogram is the element that is \( \pi/2 \) rad away from the principal direction. In Fig. 2, the histogram of a scan taken in an indoor environment is shown. The principal direction is the element \( L_9 \) and the normal direction is the element \( L_0 \). Let \( A_1'^{h} \) and \( A_2'^{h} \) be the sets of angles formed by a segment in the principal direction and by a segment in the normal direction of the histograms of \( S_1 \) and \( S_2 \), respectively. The set of possible transformations is then found comparing the angles in \( A_1'^{h} \) and \( A_2'^{h} \). The number of possible transformations generated by the above heuristic is \( O(p_1 n_1 p_2 n_2) \), where \( p_i \) and \( n_i \) are the number of segments in the principal and normal directions of the histogram of scan \( S_i \).

![Histogram](image)

**Figure 2:** The histogram of a scan

3.2 Evaluating the Transformations

Every transformation found in the previous step is evaluated in order to identify the best one. To determine the goodness of a transformation \( t \) we transform \( S_2 \) on \( S_1 \) in the reference frame of \( S_1 \) according to \( t \) (obtaining \( S_2' \)), then we calculate the approximate length of the segments of \( S_1 \) that correspond to (namely, match with) segments of \( S_2' \). The measure of a transformation is the length of the corresponding segments that the transformation produces. More precisely, the measure of a transformation is the sum of all the matching values calculated for every pair of segments \( s_1 \in S_1 \) and \( s_2' \in S_2' \). The matching value between two segments \( s_1 \) and \( s_2' \) is calculated as follows. We project \( s_1 \) on the line supporting \( s_2' \) thus getting a projected segment \( s_2'_{p1} \) and then we compute the length \( l_1 \) of the common part of \( s_1 \) and \( s_2'_{p1} \); we do the same but projecting \( s_1 \) on \( s_2' \), obtaining \( l_2 \). The matching value of \( s_1 \) and \( s_2' \) is calculated as the average of \( l_1 \) and \( l_2 \). When \( s_1 \) and \( s_2' \) do not intersect, the matching value is multiplied by \( 0.95d(s_1, s_2')/\text{POINTDISTANCETOLERANCE} \) to penalize the match between segments that are far away. Note that ln(0.95) is an empirical constant whose value has been determined during experimental activities and \( d(s_1, s_2) \) is the distance between two segments, calculated as

\[
d(s_1, s_2) = \min(\max(\text{dist}(s_1, \text{start}(s_2))), \text{dist}(s_1, \text{end}(s_2))), \max(\text{dist}(s_2, \text{start}(s_1))), \text{dist}(s_2, \text{end}(s_1))\)
\]

where start(s) and end(s) are the extremes of segment s (see Fig. 3). Finally, two special cases can appear during the evaluation of the matching values of \( s_1 \) and \( s_2' \). The matching value is set to 0.
Specifically, a matching chain algebraically closed under segment belong-to relation.

Therefore, the final map is obtained by adding the matching method is then obtained by fusing the matching chain (i.e., each set of matching segments) generates a set of (disjoint) matching chains. The matching value is set to 1 when the two segments intersect and are longer than \( \text{SEGMENT LENGTH REFUSE} \); in this case the transformation is discarded.

The above algorithm evaluates a single transformation by considering all the pairs of segments of the two scans that are \( O(n^2) \). A way to limit this computational effort is to stop the evaluation of a transformation \( t \) when its measure cannot be larger than the current maximum.

### 3.3 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 \( S_2' \).

The map that constitutes the output of our scan matching method is then obtained by fusing the segments of \( S_1 \) with the segments of \( S_2' \). To this end, we use the idea of matching chains. A matching chain of the pair of scans \( S_1 \) and \( S_2' \) is a set \( C = \{ \langle s_1, s'_2 \rangle | s_1 \in S_1 \text{ and } s'_2 \in S_2' \} \) having a positive matching value for \( t \) algebraically closed under segment belong-to relation.

Specifically, a matching chain \( C \) is such that if \( \langle s_1, s'_2 \rangle \in C \), then also \( \langle s_1, s \rangle \in C \) and \( \langle s, s'_2 \rangle \in C \) for all the segments \( s \) that have a positive match value (namely, have matched with \( s_1 \) or with \( s'_2 \). We explicitly note that, given an element \( \langle s_1, s'_2 \rangle \), the matching chain \( C \) that contains (that is generated by) \( \langle s_1, s'_2 \rangle \) 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 \( S_2' \). 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 \( \bar{s} \) in \( P_{n-1} \). If the distance \( d(s, \bar{s}) \) is less than the acceptable error, then \( P_{n-1} \) is the final approximation \( P \). Otherwise, \( s \) substitutes \( \bar{s} \) in \( P_{n-1} \) and \( s \) is connected to the two closest segments in \( P_{n-1} \) to obtain the new polyline \( P_n \).

## 4 EXPERIMENTAL RESULTS

The method we presented has been validated using a Roboter mobile platform equipped with a SICK LMS 200 laser range scanner mounted in the front of the robot at a height of approximately 50cm. For our purposes we chose to acquire scans with angular resolution of 1 degree and with 180 degrees angular range. As already said, each scan obtained by the laser range scanner has been processed to find a set of segments that approximate the points returned by the sensor, according to the algorithm described in (González-Baños and Latombe, 2002). 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 \( S_1 - S_2 \) to \( S_{11} - S_{32} \)) 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: Summary of experimental results for the different methods of computing transformations between two scans

<table>
<thead>
<tr>
<th></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># of segments</td>
<td>47</td>
<td>36</td>
<td>24</td>
<td>24</td>
<td>10</td>
<td>12</td>
</tr>
<tr>
<td>All</td>
<td>936 s [41260](^1)</td>
<td>32 s [3096]</td>
<td>0.38 s [231]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consecutive</td>
<td>1.25 s [2]</td>
<td>0.73 s [27]</td>
<td>0.13 s [4]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random(^2)</td>
<td>7.69 s</td>
<td>2.51 s</td>
<td>0.78 s</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Histogram</td>
<td>3.29 s [73]</td>
<td>1.97 s [192]</td>
<td>0.15 s [32]</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^1\) Number of possible transformation that have been evaluated  
\(^2\) Obtained by generating about 20000 angles

In the following we discuss some interesting scan matches (Table 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 and the presence of chair and table legs produces an high number of small segments (Fig. 4). The heuristic that works better is that based on consecutive segments: it was able to find a good transformation evaluating only two transformations; on the other hand, the evaluation of all the possible transformations is infeasible (over 40000 matches to evaluate!). \( S_{18} \) and \( S_{19} \) were taken along the hallway: they contain fewer segments than the scans previously discussed and are characterized by long rectilinear segments (Fig. 5). Even in this case, evaluating all the transformations is expensive, while the consecutive-segments heuristic performs well. Finally, \( S_{25} \) and \( S_{26} \) were taken in the hall: they contain only few segments since the environment is characterized by long rectilinear and perpendicular walls (Fig. 6). All the heuristics perform well in this case because, starting from a small num-
number of segments, there are only few transformations that are easy evaluate.

For scan pairs $S_1 - S_2$ and $S_2 - S_3$ our method was not able to find the correct transformation. As shown in Fig. 7, the scans, taken in the lab entrance, are extremely rich of short segments representing scattered small objects (chairs, tables, robots, and boxes). It is almost impossible, even for a human being, to find the correct match between these scans without any prior information about their relative positions. Similar problems emerged in the hall. Fig. 8 shows scans $S_{27}$ and $S_{28}$, where the second one has been taken after rotating the robot of about 100 degrees. Since the environment is large and has only few objects that can be used as reference, a drastic change of the field of view eliminates any common reference between scans, thus automatic matching is impossible.

We now briefly discuss the role of the parameters that mostly influence the performance of our method. POINTDISTANCETOLERANCE influences the matching value of two segments and the transformation discharging. In the same way, large values for SEGMENTDISTANCETHRESHOLD make segments that do not represent the same object in the environment to match; small values reduce the number of matching segments thus making the method more sensitive to measurement errors. Large values of ANGLEDIFFERENCE TOLERANCE facilitates the search of the best transformation by allowing a lot of possible transformations to be considered (but their evaluation requires more time). Small values of SEGMENTLENGTHPERCENTAGE lead to consider more short segments and to generate more transformations to evaluate, while large values allow to consider only longer segments in the map, this is useful in the case of long segments representing walls.

5 CONCLUSIONS

We have described a powerful 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 validate the effectiveness of the approach.

We are working to apply the method described in this paper to the integration of $n$ scans. This problem will be tackled in two steps: initially we will try to integrate a sequence of $n$ scans and then we will try to extend the techniques to the integration of a general set of $n$ scans, acquired by a single robot or by different robots.

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