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A New Approach to Segmentation of 2D Range Scans into Linear Regions

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Abstract—Toward obtaining a compact and multiresolution representation of 2D range scans, a wavelet framework is proposed for encoding an orientation measure called Running Angle (RA). A new shrinkage algorithm is developed using discrete wavelet transform of the RA signal, which leads to a simplified polyline approximation of the initial scanned points. This approach is evaluated in terms of segmentation of 2D range scans as a line extractor. As a proof of concept, an experiment is performed in our laboratory hallway by a mobile robot equipped with two SICK laser range finders which shows that it is possible to successfully segment raw measurements of the scanner using the proposed approach and obtain proper linear abstraction.

Besides a simple, fast heuristic line extraction algorithm is also proposed for the sake of comparison. It is based on thresholding the changes of the incident angles between the laser beam and the vertices of the initial polygon observed by the scanner. Despite its simplicity, this approach performs rather well and can be used in structured environments with low measurement noise. Both approaches are experimentally evaluated and compared with some well known and commonly used line extraction algorithms.

I. INTRODUCTION

Obtaining abstractions over raw sensory measurements is an important capability of a mobile robot and a key issue in autonomous navigation. When dealing with range sensors, the abstraction is usually achieved via grouping the measurements into objects or extraction of some geometrical primitives. Range sensors are quite common in mobile robotics. With the laser scanners available today such as SICK, a rather precise range measurement is achievable with a wide field of view in high frequency. They are very well accepted in the mobile robot community as a basic range sensor and many researchers have already used them [1], [2], [3]. Starting with an array of 2D scanned points, line extraction is commonly used for localization and mapping [4], [5], [6].

Piecewise linear approximations are also very common in simplification of object boundaries and shape encoding or representation of obstacles and navigable areas in path planning. For such applications usually polylines are used. Polyline is a sequence of line segments connected at their endpoints. Polyline, in comparison to line or segment based representations, offer more information by preserving the connectivity between segments which in turn gives rise to the features like corners or higher level interpretations of the scene toward understanding its topology. In the context of mapping, representing indoor environment by polylines leads to less features in the map and provides some enhancements over line-based models; mainly by linking individual line segments to a more comprehensive spatial context and allowing for better

approximation of arbitrary (e.g. curved) contours. Also, self-intersecting boundaries are avoided [7]. In addition, as the map gets more compact, single features become more informative and distinctive, reducing the complexity of data association.

In the mobile robotics community, line extraction is well studied (see the next section) but polylines are not considered by many researchers. Only a few authors study them [8], [7], [9], [10]. However, in computer vision, polylines have been extensively studied in context of handling boundary contours of objects or image segments, see [11] for an overview. A major difference is that usually in computer vision, the polyline vertices are assumed to be a subset of the given initial points. While in robotic mapping each single measurement is not reliable enough, so final vertices should be obtained by fitting a polyline model to the sensory readings which makes the problem more complex. In this paper these two problems are referred to as polyline simplification and polyline extraction respectively.

In our research, we pursue compact representations of the sensory data, mainly range scans, with application to autonomous navigation. In particular we are interested in creating a multi-resolution representation using wavelet transform to better capture the important and more informative parts of the raw sensory input in the form of a hierarchy of polylines at different levels of abstraction. This is very useful in place recognition/loop detection and also creation of the structure annotated maps for mobile robots.

In the present paper some of the preliminary results are reported in the segmentation of 2D scans. The wavelet based approach in this stage, simplifies the obtained polygon from the scanner by accepting a subset of initial points as vertices and rejecting the rest. This serves as the first stage in polyline extraction needed in robotic mapping. The necessary fitting algorithm will be studied in the future work. Hence, the proposed method is evaluated as a line extractor which reflects the segmentation performance. It is worth mentioning that in polyline extraction, segmentation is the most important step in which it is decided how much details to keep and where are these details located. It is shown that it is possible to do this using the presented wavelet shrinkage algorithm. In fact, in an analogy to polyline extraction using EM [10], segmentation is the result of the expectation phase.

In order to perform the desired segmentation, two measures of direction are introduced, called *Bearing Angle* (BA) and *Running Angle* (RA). The BA considers incident angles between the laser beam and the vertices of the initial polygon

observed by the scanner. The RA is obtained by adding the beam direction to the BA and shows the orientation of edges of the observed polygon. The discontinuities in the laser path are detected by thresholding the BA, which gives better results when compared with the common approach of thresholding directly the changes in range values. Then each continuous segment is broken into linear parts by two different approaches: thresholding of the BA derivative and wavelet based simplification of the RA. The first approach is a heuristic algorithm useful for line extraction. It is mainly discussed here for the purpose of comparison and also to show how much one can gain out of such a simple method. However, the main focus of the paper remains in the second approach. Although in the experiments presented here, it sits beside other line extraction algorithms; it is actually aimed for the multiresolution representation of the range information in the form of polylines. In this paper, the goal is to test it as a line extractor to quantitatively study its outcome in the segmentation. This is a key issue considering its wavelet-based nature. Successful segmentation means the algorithm is able to detect informative and important details among the rest of coefficients affected by measurement noise.

In order to quantitatively test the outcome of each approach in segmenting the range scans, a comparison is made using the results of the experiment originally reported in [12] including the performance of six well known and commonly used line extraction algorithm in mobile robotics and computer vision fields. The same dataset as [12] is used here including 100 real 360 degree 2D range scans collected in an office environment covering roughly $80m \times 50m$ area and the corresponding manually extracted lines as the ground truth. Finally the output of each algorithm is statistically evaluated using the ground truth.

II. RELATED WORK

Apart from the line fitting stage, approaches to line extraction described in the literature can be classified into four groups: generalization (also called incremental), iterative splitting, Hough Transform and general random optimization.

Generalization techniques [7] also called Incremental, use the circular order of the points provided by the laser range finder and start with a window of consecutive points. Line parameters are obtained for these points and subsequent points are tested whether they belong to the current line or not based on their distance to the line or certain condition on the updated line parameter with their contribution (e.g. max variance). Examples of such algorithms are used in [13], [14], [15].

Iterative splitting is performed recursively. In the beginning all points are considered to be on the same line. Thereafter at each step, the line is broken at the furthest point and the process is repeated for each of the two segments. The stopping criterion is usually defined using the distance of the furthest point or based on the covariance matrix of the line parameters. Different variations of this idea exist, also called *Split and Merge* [16], [17], [12]

Hough Transform (HT) is brought from computer vision [16] to robotic mapping. Approaches based on the HT map Euclidean space of the data points to the parameter space; in this case line parameters. Cells or clusters in Hough space are interpreted as support for a specific set of parameters. Hence, it is basically a voting mechanism and can be particularly valuable to deal with fragmentary observations and scattered points (when no order information is available). This idea is extended to handle uncertainty of measurements [6]. The *Line Regression* approach presented in [5] is also similar to the idea of HT but benefits from the order of the points.

As examples of the fourth group, the *Expectation Maximization* (EM) [13], [6] and *Random Sample Consensus* (RANSAC) [18] are among the most famous line extraction methods. The main drawback of these algorithms is their inherent random nature which does not let to guarantee their performance or in case of EM the final outcome may be a local minima. Therefore, they are less suitable for real-time applications.

When dealing with polylines, EM is still applicable. In [9], an extension to EM is proposed for adapting the number of model components. The approach presented in [10] also lies in the same category. However, in these approaches first map is build by registering the scan points and then the simplification process is started. In the context of computer vision, Discrete Curve Evolution (DCE) introduced in [19], [20] does the polyline simplification based on a relevance measure in $O(n \log n)$.

The direct thresholding approach presented in this paper is a heuristic method that does not belong to any of these categories. However, among them, it is most similar to the incremental category but without intermediate line fittings which is done to decide where to break the line. This difference make it much faster but also more sensitive to noise. The wavelet based approach is a polyline simplification method tested as line extractor here. It is similar to DCE in the sense that it simplify the initial point array by rejecting some of the wavelet coefficient as irrelevant details. In its current state, it can be used for boundary simplification tasks. However, it should be further developed and enhanced with a polyline fitting process to be able to extract polylines out of range scans as features suitable for robotic mapping.

III. LINE EXTRACTION

A. Bearing and Running Angles

To benefit from circular order of points obtained from laser range finder, a relative measure of direction is introduced called *Bearing Angle* (BA). BA is the angle between the laser beam and the line passing through each pair of measurement points; see Fig. 1(b). Having an array of range measurements as input, a corresponding array of BA values is calculated (Fig. 1(c)). More formally:

$$BA_i = \arccos \frac{\rho_i - \rho_{i-1} \cos d\phi_i}{\sqrt{\rho_i^2 + \rho_{i-1}^2 - 2\rho_i\rho_{i-1} \cos d\phi_i}}$$

ρ_i is the i th depth value and $d\phi_i$ is the corresponding angle increment (scanner angular resolution). Since normally $d\phi_i$ is constant with laser scanners, the term $\cos d\phi_i$ is a constant factor depending on the resolution of the scanner and need not to be recalculated for each point. It is worth mentioning that BA can be calculated for range matrices also. It is enough to choose a direction for tracing the matrix (row-wise, column-wise, or any diagonal direction) and then calculate the BA for the resulting array. With this approach, it is possible to get a one-dimensional direction measure which highlights direction changes along the selected axis in the range image. This can be used in range image segmentation [21].

To obtain a angular measure which remains constant in linear parts of the scene, *Running Angle* (RA) is defined as the orientation of the line passing through each pair of measurement points in the scanner coordinate system (Fig. 1(c)). RA is simply obtained by adding orientation of the laser rays to the BA: $RA_i = BA_i + \phi_i$ where ϕ_i is the orientation of the i th laser ray. When the scanner measures the range counter clockwise at constant angular steps, $\phi_i = (i - 1) * d\phi_i$.

Apart from a length normalization, RA is very similar to tangent space representation used in shape encoding and recognition. Tangent space representation uses normalized curvature length. This leads to a fixed-length vector and is considered as a shape characteristic, while RA is a boundary representation with variable length. RA is later encoded in wavelet domain as a rectangular signal.

B. Finding Breakpoints

As a preprocessing step, the input range array should be segmented into continuous parts corresponding to single

entities or connected regions of the environment. Discontinuities, i.e. where the laser beam jumps from one object to another, are usually detected by thresholding depth changes. For example, in [12] step changes in range values are used to cluster the point array for speeding up the line extraction process. Likewise [7] uses such an approach to find continuous segments in the data for polyline simplification. However, since in laser range finders like SICK, the environment is sampled at constant angle increments, the distance between successive points changes with their range and is not a good indicator of discontinuity. We detect the discontinuities by thresholding the BA; see blue circles in Fig. 1(a). When BA is near 0 or 180 degrees and the range change is beyond the sensor noise, the direction of the environment is nearly parallel to the laser beam; hence, the laser does not hit the target and jumps to the next visible surface. Therefore, detection of the laser jumps is possible by thresholding the BA:

$$Jump = \{i \mid |\cos BA_i| > \cos \Phi_{Jump} \ \& \ |\rho_i - \rho_{i-1}| > d_{min}\}$$

where Φ_{Jump} and d_{min} are fixed thresholds, set to 5 degrees and 6 centimeters respectively in the experiments presented in this paper. We use cosine of the BA for thresholding since this is more efficient in the implementation.

Since both BA and RA are calculated based on just two successive points, they are affected by measurement noise. However, we will show that they are still useful for segmentation of the range scans as long as the scene does not contain open angle corners. This fact can help to distinguish between the effect of noise and the change of direction in the environment. Two different approaches is considered for segmenting the input range array:

1) *Direct Thresholding*: Changes in successive values of the BA when the laser is scanning planes or smooth surfaces in the scene, is generally smaller than the step jumps coming from changes of direction in the environment. Therefore, the BA can be used to extract lines or smooth curves simply by searching for its big jumps:

$$Turn = \{i \mid |BA_i - BA_{i-1}| > \Phi_{Turn}\}$$

where the line break threshold, Φ_{Turn} , is set to 40 degrees in our experiments. Line or smooth curve break points are given by the union of the tagged discontinuities (*Jump*) and turn points (*Turn*).

2) *Wavelet Shrinkage*: A more robust approach for simplifying the environment shape and segmenting its range scan into linear regions is to try to simplify the corresponding RA as a direction signal using signal processing methods. We propose to benefit from *Discrete Wavelet Transform* (DWT) [22]. In each continuous region, RA is simplified and compressed as a rectangular signal by ignoring unimportant details. Resulting RA signal (Fig. 2(d)) gives an abstraction over initial signal since it is reflecting more or less the same geometry but its value (corresponding to the environment direction) changes much less frequently. Using changes of the simplified RA signal, which correspond to major direction changes in the environment, line end points are obtained:

Fig. 1. (a) A sample 2D laser scan taken in our laboratory hall and the extracted lines using direct thresholding approach. Small blue circles show discontinuous points (*Jump*) and the other line-end points are obtained as major changes in the environment orientation (*Turn*). (b) the Bearing Angles for the region in the green oval. (c) the BA (blue, thin) and the RA (red, thick) obtained from the represented scene.

$$Turn = \{ i \mid |\widetilde{RA}_i - \widetilde{RA}_{i-1}| > \Psi_{Turn} \}$$

where $\widetilde{RA}$ denotes the simplified RA signal and $\Psi_{Turn} = 10^\circ$. A simplified polyline representation of the initial continuous region is given by connecting these turn points. In fact, in the process of rejecting some coefficients of the RA signal, it is decided that corresponding points are not contributing much in the simplified polyline and hence they are ignored.

The Haar wavelet (see [23] for an easy introduction) is selected for the DWT, since it best replicates the final desirable signal shape in our case. Common wavelet shrinkage algorithm based on thresholding of the coefficients is not applicable here, since contribution of noise may be very big. In fact, changes of orientation caused by measurement noise can be more noticeable than angle changes coming from corners in the scene. Hence, amplitude of the coefficient cannot be used to separate noise or unimportant details. Therefore a new shrinkage algorithm is proposed.

To distinguish which coefficients to keep and which to ignore (replace by zero), first a smooth version of the initial

signal is obtained by reconstructing the signal excluding its first S levels of detail coefficients. In this stage, discrete *Stationary Wavelet Transform* (SWT) [24] is used since we are interested in major components of the signal regardless of the starting point in the circular order of the input measurements (which is actually determined by the robot orientation). As a result, short lasting noise effects and minor details of the scene are separated. The outcome is similar to a low-pass filtering procedure which at the same time smoothens the informative edges. To be able to keep useful edges in the data unaffected, we don't use the smoothed signal directly. Instead, it is just used as a guide for selection of the important wavelet coefficients of the initial signal. To do this, both original and smoothed signals are transformed to wavelet domain using DWT. Then, the final filtered signal is reconstructed by just picking the DWT coefficients which are corresponding to local extrema of the DWT coefficients of the smoothed signal (Fig. 2(c)). Thus, the smoothed signal just provides the information on which coefficients to select and its coefficients are not used directly in the reconstruction. In other words, the smoothed signal coefficients provide the indices and the values are taken from the coefficients of the original signal. The reconstruction in the second stage is performed by processing the first D levels of the detail coefficients.

S and D are two parameters of the shrinkage algorithm which determine how much abstraction is needed. They directly affect the amount of compression and consequently shape of the final polyline (compare Fig. 2(a) and Fig. 2(b)). For our experiments, we put $S = 3$, $D = 2$

C. Line Fitting

Knowing the break points, a linear model is fitted to each segment in a least square sense (see [5]), and lines with similar parameters are merged. Points with distance greater than 2cm to the line are considered as outliers and segments with more than 20% of outliers are rejected as linear segments. Covariance matrix of each line is also calculated and used in merging collinear adjacent segments based on Mahalanobis distance and 75% confidence interval. After merging, segments shorter than 40cm or supported by less than 9 points are filtered out. These parameters are adjusted for navigation and mapping, mainly in order to filter out moving humans and small furniture which may be moved later on.

IV. RESULTS

To evaluate the effectiveness of the introduced algorithms in segmentation of the range scans in real scenarios and compare their performance against common line extraction algorithms, the same benchmark dataset as [12] is used. Likewise, the same setting is chosen for the common parameters of the algorithms. The benchmark consists of one hundred 2D laser scans (360° view) of our laboratory hallway. The raw data is obtained using a mobile robot in a normal working day and without any preparation of the environment. Dataset also includes manually extracted line segments considered as ground truth (totally 679 lines). Apart from speed which is

Fig. 2. (a) Output polylines of wavelet based approach with $S = 3$, $D = 2$ (b) More abstraction is obtained when $S = 7$, $D = 5$ (c) DWT coefficients of a sample continuous segment: original RA in green(light) circles, smoothed RA in red(dark) circles and selected for reconstruction in blue asterisks (d) Reconstruction of RA signal (depicted in Fig. 1(c)) with two different parameter settings for high and low level of abstraction

TABLE I
BA-BASED LINE EXTRACTION PERFORMANCE VS. OTHER ALGORITHMS

Algorithm ^a	Complexity	N.Lines	Correctness		Precision	
			TruePos [%]	FalsePos [%]	$\sigma_{\Delta r}$ [cm]	$\sigma_{\Delta \alpha}$ [deg]
Direct Thresholding	N	835	75.6	16.7	1.99	0.67
Wavelet Shrinkage	N	828	76.9	11.2	1.80	0.63
Split-and-Merge	$N \times \log N$	641	86.0	8.9	1.95	0.74
Incremental	$S \times N^2$	567	79.2	5.1	2.04	0.76
Line Regression	$N \times N_f$	562	75.8	8.4	1.97	0.79
RANSAC	$S \times N \times N.Trials$	547	70.7	12.2	1.37	0.70
Hough Transform	$S \times NC \times (N + NR)$	600	79.5	10.0	1.51	0.67
EM	$S \times N1 \times N2 \times N$	709	80.3	23.1	1.58	0.73

^aFor comparison purpose, this table is partly reprinted from [12] with permission of the authors.

not applicable, other measures originally reported in [12] are given in Table I. Correctness is measured by:

$$\text{TruePos} = \frac{N_M}{N_T} \quad \text{and} \quad \text{FalsePos} = \frac{N_A - N_M}{N_A}$$

where N_M , N_T and N_A are number of correctly matched lines, number of true lines and number of lines extracted by the algorithm respectively. Precision is obtained by calculating sample variance of the line parameters on the set of matched lines. Matching is done by considering the Mahalanobis distance and 75% confidence interval. Since uncertainty of lines is usually very low, a relatively precise matching is obtained.

As it can be seen from TABLE I, direct thresholding based on the BA, performs well despite its simplicity and speed. In fact, its performance is better than what is expected. However, its main drawback is its sensitivity to noise since it is a heuristic approach which does not benefit from line fitting in intermediate steps to decide about breaking points (in contrast to the algorithms like Split-and-Merge [16] or Incremental [14]). The increase of false positives is the cost of reduced complexity. However, still simple thresholding may perform acceptable when the target environment has sharp corners and a precise sensor is used. Fig. 1(a) shows one of the benchmark scenes with extracted lines.

The wavelet based approach performs slightly better than direct thresholding. However it sometimes extracts lines shorter than their true length. This can be improved by taking into account some more weights for poorly sampled areas besides manipulating the wavelet coefficients instead of simply accepting or rejecting them. However, the main goal of this approach is not line extraction and here we just present it as a proof of concept. It needs to be enhanced and will be further studied in the field of polyline representation in our future work.

A great advantage of the wavelet based approach is its innate multiresolution nature. For the simplicity in the first implementation, the whole scene is treated evenly within the same range of scales and parameters here. However, adaptively adjusting the scale separately for each part of the scene will lead to much better approximation of the initial observation and help a lot to capture true details of the scene.

V. DISCUSSION

The introduced line extraction method based on direct thresholding has linear complexity (as it needs to go through the data one time and calculate the BA). It can be easily implemented for real-time applications with some considerations, e.g. creating lookup tables for triangulation functions when floating point calculation are costly. It makes use of the geometry of the sensor (order of points in the scan) and hence is an incremental algorithm. Since basically it segment the input array to the smooth regions, this method had the possibility to be adapted for extraction of curves regions. This is an advantage over traditional line extraction algorithms and necessary in some applications. As an example we used BA-based extraction of the smooth regions in the context of detecting traversable areas for an autonomous car in outdoor settings. Even dealing with planar surfaces and structured environments may lead to curved laser paths. For example, in range images obtained using a nodding SICK, tracing the depth matrix in vertical direction (column-wise) gives elliptic curves on walls (Fig. 3).

Basically the approach based on thresholding is an edge detection procedure and it may break the lines less or more, based on the threshold. It is discussed in this paper as a means of comparison with the main work on wavelet based algorithm and is not suggested for line extraction when there is a lot of noise in the measurements. However, SICK laser scanners have a better signal to noise ratio when the target is further away.

Fig. 3. 3D point cloud acquired in an office, at left colored column-wise and at right row-wise to better show traces of laser in vertical and horizontal directions

This fact may be used to enhance the method using an adaptive threshold. In addition, dealing with 3D range scans may leave more degrees of freedom in handling the sensitivity to noise. Using morphological operators for noise removal, in [21] BA-based range image segmentation is implemented successfully.

The wavelet based approach in its current configuration basically acts like an anisotropic or shape preserving filter for a rectangular wave (i.e. RA signal). It is important to carefully select the amount of abstraction considering the desired task. In robotic mapping, the repeatability of observations is important, hence the observation should not be simplified too much (as depicted in example shown in Fig. 2(b)) in order to consistently observe the desired features. More abstraction may be useful in reasoning about the scene (ex. place recognition). However, since the scene is evenly sampled in an angular sense, there is a problem with regions far from the sensor which are poorly sampled. In fact such regions will be over simplified and the presented wavelet based algorithm may fail to capture the correct geometry of the environment under this condition (Fig. 2(b)). Adaptively adjusting the scale or compensating the poorly sampled areas with interpolation may be useful, but it needs to be carefully investigated.

Generally, the initial results are promising and suggest that the combination of two different wavelets may enhance the results on capturing the environment shape more efficiently. While the Haar wavelet can capture corners, a regular alternative is more suitable to deal with curved areas. In addition, the shrinkage algorithm explained in this paper may be enhanced by allowing for modification of coefficients instead of just keeping a subset of them. This domain needs much more detailed investigations which are among our current research efforts.

VI. CONCLUSIONS AND FUTURE WORK

Toward obtaining a compact and multiresolution representation of 2D range scans, a wavelet framework was proposed. The orientation of the edges of the initially observed polygon was considered as *Running Angle* (RA) signal. Based on a new shrinkage algorithm applied on the discrete wavelet transform of the RA signal, a simplified polyline approximation of the initial scene was obtained. This approach was tested as a line extractor in order to evaluate its effectiveness in capturing the important details of the scene and segmentation of 2D range scans. The experiments, as a proof of concept, showed that it is possible to successfully simplify raw measurements of the scanner and obtain reasonable segmentation. However, special care should be taken into account to overcome the problem of poorly sampled regions of the scene.

Besides a simple, fast heuristic line extraction algorithm was also proposed and experimentally evaluated. It was based on thresholding the changes of the incident angles between the laser beam and the vertices of the initial polygon observed by the scanner. Despite its simplicity, this approach performed rather well and can be used in structured environments when measurement noise is low.

Investigating the wavelet based approach in more detail and developing a proper polyline fitting phase are among our current undergoing research efforts.

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