Significant Feature Selection in Range Scan Data for Geometrical Mobile Robot Mapping

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Abstract – **Simultaneous Mapping and Localization (SLAM) has become a very important task for mobile robots. Different approaches have been proposed over the last years. Most of them use directly raw data or simple features as geometric representations. Recent works on SLAM have been proposed different geometric representations, which captures more context than other features, permitting an additional cognitive and reasoning mapping. In this paper, we propose a method to select significant features used for constructing polygonal maps for indoor mobile robot navigation. To segment and group raw laser range scan data in polygonal curves (polylines) a discrete curve evolution method (DCE) has been applied. Relevance measure computations derived from DCE, together with length of line segments and turn angles are used to select relevant features. Features selected for a single scan S_t at time t are matched against a subgroup g_{t-1} of features from the global map G_{t-1} at t – 1, obtained from the last known position. A least squares method is applied to find optimal translation and rotation between partial map S_t and the global map G_{t-1}. Finally, maps are merged to get the actualized map G_t.**

Index Terms – Geometric mapping; Autonomous navigation; landmarks; Self-localization.

I. INTRODUCTION

Autonomous mobile robot navigation, a classical topic in mobile robotics, sometimes, it is considered that is now solved. Nowadays, other challenges like cognitive robotics, multi-robot coordination or human robot interaction have been attracted many research teams.

Simultaneous Localization and Mapping (SLAM) techniques are used to construct and maintain regularly a map while at the same time the robot it is self-localized on it. Commonly statistical techniques are used to attack the SLAM problem [1, 2]. Robot's internal geometric representation plays an important role on SLAM techniques. Typically, either, the planar location of laser range finder (LRF) is used directly as geometric representation, or simple features in the form of line segments or corner points are extracted [3, 4]. However, these simples and primitive geometric representations affect the overall performance of SLAM techniques.

Recently, polygonal curves or polylines representations have been used to deal with geometric mapping [5, 6, 7]. This geometric representation is more compact and useful. Polyline representation captures more context than other features typically employed in scan matching approaches. Moreover, this internal representation fulfills requirements for the desired cognitive and reasoning mapping.

Not many research groups have been work with this representation. Amigoni and Gasparini in [5] propose to build a global polyline map from partial maps obtained on different scans positions, which can be get it from one or multiple robots without using any odometry or position estimation method. In [6] Veeck and Burgard propose a method for learn polyline maps for mobile robots. However, last two approaches do not deal with self-localization problem and the global map is constructed as an offline process, once all data has been acquired. Moreover, latter takes several minutes.

Latecki et al. in [7], propose a method for construct a global map sequentially from partial maps obtained from a mobile robot with a LRF, but as we show in this paper features selected not always works on complex environments.

In this paper, we present a different approach to select significant features or landmarks. The selected features are obtained directly from the DCE computation. We show that the proposed approach gets better results with less computational effort. In this paper, we consider a mobile robot equipped with LRF for indoor navigation. Our robot is also equipped with ultrasonic sensors used for obstacle detection and avoidance functions that are not in the scope of this paper. Raw scan data are sample at frequencies commonly greater than 2Hz.

This paper is organized as follow, in section 2 we describe how raw data are segmented and grouped by means of discrete curve evolution method (DCE). The proposed method for selecting significant features is presented on section 3. In section 4 we show features matching and the merging procedure together with some results and finally in section 5 we give our remarks and conclusions.

II. GROUPING AND SIMPLIFICATION OF RAW SCAN DATA

Initially, range data acquired by the laser range finder are stored as locations of reflection points in the Euclidean plane, represented as points. Thus, we obtain a sequence of scan points in the plane in a local coordinate system, the robot's heading aligned with the positive *y*-axis.

A. Segmentation

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The order of the sequence of data reflects the order returned by the LRF. Nevertheless, in this sequence two consecutive points do not necessarily belong to the same object. The next step is to segment this sequence into polylines that represent visual parts of the scan. In this way, different objects in the scan sequence will not be represented by the same polyline. An object transition is said to be present wherever two consecutive points measured by the LRF are further apart than a given distance threshold.

For this segmentation, a simple heuristic is used: whenever the Euclidean distance of two consecutive points exceeds a given threshold we finish a polyline and start a new one. The obtained polylines represent boundaries of objects (Fig.1). Generally indoor environments are very structured, e.g. long walls, corridors, polygonal rooms, etc. We consider small polylines structures as noise, obstacles or moving objects no forming part of the map, talking about small the total length and/or the number of vertexes in the polyline structure.

This part let us keep just the relevant polylines in the map reducing accumulative errors. Segmented polylines still contain all the information read form the LRF.

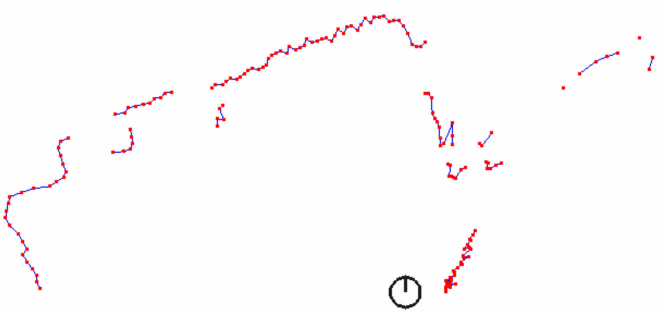

Fig. 1. Initially polyline map formed from segmented raw scan data, each polyline represent different objects. Smalls groups in length or number of vertex are considered noise or obstacles

B. Discrete Curve Evolution

We apply discrete curve evolution method (DCE), as proposed in [8], to reduce noise as well as to make the data compact without loosing valuable information. DCE is a context sensitive process that proceeds iteratively:

Let $\boldsymbol{P}$ be a polyline, we will denote the vertices of $\boldsymbol{P}$ with *vertices*($\boldsymbol{P}$). A discrete curve evolution produces a sequence of polylines $\boldsymbol{P} = \boldsymbol{P}_0, \ldots, \boldsymbol{P}_m$, such that each segment on the polyline has a cost function K greater than a given threshold. DCE can be summarized as follow:

> For every evolution step i = 0,…, m – 1, a polyline $\boldsymbol{P}_{i+1}$ is obtained after the vertices whose relevance measure is: a) minimal and b) less than a given threshold, have been deleted from $\boldsymbol{P}_i$.

To each vertex $\boldsymbol{v}$ in $\boldsymbol{P}_i$ is assigned a relevance measure $K(v, \boldsymbol{P}_i)$ that can be see as the cost of removing the given vertex in order to get a straight-line segment between its two neighbors.

In order to give a precise definition of the discrete curve evolution, we define $K_{min}(\boldsymbol{P}_i)$ to be the smallest value of the relevance measures for vertices of $\boldsymbol{P}_i$:

$$K_{min}(\boldsymbol{P}_i) = min\{K(\boldsymbol{u},\boldsymbol{P}_i) : \boldsymbol{u} \in vertices(\boldsymbol{P}_i)\} \qquad (1)$$

and the set $\boldsymbol{V}_{min}$ to contain the vertices whose relevance measure is minimal in $\boldsymbol{P}_i$:

$$\boldsymbol{V}_{min}(\mathbf{P}_i) = \{\mathbf{u} \in vertices(\mathbf{P}_i): K(\mathbf{u}, \mathbf{P}_i) = K_{min}(\mathbf{P}_i)\}, \quad \text{for } i = 0, \ldots, m - 1. \qquad (2)$$

For a given polyline $\boldsymbol{P}$ and a relevance measure K, we call a discrete curve evolution a process that produces a sequence of polylines $\boldsymbol{P} = \boldsymbol{P}_0,\ldots,\boldsymbol{P}_m$ such that

$$vertices(\boldsymbol{P}_{i+1}) = vertices(\boldsymbol{P}_i) \,/\, \boldsymbol{V}_{min}(\boldsymbol{P}_i), \qquad (3)$$

The process of the discrete curve evolution is guaranteed to terminate, because it stops when the number of vertices are less than a given vertex threshold T_v or when there is no more relevance associated measures under the given relevance threshold T_r. On the other hand, if precedent conditions are not satisfied, in each evolution step, the number of vertices decreases by at least one.

The key property of the evolution we used for our experiments is the order of the deletion determined by the relevance measure $K(\boldsymbol{v},\boldsymbol{P}_i)$ which depends on vertex $\boldsymbol{v}$ and its two neighbour vertices $\boldsymbol{u}$ and $\boldsymbol{w}$ in $\boldsymbol{P}_i$. It is given by the formula:

$$K(v,u,w) = K(\beta, l_1, l_2) = \beta \frac{l_1 l_2}{l_1 + l_2} \qquad (4)$$

where β is the turn angle at vertex $\boldsymbol{v}$ in $\boldsymbol{P}_i$, l_1 is the length of segment $\boldsymbol{vu}$, and l_2 is the length of segment $\boldsymbol{vw}$ (Both lengths are normalized with respect to the total length of the polyline $\boldsymbol{P}_i$). Intuitively it reflects the shape contribution of vertex $\boldsymbol{v}$ in $\boldsymbol{P}_i$. The main property is the following:

The higher the value of $K(\boldsymbol{v},\boldsymbol{u},\boldsymbol{w})$, the larger is the contribution of arc $\boldsymbol{vu} \cup \boldsymbol{vw}$ to the shape of polyline $\boldsymbol{P}_i$. Relevance measure (4) has been defined in [8], where the tangential space is used to derive (Fig. 2).

Observe that this relevance measure is not a local property with respect to the polygon $\boldsymbol{P}$, although its computation is local in $\boldsymbol{P}_i$ for every vertex $\boldsymbol{v}$.

Finally, proceeding this way we obtain an ordered vector of polylines for each scan raw data.

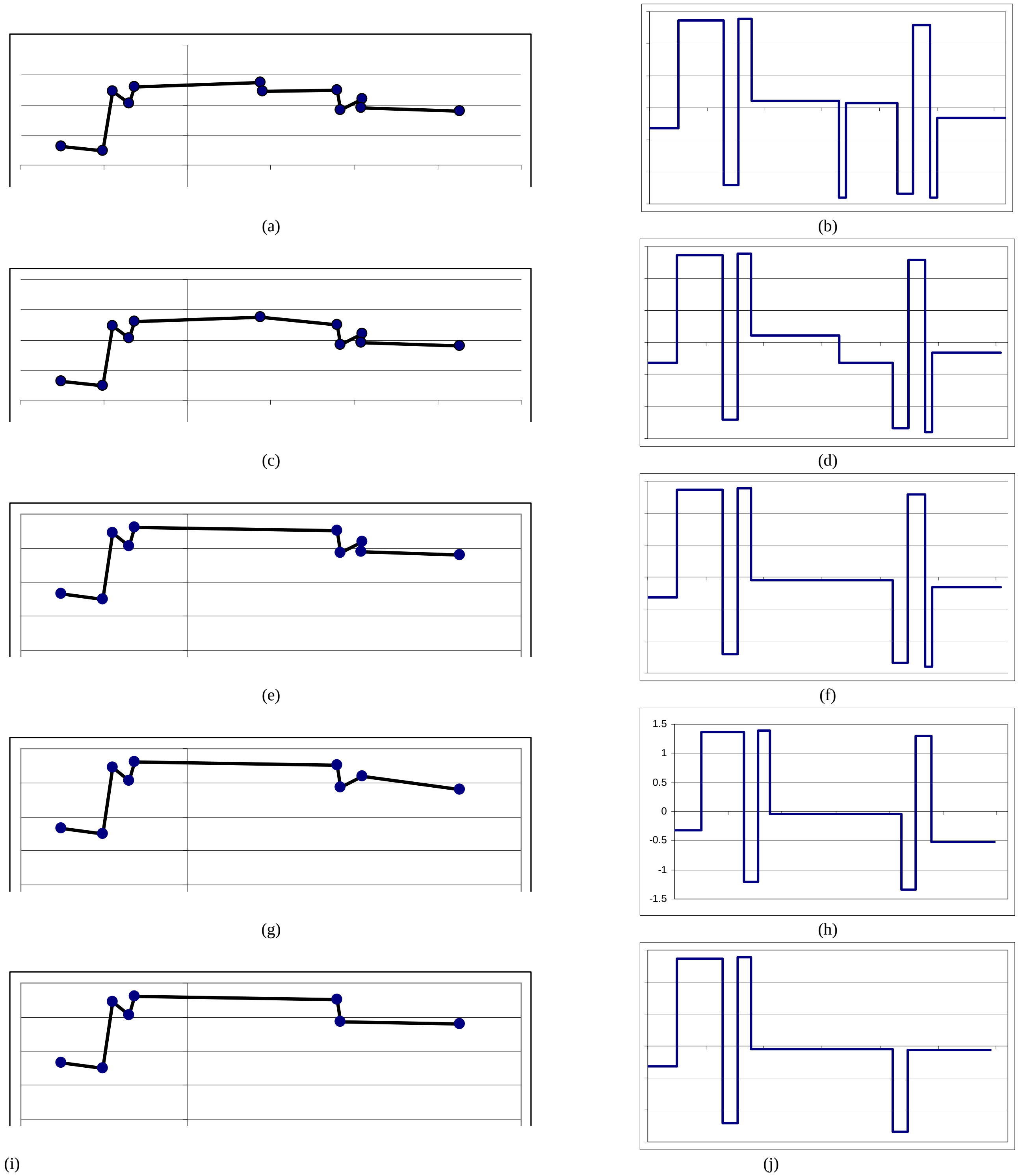

Fig. 2. Discrete curve evolution. In left images, it is shown different stages of the DCE method applied to one polyline structure. Images on the right side are the tangent space representation, used to compute the relevance measure *K*.

III. FEATURE SELECTION

Matching local sensor readings $\boldsymbol{S}$ against the global map $\boldsymbol{G}$ is the key challenging in mapping. Odometry commonly used to give localization and movement estimation has show to be very inaccurate. It is because the nature of sensor and other problems, e.g. over certain kinds of surfaces, robot wheels can slide or sometimes, the bad distribution of the robot weight could cause different friction factors on each wheel. In Fig. 3 it is show, a global map built applying only odometry transformation (translation and rotation) to various local LRF readings. As we can clearly see, this information it is not enough to guarantee a good matching between features over the scans sequence. We get something as object volumes while we should expect to get it is only objects contours.

In order to get a realistic and useful map, it is necessary to get correct transformation between current scan and global map. Different approaches have been work with directly raw data or line segments and corners extracted from this data [1, 2].

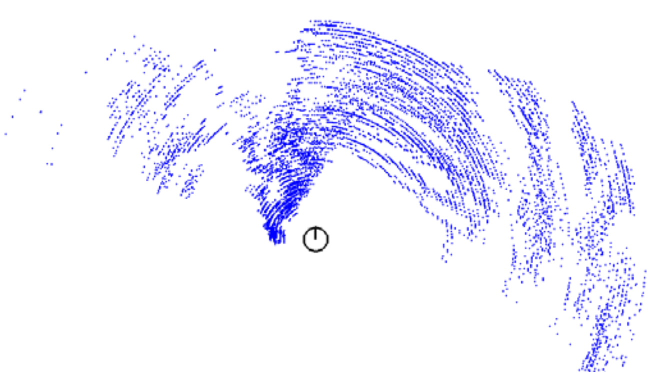

Fig. 3. Mapping only with odometry estimation.

Selection of significant features or landmarks is of high importance in order to get a good match, in a reasonable time. We exploit the high-level structures or polylines extracted from raw data, to compute relevance features, making easier and more comprehensive the matching between them. While, at the same time these structures can give us extra cognitive information about the environment.

A. Selecting and Matching Significant Features

Many works have been deal with significant features extraction, however must of them works with a simple geometric representation.

Latecki et al. in [7] propose to extract the maximal convex arcs in polylines in order to get shape information. Then it is search the correspondence for maximal arcs between the local scan $\boldsymbol{S}_t$ and the global scan at $\boldsymbol{G}_{t\text{-}1}$. A similarity value, based on differences in the tangent space between polylines in the current scan $\boldsymbol{S}_t$ and the previous global map $\mathbf{G}_{t\text{-}1}$ is proposed.

This similarity measure considers the correspondence between a polyline in the global scan $\mathbf{G}_{t\text{-}1}$ and the local $\boldsymbol{S}_t$. However for mobile robots, building incrementally a global map, shapes of polylines between partial and global scans could differ greatly. It is mainly, because unseen features like not visible corners can divide polyline structures (Fig. 4a). As, robot moves toward these regions, features initially not seen could appear in the visual field of the robot. Consequently, what initially were two polyline structures now correspond to a single structure (Fig. 4b). This makes very difficult a similarity computation between polylines, two or more in the global map to one in the current scan in the approach proposed in [8].

To deal with this problem, we propose to extract significant features, here also called landmarks, as the set of vertex in each polyline with higher relevance measures K, as computed in (4). As we can see in (Fig. 5), these vertexes are commonly the turning points on the polyline structure with most influence on its shape. These relevance measures K are the same computed on the final step of the DCE method.

Once this set features $\boldsymbol{f}_s$ have been selected for all the polylines in the current scan. We search the correspondence with a selected group of similar features in the global map.

We select a subset $\boldsymbol{f}_g$ of visible features on the previous global map $G_{t\text{-}1}$ at the previous robot location $\boldsymbol{x}_{t\text{-}1}$. These features are obtained in a similar way as for the single scans, determined by the relevance measure K over the polyline structure.

As mentioned on section 1, LRF acquisition frequency is at least 4Hz. We consider that robot motion is relatively small between scans. For that, we restrict to slow robot rotations, principally over its axe, typically less 15 degrees/sec.

In this work, visible features are the ones inside a 180° field of view in front of the robot to which exist a non-obstructed straight line as show in (Fig. 6).

We search for the best matching between features, considering the cyclic order. Features can be added or removed from the sets depending of visibility regions. However, precedence between matched features needs to be respected.

The matching process uses as similarity measures: the relevance K for each selected landmark, as well as, the length l_1 and l_2 of the two adjacent segments (Fig. 5).

Landmarks near both edges of the field of view are commonly difficult to match, mainly because adjacent segments can be not completely perceive, so length of segments very different. Therefore, landmarks in polylines with the entire vertex inside the field of view have more weight for the matching process, than the landmarks inside polylines touching the field of view edges.

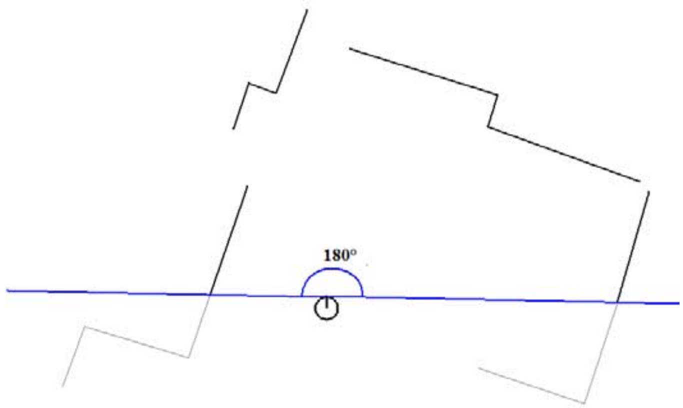

Fig. 4. Robots LRF field of view. Visible polylines (black lines) and then visible features are in front of the robot inside the LRF 180° field of view. Outside the field of view are the no visible polylines (grey).

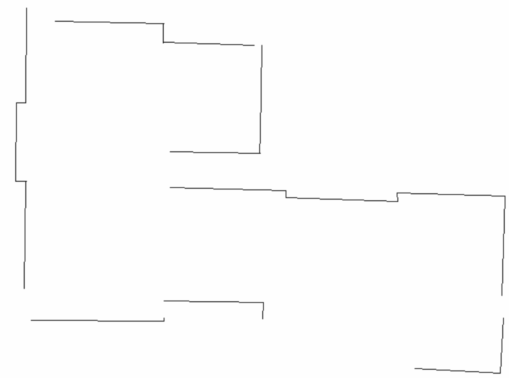

Fig. 5. Final global map, Initially not visible lines are incorporated and merged as only one structure. Some objects, obstruct the walls, but later if they are removed lines can be incorporated

B. Finding Translation and Rotation.

In order to get translation and rotation of the current scan $\mathbf{S}_t$ with respect to the previously compute global map $\mathbf{G}_{t\text{-}1}$, we use dynamic programming to minimizes the x, y, and ϕ parameters of the current scan with respect to the global map. In the proposed word, the dynamic programming method applies constant displacements to scan parameters that minimizes distance between landmarks, once the minimum has been obtained displacements are reduced to a half of their value, and dynamic programming method is applied again. This procedure is applied until the displacements are less than a given threshold.

Once the best set of parameters, which minimizes distance between landmarks, have been found, we use a least squares method to reduce landmarks positions on both local and global map. On this step, a greater weight is given to the landmarks position on the global map. This is for the reason that which the global positions have been found as a merging a large number of previous points. Weight values increase with time.

IV. RESULTS

In (Fig. 7) we show the resulting map after applying the matching method to the significant features selected. As we can see not initially visible zones are merged with the previously visible zones in one polyline structure, corresponding to the same object and not divided in two different polylines very near.

These results help the robot to interpret more easily scenes from a cognitive point of view. Objects as trashcans, boxes, etc. are not included in the map, because by their length are considered as obstacles. Some walls behind this obstacles, are not included, because the robot, do not see it. But, if robot returns when the obstacle has been removed these walls can easily included over the global map.

V. CONCLUSIONS

We have proposed a method for select significant features over laser range finder scans. This selected features permit to compute a complete Geometric Construction of Polygonal Maps for Indoor Autonomous Mobile Robot Navigation. Polylines structures are used as geometric representations, which gives a more cognitive representation than the classical points or single lines approaches. Significant features or landmarks are selected using information obtained on the previous polyline simplification step as well as map matching, making faster its computation. Not perceived initially characteristics can be merged together with previous polylines structures making easier scene interpretation. Similar works has been presented however, these use convex arcs as landmarks and complex similarity measures to compare polylines structures, not dealing with polylines structure subdivision making very difficult the process of matching and interpreting the given objects.

Our approach gives similar results in less time. More over the resulting global map merge together polylines structures corresponding to same objects, given better clues to scene interpretation.

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