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Registration of lines in 2D LIDAR scans via functions of angles

Branislav Holý

Department of Computer Science, FEECS, VŠB - Technical University of Ostrava, 17. listopadu 15, 708 33, Ostrava — Poruba, Czech Republic

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ABSTRACT

A novel algorithm for registration of 2D LIDAR scans that combines two already known but different concepts has been proposed. The algorithm combines the registration of lines and the registration in polar coordinates. The main idea is a new representation of the surrounding area that makes the mentioned combination possible. The algorithm works with line segments in polar coordinates that are expressed as functions of angles. This representation significantly decreases the computation time and enhances the resulting alignment. The presented algorithm was designed for indoor environments that are rich in objects that can be represented by line segments. The algorithm has been tested with many indoor LIDAR scans and is able to align them with high accuracy and in real-time.

1. Introduction

Over the last years, the popularity of LIDAR (Light Detection and Ranging) data is still increasing and the LIDAR technology is used in a wide range of applications. Very often, LIDAR data provide information about the surrounding area for the tasks like object tracking, robot navigation, autonomous car driving, or even mapping of an unknown environment. The robots and cars are equipped with laser scanners to scan the surrounding area in two or three dimensions. The lasers emit the rays and their reflections from the closest obstacles provide the information about the surrounding area.

One of the applications is simultaneous localization and mapping (SLAM). In the SLAM technique, the final map is composed of a set of the LIDAR scans that need to be aligned. In other words, the locations of the robot, where the scans have been taken, need to be corrected. Odometry data can provide an initial guess of the robot location, but every move of the robot increases the uncertainty about the location. Registration of the scans can decrease the uncertainty of the possible location of robot for further usage in the SLAM algorithms.

The main goal of LIDAR scan registration is to find the best orthonormal transformation between two LIDAR scans. The transformation has to align the scans with the best fitness. However, the LIDAR scans are only partially overlapped because they are scanned from different locations and also the correspondences between the points are unknown. These two properties make the registration problem difficult. The state-of-the-art algorithms solve this problem in different ways. Mostly, the correspondence problem is solved by searching for the closest point in the second set. The presented algorithm eliminates this problem by making use a continuous function that is defined in polar coordinates. In addition to this, the usage of the line segments (instead of points) decreases the computation time because the parts of the continuous function can be defined and computed analytically. The line segment representation of the 2D LIDAR scans is perfectly suitable for the indoor environments because those environments are mostly composed of objects that have straight shapes (like walls, wardrobes, commodes, and furnitures in general) and therefore can be detected as line segments. The benefits of the proposed method are the following.

- No correspondence search due to the polar coordinates.
- Usage of less objects (few line segments instead of many points).
- Fast computation of the error function and gradient due to the analytical representation.

The most commonly used algorithm for registration of two sets of points is Iterative Closest Points (ICP) in Besl and McKay (1992) and Zhang (1992). The algorithm works iteratively and tries to minimize the error between two sets of points. There are many variants of this algorithm that improve some steps of the original version. For example, Turk and Levoy (1994) introduced uniform sampling in the selection step, and Masuda et al. (1996) used random sampling with a different set of sample points at each iteration. The matching step was accelerated by Zhang (1994) who used better structures like k-D tree to find the closest points in the input sets. Other variants of these steps are described in Rusinkiewicz and Levoy (2001).

The Trimmed Iterative Closest Point Algorithm (TrICP) by Chetverikov et al. (2002) is a modification of the original ICP that

E-mail address: branislav.holy@vsb.cz.

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sorts the weights in the ascending order before the rejecting step and takes only a few of them. By this modification, the TrICP is more robust to a low overlap. Fitzgibbon (2003) introduced another variant called LM-ICP. It uses the Levenberg–Marquardt algorithm for minimization, which does not affect speed significantly but allows the use of statistics for better robustness. Generalized-ICP by Segal et al. (2010) adds a probabilistic framework to the original ICP algorithm with point-to-point and point-to-plane variants. Every point in the sets is represented by a normal distribution of probability with the mean at the point coordinates and the covariance matrix describing the error of measurement. The method for registration of RGB-D data is described by Ekekrantz et al. (2013), which uses features (points of interest) for computing the proper transformation. One of the newest modifications is Sparse-ICP (see Bouaziz et al., 2013). As mentioned in Pomerleau et al. (2013), over 400 papers have been published about ICP and its variants.

All of these ICP variants need to find the correspondences between the points by searching for the closest points in the second set. Even the mentioned k-D tree has still the asymptotic complexity of $\mathcal{O}(n\log(n))$ to find the correspondences for all points.

The Normal Distributions Transform (NDT) by Biber and Strasser (2003) is a different kind of registration method for 2D space. This registration method divides the space covered by points from the scanner into cells, and for every occupied cell, a normal distribution of probability is computed. Then it finds minimum of the $-\,\mathrm{score}$ function with Newton's algorithm. A 3D variant is described in Magnusson et al. (2007).

The NDT algorithm finds the corresponding normal distribution of probability by selecting its cell according to the coordinates of the examined point. This searching is fast ($\mathcal{O}(n)$ for all points), but some points are excluded from the error computation because no corresponding cell is found. Increasing the cell size can help with the inclusion of more points but also the covariance of the cell becomes higher.

The method of Cox (1991), or Iterative Closest Line (ICL) by Alshawa (2007) are useful for the indoor environments. Both algorithms as well as the presented method use linear features but in a different way. The method of Cox uses lines only for a model (that can be created from the first scan) and aligns the points from the second set to the model. Our new method uses the line segments for both scans, which improves the computation time. Another improvement of our method is the searching for correspondences. The condition for corresponding features is the distance between them in both previous methods. Moreover, the corresponding lines in ICL have to have similar angles within some threshold. Searching for the corresponding lines needs mn iterations in the method of Cox and n^2 iterations in ICL. In contrast, our new algorithm needs only n iterations because it uses polar coordinates.

Polar coordinates were used in some previous papers (for example Lingemann et al. 2005, or Polar Scan Matching (PSM) by Diosi and Kleeman 2005) and in the presented algorithm as well. The usage has the same purpose, which is fast correspondence search ($\mathcal{O}(n)$) preserving the inclusion of all available (visible) points. However, the description of the surrounding space differs from the presented one. Both earlier papers use the sets of points in polar coordinates, but the presented algorithm uses a function as a more general and continuous description of the surrounding area. This generalization allows the use of line segments as functions of angles as described below. Lingemann et al. (2005) also used the line segments but only for better detection of feature points, not for registration.

In this section, the introduction to the registration problematic, disadvantages of the state of the art methods, and solving the disadvantages have been explained. The remainder of the paper describes the proposed algorithm in every detail in the following Section 2, covering the mathematical background and implementation details of the proposed method. Section 3 shows some results of the experiments that have been used to prove benefits of the new algorithm, specifically its speed and accuracy. The conclusion and future plans are presented in the final section.

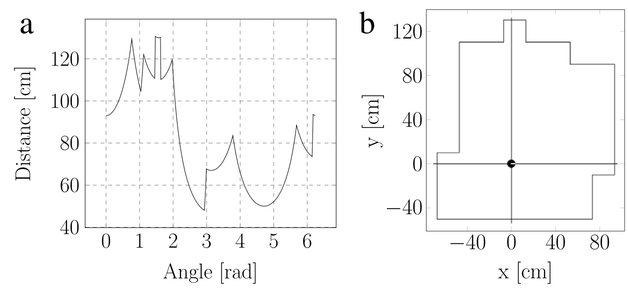

Fig. 1. The LIDAR function (a) of area (b).

2. New algorithm

The mentioned algorithms use the sets of points for the description of surrounding area. However, a set of points is too general and can contain more points that seem to be scanned in one angle. Since the LIDAR technology is able to scan only one distance in every angle, it is not necessary to use the sets of points. We can take advantage of this special property of the LIDAR scans and represent the surrounding area with a function called the LIDAR function defined as

$$\text{surrounding area} = \int_0^{2\pi} \mathrm{F}(\varphi)\,\mathrm{d}\,\varphi, \tag{1}$$

where the LIDAR function $\mathrm{F}(\varphi)$ returns a distance to the closest obstacle in angle φ (Fig. 1(a)). Sampling of the LIDAR function results in a set of points in the polar coordinate system, which is used in PSM as mentioned above.

The error of alignment between two LIDAR scans (F and F′) can be expressed with an error function E as

$$\mathrm{E}(\mathcal{T}) = \int_0^{2\pi} (\mathrm{F}(\varphi) - \hat{\mathrm{F}}'(\varphi))^2\,\mathrm{d}\,\varphi, \tag{2}$$

where $\hat{\mathrm{F}}'$ is the transformed LIDAR function F′ according to the orthonormal transformation denoted by $\mathcal{T}$ defined as follows

$$M = \left\{ \left(\hat{\varphi}, \widetilde{\mathrm{F}}(\hat{\varphi})\right) \right\} = \left\{ \mathcal{T}\,\{(\varphi, \mathrm{F}(\varphi))\} \right\}, \tag{3}$$

$$N(\gamma) = \left\{ \widetilde{\mathrm{F}}(\gamma) |\, \left(\gamma, \widetilde{\mathrm{F}}(\gamma)\right) \in M \right\}, \tag{4}$$

$$\mathcal{T} = \begin{bmatrix} [r]\cos(\theta) & -\sin(\theta) & t_x \\ \sin(\theta) & \cos(\theta) & t_y \\ 0 & 0 & 1 \end{bmatrix}, \tag{5}$$

which saves every transformed point (rotated by θ and translated by t_x and t_y) of the LIDAR function into the set M. Since some transformed points would share the angle $\hat{\varphi}$, we need to choose only one of them that has the smallest value $\widetilde{\mathrm{F}}(\hat{\varphi})$. For this purpose, we introduce the function $N(\gamma)$ that returns the set of all distances $\widetilde{\mathrm{F}}(\gamma)$ that correspond to the chosen value of γ. The final transformed function $\hat{\mathrm{F}}$ is shown in (6) where we choose the min from the set returned by the function N

$$P = \left\{ \left(\hat{\varphi}, \hat{F}(\hat{\varphi})\right) |\, \left(\hat{\varphi}, \hat{F}(\hat{\varphi})\right) = (\hat{\varphi}, \min N(\hat{\varphi}))\,;\, \left(\hat{\varphi}, \hat{F}(\hat{\varphi})\right) \in M \right\}. \tag{6}$$

The following conditions must be met (for small ε) to keep the order of transformed points. It also removes invisible points that seem to be scanned from the opposite side

$$\left(\hat{\varphi} + \hat{\varepsilon}, \hat{\mathrm{F}}(\hat{\varphi} + \hat{\varepsilon})\right) = \mathcal{T}\,\{(\varphi + \varepsilon, \mathrm{F}(\varphi + \varepsilon))\}, \tag{7}$$

$$\varphi < \varphi + \varepsilon \iff \hat{\varphi} < \hat{\varphi} + \hat{\varepsilon}, \tag{8}$$

where ε is a small number ($\varepsilon \to 0$) that describes the nearest surrounding around φ. The detailed explanation is covered in Section 2.3.

Unlike other environments, the indoor environments (consisting of doors, furniture, etc.) are ideal for the description of area via line segments. The presented method uses the line segments in the polar

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