

# High-Speed Feature Extraction in Sensor Coordinates for Laser Rangefinders

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## Abstract

The main contributions of this paper are two algorithms for extracting lines and corners present in the environment from information gathered by a laser rangefinder. The laser range scan is processed in its natural coordinates, range and bearing, to compute a parameter that is invariant to the position and orientation of straight lines present. An algorithm to extract the slopes of these lines is also presented. Log-Hough transform, that only explores a small region of the Hough space identified by the slopes computed, is then used to find the equations of the lines. An additional computation is used to identify consecutive short line segments that are perpendicular to each other in order to extract the corners present. The proposed method carries out all computations in the sensor coordinate frame yielding a fast and robust algorithm for feature extraction from laser range scans. Practical examples are presented to demonstrate the efficacy of the algorithm. An implementation of the simultaneous localisation and mapping that does not use any odometry is also provided to illustrate the use of the features extracted by the algorithm in robot navigation.

## 1 Introduction

Localisation is a fundamental requirement for autonomous navigation systems. In applications associated with indoor environments, use of features present such as straight lines and corners for localisation has been demonstrated by a number of researchers. If a map of the environment is known, either particle filter techniques that directly use raw sensor information or Kalman filter based techniques that use features extracted from sensor information are effective. In situations where a map of the environment is not available, feature based simultaneous localization and mapping algorithms can be used to automatically generate navigation maps. Therefore, robust extraction of geometric features from sensor data is important in the field of robot navigation. The presence of sensors such as the SICK laser rangefinder that can provide information at a rate of 75

Hz, it has become necessary to develop feature extraction algorithms that are computationally efficient. Furthermore, with information gathered at such high rates, it may be possible to develop navigation systems that do not rely on any additional information such as odometry.

In this paper, a parameter invariant to the equation of the line segments is used to segment scans obtained from a laser rangefinder and identify potential candidate data points that belong to straight lines. The parameter derived is not sufficiently sensitive to discriminate between straight lines and gradual curves. An additional parameter approximating the angle at which the line may lie is then computed. Following this, a Log-Hough transform is used to eliminate false candidates and obtain equations of the lines present. Corners are extracted by identifying slopes of consecutive line segments that are perpendicular to each other. Since the geometric features are extracted within the sensor coordinate system and the search space used for computing the Log-Hough transform is now dramatically reduced, the combined algorithm produces a reduction in the computational time compared to previously reported algorithms.

The capability of Laser rangefinders to produce data at a high rate has made them an extremely popular and reliable sensor for robot navigation, particularly in indoor environments. The reduced computational time of the proposed algorithm could maximise the laser data throughput. The intention is to use the extracted features within a simultaneous localisation and mapping algorithm.

This paper is organized as followed. Section 2 provides a literature review of existing algorithms for geometric feature extraction. The proposed algorithm is developed in section 3. Section 4 provides practical examples of line and corner extraction and a SLAM implementation that only uses the extracted geometric features and does not rely on odometry. Discussion and conclusions are presented in section 5

## 2 Existing Approaches to Feature Extraction

In an indoor environment the predominant features tend to be straight lines and right angle corners. Numerous algorithms for extracting lines and corners for laser range scans have been reported in the literature. Most of these algorithms first transform the range scan to the Cartesian coordinate frame and then proceed to line fitting or corner extraction. Some techniques such as the Hough transform are able to deal with feature extraction in the sensor coordinates but can be computationally expensive. The following paragraphs review some of the vast literature in this area.

A number of algorithms have been reported for obtaining line features. Least square line fitting [Crowley, 1985] has been used to select points that belong to a line. Adaptive clustering [Zezhong, 2003] through a split and merge algorithm has also been used. These methods require a number of different threshold parameters which can vary depending on the region where the laser scan has been obtained. Roumeliotis and Bekey report a layered, dual Extended Kalman filter algorithm [Roumeliotis, 2000] for the purpose of extracting features. The dual layered algorithm works by initiating straight line segments in one Kalman Filter and then estimates the line parameters in the successive filter. The Filters are tuned with a different threshold being a trade-off between sensitivity and flexibility to detect new line segments. Monitoring both filters the algorithm decides which filter is more appropriate for a certain section of the scan. A separate post-processing module is added to extract the set of wall segments and corners. Instead of using a line specific decision on a single point, Arras [Arras et al, 2000] uses a model independent criterion on a group of points. Multiple segments which lie on the same physical object are merged for particular precise re-estimates of the line position by a clustering algorithm with a Mahalanobis distance matrix. It merges segments until their distance in the  $r, \theta$  space is greater than a threshold from a  $\chi^2$  - distribution.

In the Hough transform, a given observation is mapped to all points that specify a possible line through that point. This set will form a sinusoid and points on a particular line will all map to sinusoids that intersect at a common point. When a given point in the scan indicates the presence of a line through a given point, an accumulator is incremented. When all points in a scan are accounted for, the accumulators with the highest count will be taken to indicate the parameters of the line that best explain the points. One of the most difficult questions on solving the Hough Transform is selecting the quantization level for  $r$  and  $\theta$  [Niblack, 1988], Kesidis, 1999]. Computational efficiency of the Hough transform can be significantly improved by operating in log-space. [Geisler, 1998]

Extracting corners from a laser scan has been widely addressed in literature. Castellanos, [Castellanos et al, 1996] identifies corners by establishing corresponding between the intersection of two consecutive laser segments. It is worth noting that calculations are not completed in the sensor coordinate frame. The aforementioned SEGMENTS algorithm

[Stergios et al, 2000] employs a Kalman Filter and compares the result of a fitted line on two consecutive range estimates against a certain threshold to detect edges.

## 3 Proposed Method

Consider a straight line and three consecutive observations located from a scan of a laser manifested as shown in Fig 1.

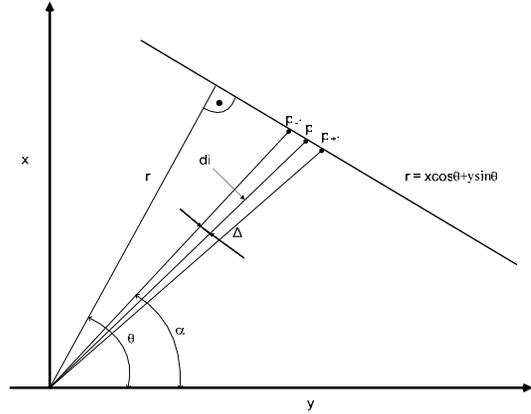


Figure 1 - Laser Scan of Straight Line

The observations are  $p_{i-1}, p_i, p_{i+1}$ ,  $d$  is the distance to the point from the coordinate origin and  $\Delta$  is the angular resolution of the laser rangefinder.

$$d_k = \frac{p}{\cos(\theta - \alpha - (k - i)\Delta)} \text{ where } k \in (i-1, i, i+1) \quad (1)$$

If we consider

$$AD = \frac{\frac{1}{d_{i-1}} + \frac{1}{d_i} + \frac{1}{d_{i+1}}}{\frac{1}{d_i}} \quad (2)$$

Substituting (1) in (2) and simplifying gives

$$AD = 1 + 2 \cos(\Delta) \quad (3)$$

The parameter AD is independent of the equation of the straight line and is only a function of the angular resolution of the laser rangefinder. A more generalized form of the parameter AD can be written as

$$AD_{ik} = \frac{\sum_{j=-k}^k \frac{1}{d_{i-j}}}{\frac{1}{d_i}} = 1 + 2 \sum_{j=1}^k \cos(j\Delta) \quad (4)$$

It should be noted that (4) represents a sufficient condition for  $p_{i-k}$  to  $p_{i+k}$  to belong to a straight line. However, there are many other smooth curves that give rise to the same value  $AD_{ik}$ . The most trivial example is an arbitrary curve that passes through all points  $p_{i-k}$  to  $p_{i+k}$ .

Figure 3 shows a scan from a SICK LMS 200 laser rangefinder obtained from an office environment. Following Figure 4 shows the  $AD_{i10}$  ( $i=9, \dots, 352$ ) for this scan..

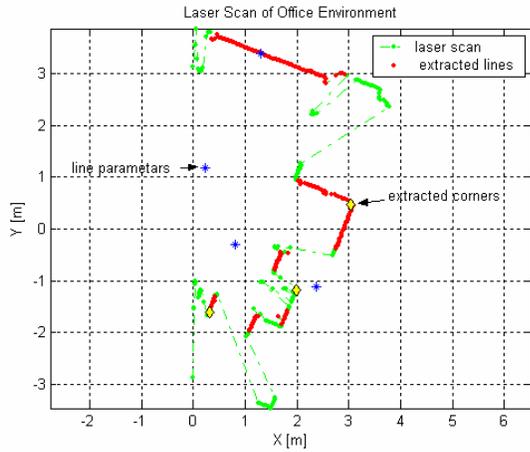


Figure 3 - Laser Scan of an office environment

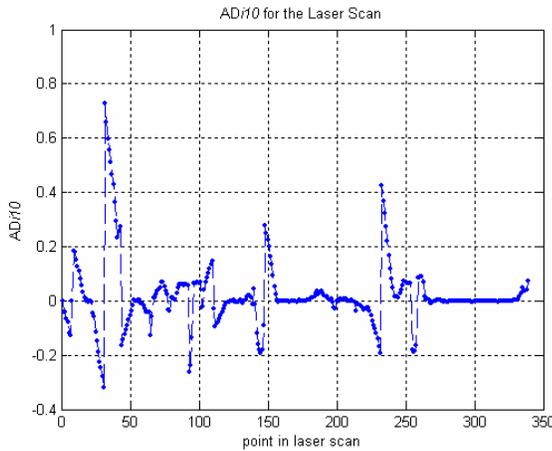


Figure 4 -  $AD_{i10}$  of the Laser Scan shown in Fig 3.

It can be seen from Figure 4 that computing  $AD_{ik}$  enables identification of potential observations belonging to straight lines within the laser scan. As noise is always present in the laser scans and as parameter  $AD_{ik}$  does not sufficiently discriminate in the presence of shapes with slight curvature, it is proposed that an efficient variant of the Log-Hough transform is used to extract the equations of the line segments. A brief outline of this method is described below. For a detailed explanation the reader is referred to [Giesler, 1998].

Consider a straight line  $r = x \cos \theta + y \sin \theta$  and an inner measurement limit of  $r_0$ .

$$\log \left[ \frac{r}{r_0} \right] = \log d - \log r_0 + \log (\cos(\theta - \alpha)) \quad (5)$$

Above,  $(d, \theta)$  denote single observations from a laser scanner. For all possible values of  $\theta$ ,  $\log[r/r_0]$  can now be computed. Note that if  $\log(\cos(\theta))$  is pre-computed and stored then  $\log(\cos(\theta - \alpha))$  only involves an indexing operation. Thus the computation involved in (6) is not particularly demanding. However, in the present example straight line segments are already identified. Therefore, the search space for the Log-Hough transform can be

significantly reduced if approximate orientations of the line  $(\theta)$  are available. Consider:

$$ad_{ik} = \frac{-\sum_{j=i-k}^{i-1} 1/d_j + \sum_{j=i}^{i+k} 1/d_j}{1/d_i} \quad (6)$$

Using (1) and simplifying it can be shown that

$$\theta_i = \tan^{-1} \left( \frac{ad_{ik}}{\sum_{j=-k}^k \sin(j\Delta)} \right) + \alpha_i \quad (7)$$

Equation (7) can now be used to obtain a value for  $\theta$  for the straight line that is defined by points  $p_{i-k}$  to  $p_{i+k}$ . Figure 5 illustrates the implementation of (7) on the laser scan data. It is now necessary to search only the space surrounding the value for  $\theta$  in (7) in the Hough space

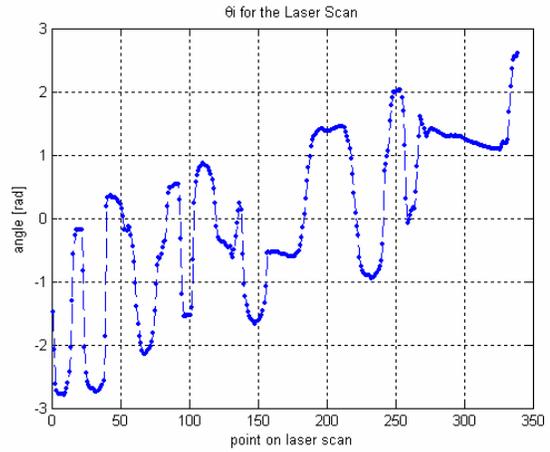


Figure 5 -  $\theta_i$  for the Laser Scan shown in Fig. 3

Corners within an office environment are typically located at intersections of perpendicular lines. From  $\theta_i$  obtained in Equation 7 we can calculate the angle between points lying on the line  $\psi_i = \theta_i - \theta_{i+k}$ . This provides the angle  $\psi$  between the detected line segments as in Figure 6.

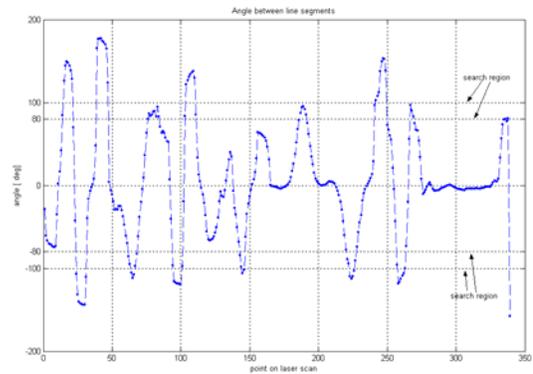


Figure 6 -  $\psi_i$  for the Laser Scan shown in Fig. 3

As parameter  $\psi_i$  is quite sensitive to noise and can cause fictitious corners in the case of acute angles present in the environment Figure 7. However, it is

possible to use the line segments computed from  $AD_{ik}$  in Equation 5 for validating the corners. The detected corners can only lie at the end of line segments.

It is important to note that all the computations described above are performed in the sensor space ( $d, \theta$ ) without any transformation to the Cartesian co-ordinates ( $x, y$ ) thereby resulting in significant reduction in computation time. Currently the algorithm is implemented in Matlab and compiled using the Matlab C compiler. The times from Figure 7 are obtained when analysing successive laser scans. The variation in processing time is directly related to the number of detected line segments. It is expected that a direct implementation in C will significantly reduce the computational times.

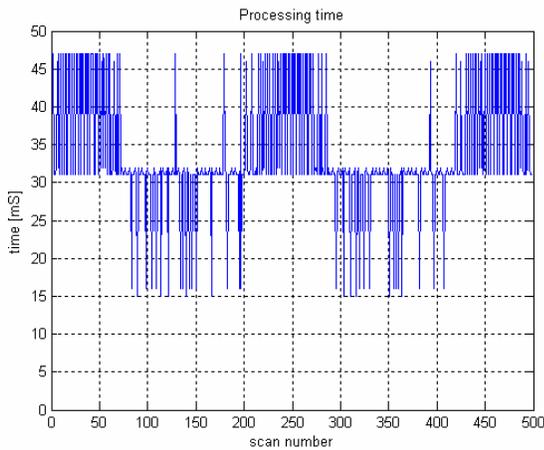


Figure 7 – Processing time for successive Laser Scans

## 4 Practical Examples

The proposed method was evaluated as a stand alone feature extractor and implemented as a SLAM algorithm without odometry.

### 4.1 Feature Extractor Implementation

To demonstrate the proposed method features were extracted from a typical office environment using the data set available on the Radish Repository [Howard, 2004] and the run conducted in the Intel Seattle Laboratory, Figure 8.

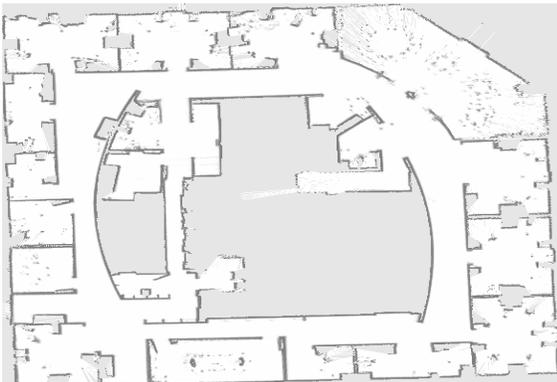


Figure 8 – Method Test Environment, Intel Lab Seattle

A number of laser scans obtained from the environment were analysed. The laser range scan and detected line segments are superimposed. Line parameters are marked with asterix (\*) whilst detected edges are marked with a diamond ( $\diamond$ ), refer Figure 9a-9e.

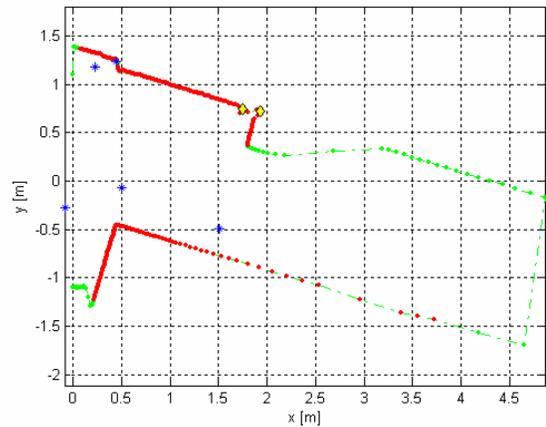


Figure 9a – Extracted Features, Intel Lab Seattle

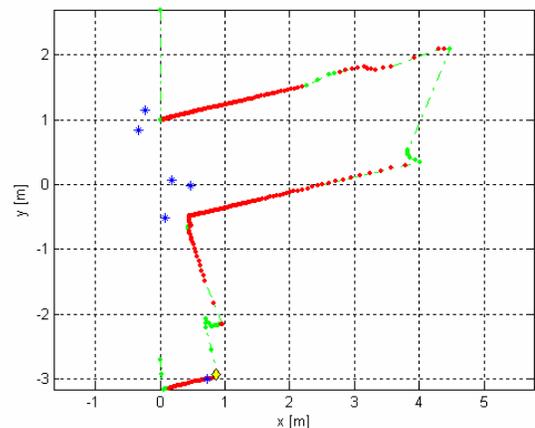


Figure 9b – Extracted Features, Intel Lab Seattle

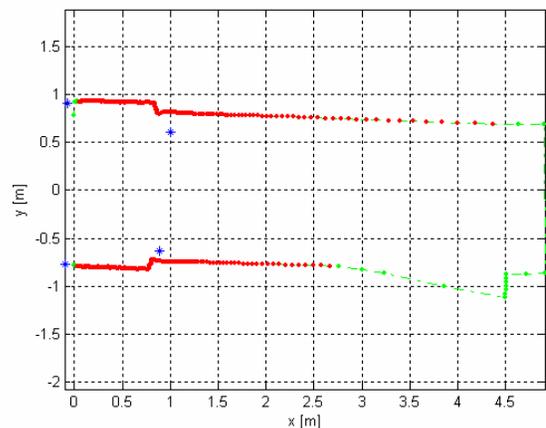


Figure 9c – Method Test Environment, Intel Lab Seattle

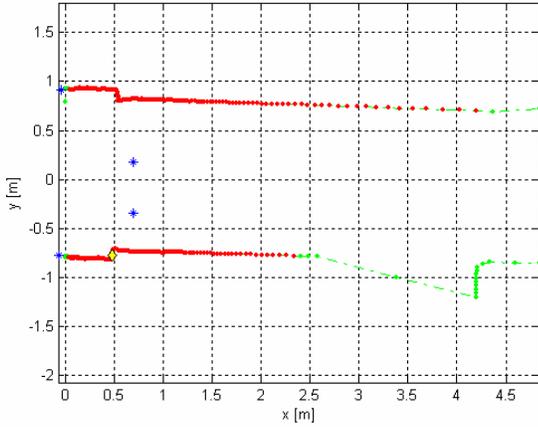


Figure 9d – Method Test Environment, Intel Lab Seattle

Figure 9a, 9b and 9d indicate successful performance of the proposed method. Figure 9c depicts the trade of in selecting a window size  $k$ , Equation 4 and 6, between sensitivity and accuracy of the method. It is also worth noting that in Figure 9c no corners have been detected due to the obtuse angle at which the passageway at distance  $x=0.7m$  has been detected. However, in a successive frame, when further approaching the section at  $x=0.5m$  the angles corner becomes visible.

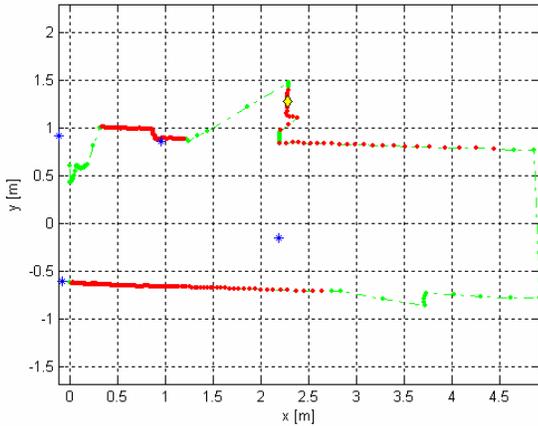


Figure 9e – Method Test Environment, Intel Lab Seattle

Another anomaly of the proposed method is illustrated in Figure 9e. Presence of acute angles within the environment may cause false edge detection. An extension to the proposed method will be to rule out detected corners where the variance in range between neighbouring points is below a threshold.

#### 4.1 SLAM Implementation

Extracting geometric features from the environment is particularly useful for the purpose of localisation and mapping. The intention is to use the algorithm for fast feature extraction irrespective of the mobile robot and use these features for building a map of the environment. The following paragraphs briefly describe an implementation of the SLAM that does not use odometry and relies solely on the line features extracted by the proposed algorithms. The intention is to examine the possibility of developing a self-contained sensor package for indoor navigation that

does not require any installation of mechanical hardware. Preliminary results presented below are encouraging.

As odometry is not available, the vehicle is modelled using a constant acceleration model. The vehicle states are:

$$[X_v, Y_v, \Theta_v, V, \omega]^T \quad (8)$$

The State prediction equations are:

$$\dot{X}_v = V * \cos \omega * \Delta t + X_v$$

$$\dot{Y}_v = V * \sin \omega * \Delta t + Y_v$$

$$\dot{\phi} = \omega * \Delta t + \phi_v$$

$$\dot{V} = \delta V$$

$$\dot{\omega} = \delta \omega$$

In selecting a constant acceleration model  $\delta V$  and  $\delta \omega$  are zero mean Gaussian white noise with variance  $\sigma_v^2$  and  $\sigma_\omega^2$ . To the State vector we add Line observations with parameters  $R$  and  $\theta$ ,  $R$  being the distance from the world coordinate frame origin to the Line and  $\theta$  the corresponding angle. Therefore the observation equations are:

$$\theta_{obs} = \theta - \phi_v$$

$$R_{obs} = R - \sqrt{X_v^2 + Y_v^2} * \sin\left(\frac{\pi}{2} - \theta + \text{atan}\left(\frac{Y_v}{X_v}\right)\right)$$

Results of mobile robot localisation within the office environment in Figure 3 are shown in Figure 10. Further enhancement to the SLAM algorithm will include the extracted edges as transient features.

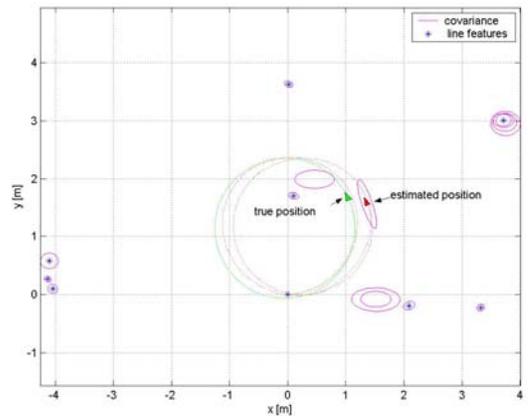


Figure 10 - SLAM Implementation Results

#### 4 Conclusions

The proposed feature extraction method and application on a SLAM implementation have provided promising results. The implemented algorithm performs calculations at above 20Hz which is currently higher than the laser rangefinder data sampling rate. Feature extraction has been tested on a number of samples and proved independent of the office environment. Future work will

need to be focused on deriving a quality measure for the extracted parameters by approximating the uncertainty using the estimator behaviour. We intend to further enhance the SLAM implementation by utilising the edges detected as transient features complementing the line segments.

## Acknowledgments

This work is supported by the ARC Centre of Excellence programme, funded by the Australian Research Council (ARC) and the New South Wales State Government. The author also wishes to acknowledge the advice of Professor Gamini Dissanayake in completing the work reported in this paper.

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