Adaptive Line Extraction Algorithm for SLAM Application

M. Yaghobi, M. Jadaliha, J. Zolghadr, M. Norouzi

Abstract— **This paper proposes a modified split and merge algorithm for line extraction with high accuracy, efficient speed and low complexity. It is robust against measurement noises and demonstrates satisfactory results on different surfaces in determining line boundaries. The method is based on the least square equation to fit a line on a series of uncertain points. Different least square criterion is investigated to choose the best one for line extraction. A novel approach is proposed here to adopt threshold on different surfaces.**

Although the SLAM is not main goal of this paper, a feature based SLAM is implemented on a mobile rescue robot to observe the proposed line extraction performance, practically.

Index Terms— **Least square, Line extracting, Adaptive parameter estimation, SLAM**

I. Introduction

Localization and map building is an important task of mobile robots. A precise and stable self localization is a key feature to act successfully in an unknown environment. Dead reckoning such as odometry (wheel rotation count or IMU) may conventionally be used, to estimate a robot position. Due to unbounded position error generated by the odometry, it doesn't suffice alone for localization. A large number of experiments using various kinds of sensors has shown that range sensor based SLAM techniques using laser [1], sonar [2],[3], and vision [4] work well in a real environment for both indoor [5] and outdoor applications [6]. A possible way to enhance localization is to use laser scan matching. Compared to other sensors, laser scanners have unique advantages such as: dense and accurate range measurement, high sampling rate, excessive angular resolution, as well as good range and distance resolution. In laser scan matching, the position and orientation or pose of the current scan is sought with respect to a reference laser scan. The pose of the current scan is adjusted until the best overlap with the reference scan is achieved.

Laser scan matching methods are categorized based on their association: point to point and feature to feature. The point to point matching approach [1],[7],[8], is to approximate the alignment of two consecutive scans, and then iteratively improve the alignment by defining and minimizing a distance between the scans. Moreover, it does not require the environment to be structured or contain predefined features. In the feature to feature matching approach, instead of working directly with raw scan points, the raw scans are transformed into geometric features. These extracted features are used in matching at the next step. Such approaches interpret laser scans and require the presence of chosen features in the environment. Features such as line segments [9], corners [10] or range extrema [6] are extracted from laser scans, and matched. Features require less memory space while provide rich and accurate information. Algorithms based on parameterized geometric features are expected to be more efficient compared to the point-based algorithms.

Among different geometric primitives, lines segments are the simplest one. Most office environments are easily described using line segments. Line-based maps are suitable for indoor applications, or structured outdoor applications, where straight edged objects comprise many of the environmental features. Because a line is composed of many points, the noise on a point usually does not affect the position and orientation of the line substantially. Therefore it is robust to noise. The sets of segments can be input to another algorithm that extracts high level features such as doors or corners. The line segments can be used as a part/all of a local map representation at the core of a SLAM algorithm.

Several algorithms have been proposed for extracting line segments from 2D range data. Since the algorithms do not incorporate noises of the range data, the fitted lines do not have a sound statistical interpretation. Nguyen et al. [11] presents an experimental evaluation of different line extraction algorithms on 2D laser scans for indoor environment. Diosi et al. [12] consider line fitting systematic errors as they mainly depend on a specific hardware and testing environment. S. T. Pfister et al. [9] suggest a line extraction algorithm using weighted line fitting for line-based map building. T. Pavlidis et al. [13] proposed a split-and merge algorithm for the line extraction which is extracted from computer vision. This method is very popular and has been used by others.

Split-and-Merge is clearly the best choice for real-time applications, due to its superior speed. It is also the first choice for localization problems with a priori map, where *FalsePos* is not very important. However the quality of the split and merge method is not guaranteed in all applications.

M. Yaghobi is with the Mechatronic Research Laboratory, Electrical and Computer Engineering Department, Islamic Azad University, Qazvin, Iran (e-mail: yaghobi@mrl.ir).

M. Jadaliha with the Electrical Engineering Department, Sharif University of Technology, Tehran, Iran, (e-mail: jadaliha@ ee.sharif.edu).

J. Zolghadr is with the Mechatronic Research Laboratory, Electrical and Computer Engineering Department, Islamic Azad University, Qazvin, Iran (e-mail: javad.zolghadr@gmail.com).

M. Norouzi is with the Mechatronic Research Laboratory, Electrical and Computer Engineering Department, Islamic Azad University, Qazvin Branch, Iran (e-mail: mnorouzi@ee.iust.ac.ir).

For example in line based SLAM, bad feature extraction may lead to the system divergence.

This paper introduces an Adaptive Line Extraction Algorithm (ALE) to create line-based maps using a series of range data collected from multiple poses. ALE is a modified version of the split and merge method with increased quality and robustness in application where Split-and-Merge fails to function.

This paper is organized as follows; in section II sensor noise model is described, section III describes our method, in section IV SLAM algorithm is discussed and finally details of experiments setup and conclusion is presented.

II. Sensor noise model

Range sensors are subjected to both random noises and bias [12]. Equation (1) describes the polar representation of scanned data. Let the range measurement, d be comprised of the "true" range, D, and an additive noise term, ε_d (2):

$$u_i = \begin{bmatrix} x_i \\ y_i \end{bmatrix} = d_i \begin{bmatrix} \cos\phi_i \\ \sin\phi_i \end{bmatrix} \tag{1}$$

$$d_i = D_i + \varepsilon_{di}. \tag{2}$$

ε_d is assumed to be a zero-mean Gaussian random variable with variance σ_d^2. In a similar way (3) represents the measurement error of angle ϕ i.

$$\phi_i = \Phi_i + \varepsilon_{\phi i} \tag{3}$$

where Φ_i is the "true" angle of the *ith* direction, and ε_ϕ is again a zero-mean Gaussian random variable with variance σ_d^2. Hence:

$$u_i = (D_i + \varepsilon_{di}) \begin{bmatrix} \cos(\Phi_i + \varepsilon_{\phi i}) \\ \sin(\Phi_i + \varepsilon_{\phi i}) \end{bmatrix}. \tag{4}$$

Generally, one can think of the scan point u_i as the sum of the true component, U_i, and the uncertain component, δu_i:

$$u_i = U_i + \delta u_i \tag{5}$$

if $\max\{\varepsilon_\phi, \varepsilon_d\} \ll 1$, which is a valid for most laser scanners, by replacing the values of u_i and U_i form (4) into (5), it can be written in the form of (6)

$$\delta u_i = D_i \varepsilon_{\phi i} \begin{bmatrix} -\sin\Phi_i \\ \cos\Phi_i \end{bmatrix} + \varepsilon_{di} \begin{bmatrix} \cos\Phi_i \\ \sin\Phi_i \end{bmatrix} \tag{6}$$

Assuming ε_ϕ and ε_d are independent, the covariance of the range measurement data is:

$$Q_i \triangleq E[\delta u_i (\delta u_i)^T] = \frac{(D_i)^2 \sigma_\phi^2}{2} \begin{bmatrix} 2\sin^2\Phi_i & -\sin 2\Phi_i \\ -\sin 2\Phi_i & 2\cos^2\Phi_i \end{bmatrix} + \frac{\sigma_d^2}{2} \begin{bmatrix} 2\cos^2\Phi_i & \sin 2\Phi_i \\ \sin 2\Phi_i & 2\sin^2\Phi_i \end{bmatrix} \tag{7}$$

For practical purposes, ϕ_i and d_i are good estimates of the quantities Φ_i and D_i [9]. Eq. 7 describes the impact of noise on data distortion.

III. Adaptive line extacting

A. Smoothing data to increase the algorithm efficiency

To increase the algorithm efficiency data are split into segments. The segmentation is based on the continuity of the distance data acquired from laser.

Each segment is smoothed and fed into ALE. If laser scanner data contain outliers, the smoothed values might be distorted, and lose to reflect the behavior of the bulk of the neighboring data points. To overcome this problem, the data can be smoothed using a robust procedure which is not influenced by a small number of outliers (fig. 1).

Lowess is a good candidate to handle this type of smoothing. The terms *lowess* is derived from "locally weighted scatter plot smooth." Since adjacent data points and their assigned regression weight function, in the defined span, determine each smoothed value, the method is considered to be both local and weighted. In addition, it is possible to use a robust weighted function to make the smoothing process resistant to the outliers. This method utilizes a linear polynomial. ALE takes advantage of *robust lowess* smoothing method. The *robust lowess* smoothing process follows these steps for each data point:

- Compute the *regression weights* for each data point in the span. The weights are given by the tri-cube function represented by (8).

$$w_{i1} = \left(1 - \left|\frac{r - r_i}{d(r)}\right|^3\right)^3 \tag{8}$$

  where r is the predictor value associated with the response value to be smoothed, r_i is the nearest neighbors of r as defined by the span, and $d(r)$ is the distance along the abscissa from r to the most distant predictor value within the span.

- Calculate the *robust weights* for each data point in the span. The weights are given by the bisquare function.

$$w_{i2} = \begin{cases} \left(1 - (e_i / 6M)^2\right)^2 & |e_i < 6M| \\ 0 & |e_i \geq 6M| \end{cases} \tag{9}$$

  e_i is the residual of the *ith* data point produced by the regression smoothing procedure, and M is the median absolute deviation of the residuals.

- The final smoothed value is calculated using both the local regression weight and the robust weight.

$$w_i = w_{i1} \times w_{i2} \tag{10}$$

A weighted linear least squares regression is performed by weight w_i on the each r_i to estimate filtered values. The regression employs a first degree polynomial for lowess. For more information about this section refer to [14].

B. Split and merge with binary search

Split and merge method has a better performance from speed point of view [11] and therefore a suitable choice for real-time localization or SLAM applications. The novel approach (ALE), proposed in this paper, is based on the split and merges procedure with a higher accuracy. Furthermore, the least square criterion is used instead of maximum

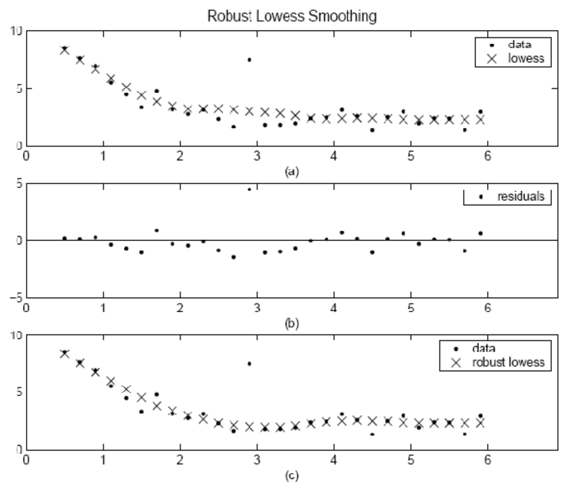

Fig. 1. Plot (a) shows that the outlier influences the smoothed value for several nearest neighbors. Plot (b) suggests that the residual of the outlier is greater than six median absolute deviations. Therefore, the robust weight is zero for this data point. Plot (c) shows that the smoothed values neighboring the outlier reflect the bulk of the data.

distance between data points and fitted line [15] to evaluate fitting.

When a line is fitted, the only decision algorithm makes is whether the fitting is proper or not. Hence, the idea of binary search is used to obtain the estimated line with the maximum length and precision. Fig.(2) illustrates three states of the binary searches to find the break point of i-th line. In each step, the method makes progressively better guesses for the break point of the i-th line, $\hat{p}_i$, and closes in on the location of the sought p_i value by selecting the middle element in the span, comparing whether $(p_{i-1}+1)$ and $(\hat{p}_i)$ is in the same line (i.e. $\hat{p}_i \leq p_i$), and determining if the $\hat{p}_i$ is greater than, less than, or equal to the p_i.

In spite of traditional Split and Merge, ALE does splitting procedures and merging procedures simultaneously. Consequently, the line boundaries can be identified with more precision.

C. *Least square line fitting criterion*

To obtain the coefficients' estimates, the least squares method minimizes the summed square of residuals (11). The residual for the *ith* data point r_i is defined as the difference between the observed response value y_i and the fitted response value $\hat{y}_i$, and is identified as the error associated with the data.

Let p_1 and p_2 to be the slope and the intercept of the fitted line over x_i and y_i data. The least square method determines *p* parameter for minimizing SSE:

$$SSE = \sum_{i=1}^{n} (y_i - (p_1 x_i + p_2))^2 \tag{11}$$

By solving least square, the *p* parameter is obtained by (13)

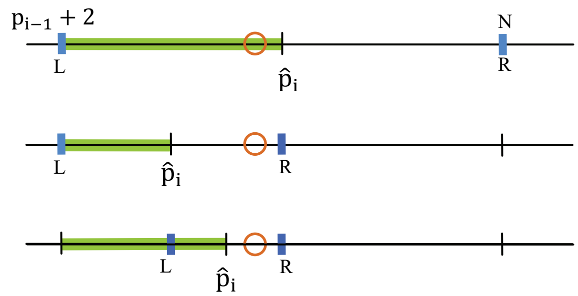

Fig. 2. Thick blue lines show search span, [L, R]. Orange circle shows actual break point. The procedure starts to search after the break point of last line, and select the middle of span as first guess. Step 1: Fitting is not satisfactory, split. Step 2: Fitting is satisfactory, add a half. Step 3: Check if fitting is satisfactory? This process is repeated until $\hat{p}_i$ placed in the circle.

$$A \triangleq \begin{bmatrix} x_1 & 1 \\ x_1 & 1 \\ \vdots & \\ x_n & 1 \end{bmatrix} \tag{12}$$

$$p = (A^T A)^{-1} A^T y \tag{13}$$

$$H \triangleq A(A^T A)^{-1} A^T \tag{14}$$

$$\hat{y} = Ap = Hy \tag{15}$$

In order to evaluate parameter estimation performance, a different criterion might be required. Usually a threshold is needed when the least square method is used for line segmentation. The threshold assigns whether a line can be fitted above this number of points or not. To best of our knowledge, the benefit of different least square criteria to select the line segmentation threshold is not addressed in any research. Several least square criteria for a straight wall from different ranges and views (fig. 3) have been measured (fig. 4). The best criterion must have similar values for identical bodies in different ranges and views, since all measured criterions belong to the same 20 cm wall. SSE, RMSE, MAE and R-square criterion in the order, is defined by equations (17), (19), (20), and (22):

$$r = y - \hat{y} = (1 - H)y \tag{16}$$

$$SSE = \sum_{i=1}^{n} r_i^2 \tag{17}$$

$$MSE = \frac{SSE}{n} \tag{18}$$

$$RMSE = s = \sqrt{MSE} \tag{19}$$

$$MAE = \frac{\sqrt{SSE}}{n} \tag{20}$$

$$SST = \sum_{i=1}^{n} (y_i - \bar{y})^2 \tag{21}$$

$$R^2 = 1 - \frac{SSE}{SST} \tag{22}$$

If the fitted line perfectly matches the wall:

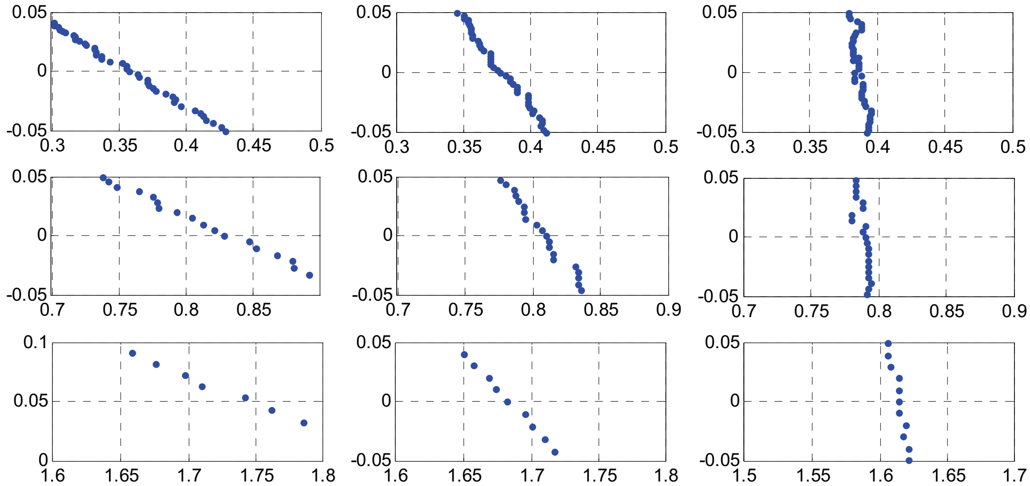

Fig. 3. Sample of raw data in Cartesian coordinate for different ranges and views angles

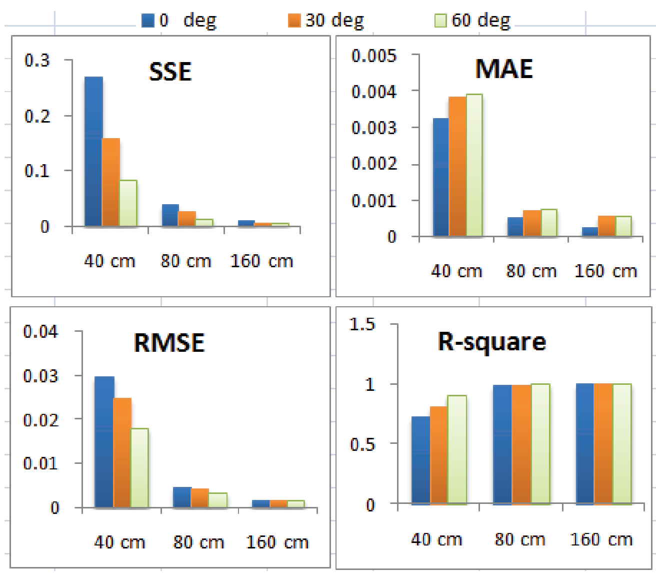

Fig. 4. The amount of different criteria for raw data from a straight wall in different angle of views and different distances, depicted in Fig (3)

$$Y_i = p_1 X_i + p_2 \tag{23}$$

$$u_i = \begin{bmatrix} x_i \\ y_i \end{bmatrix} \simeq \begin{bmatrix} X_i \\ Y_i \end{bmatrix} + \delta u_i \tag{24}$$

As explained in section II, the MSE can be estimated by sensor noise parameter for a straight line.

$$M\hat{S}E = E\left[\left(y_i - p_1 x_i - p_2\right)^2\right] = E\left[\left(\delta y_i - p_1 \delta x_i\right)^2\right] \tag{25}$$

$$\begin{aligned} M\hat{S}E &= E\left[\left(\delta y_i\right)^2\right] + p_1^2 E\left[\left(\delta x_i\right)^2\right] - 2 p_1 E\left[\delta x_i \delta y_i\right] \\ &= \left[(D_i)^2 \sigma_\phi^2 \cos^2 \Phi_i + \sigma_d^2 \sin^2 \Phi_i\right] \\ &\qquad + p_1^2 \left[(D_i)^2 \sigma_\phi^2 \sin^2 \Phi_i + \sigma_d^2 \cos^2 \Phi_i\right] \\ &\qquad + 2 p_1 \left[(D_i)^2 \sigma_\phi^2 \sin 2\Phi_i - \sigma_d^2 \sin 2\Phi_i\right] \end{aligned} \tag{26}$$

Using the relation between MSE and other least square criteria, we can interpret them as stochastic variable. However, the main goals of this section are:

1. Quantity of criteria differs for several surfaces by different roughness.
2. Each of the criteria SSE, RMSE, MAE and R-square is a function of range and status of the wall relative to the laser and sensor noise model; furthermore, usually criteria are functions of the number of points except for RMSE.
3. According to the theoretical results (26), RMSE must increase when the range increases. However, the experimental results are the other way around. The nonlinearity in sensor noise model could be the reason. Thereby the threshold cannot be determined via a static function of range or view angle.

D. *Floating threshold*

In split and merge methods, choosing threshold values is an important task since the algorithm performance is very sensitive to the values used [11]. A low threshold may break the line in two segments (fig. 5-a), and a high threshold could include the next line data (see fig. 5-b).

It is expected for the RMSE to rise sharply at the refraction point of two lines. To capture this point both the gradient and value of RMSE are used in ALE. Therefore we propose to select threshold of Least Square Criterion where the gradient of RMSE growth suddenly.

In this paper to achieve this goal, a floating method is suggested which dynamically changes threshold between a maximum and minimum value. A method that uses binary search is described in following pseudo code.

It is clearly seen that by using the ALE, the final threshold is 0.0037 and the fitted RMSE is 0.0035. The test results are obtained by defining the minimum threshold to 0.0025 (see fig. 5-a) and the maximum threshold to 0.008 (see fig. 5-b). Fig. 6 and fig. 7 illustrate the output.

1. If the beginning point of the segment, K_{min}, minus the end point of the segment, K_{max}, is more less than minimum allowed point in a line, then goto 2; else end.
2. Let $L=K_{min}$ and $R=K_{max}$.
3. Let P = middle of L and R.
4. Fit a line over points between K_{min} and P and calculate the RMSE of fitted line.
5. If RMSE is less than E_{RMSE} (RMSE threshold) and the increase rate of RMSE is less than G_{RMSE} (RMSE gradient threshold) the fitted line is acceptable, so L=P; else R=P.
6. If R-P>1 goto 3.
7. If P minus K_{min} is more than minimum allowed point in a line then extracted line over points between K_{min} and P is acceptable.
8. K_{min}=P+1.
9. Goto 1

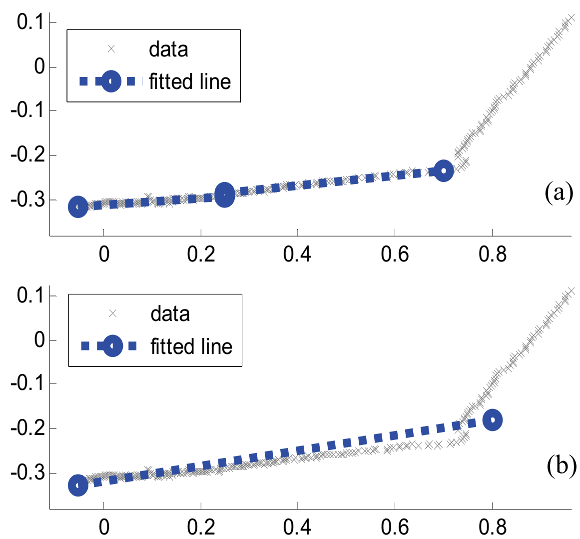

Fig. 5. Fit by low threshold (a), fit by high threshold (b)

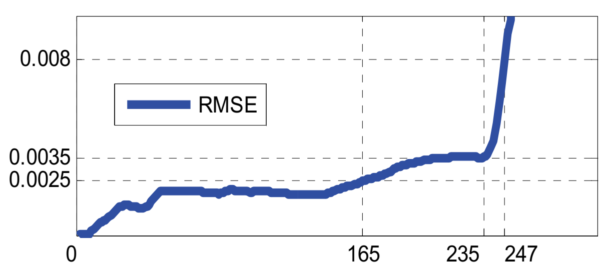

Fig. 6. Plot of RMSE criterion change

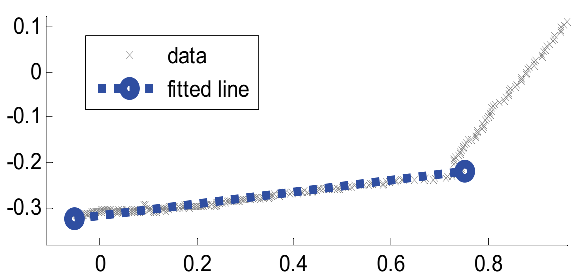

Fig. 7. Extracted line by proposed approach in this paper

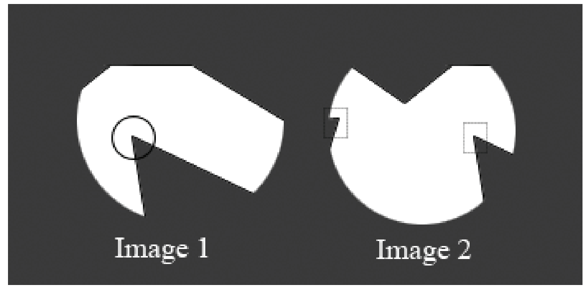

Fig. 8. Similar corner in two images

IV. SLAM

Today, lightweight SLAM algorithms are needed in many embedded robotic systems. We are planning to perform simultaneous localization and mapping (SLAM) by fusing corners, edges and line segments which are measured by a laser range finder sensor.

The scan matching algorithm computes a transformation Δd and a rotation $\Delta\phi$ such that a set of features, extracted from the first scan, is mapped optimally to a feature set of the second scan. The goal of this approach is to build a map containing line features representing the walls, cupboards, doors, windows, etc. in the environment.

Human brain uses a simple method to adopt images. In this process, brain detects and compares corners between the two images, and tries to find a proper match. By adopting one corner in each image, a rotation is used to increase the overlap between images. If the result is not satisfied, then it checks the next match in the same way. For example in fig. 8, the corner marked with a circle is similar to the corners marked with a square. Thus, there are two matches for this corner. A comparison between the square marked flags shows that the right corner is a better match.

A similar idea is used in our practical experiment to find the matched lines in different scans. In each laser scan, lines are extracted to identify the corners. The combination of these two features is used in a feature based SLAM. By comparing the poses and angles of a pair of features in two scans, the corresponding corner is identified. In the next step, a transformation is performed to find the maximum overlapping between corresponding corners and lines. At the end, the transformation is applied to the current image and is added to reference. Robot position is updated by the following formula.

$$\begin{pmatrix} x_{n+1} \\ y_{n+1} \\ \phi_{n+1} \end{pmatrix} = \begin{pmatrix} x_n \\ y_n \\ \phi_n \end{pmatrix} + \begin{pmatrix} \cos\phi_n & \sin\phi_n & 0 \\ -\sin\phi_n & \cos\phi_n & 0 \\ 0 & 0 & 1 \end{pmatrix} . \begin{pmatrix} \Delta x \\ \Delta y \\ \Delta\phi \end{pmatrix} \tag{29}$$

V. EXPERIMENTAL SETUP

The MRL Naji2 is used to gather the experimental result. The robot is equipped with an embedded PC and a laser sensor. The laser sensor is laser rangefinders HOKUYO URG-04LX with the maximum measurement range of 4094mm, and range resolution of 1mm. The sensor is able to scan an angle of 0◦ – 240◦ with the angular resolution of

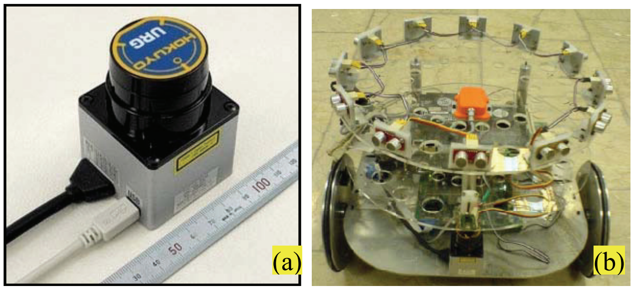

Fig. 9. HOKUYO URG-04LX laser scanner (a) Naji2 mobile robot (b)

0.36° and the maximum sampling frequency of 10Hz.

The robot employs a real-time operating system (RTAI Linux) with an embedded exploration system and a remote control module via wireless network (see Fig.9).

The algorithms are programmed in C++. The benchmarks are performed on a PC with PentiumIV-3.4GHz and 1GB of memory. Fig. 10 depicts a map which is obtained by this robot.

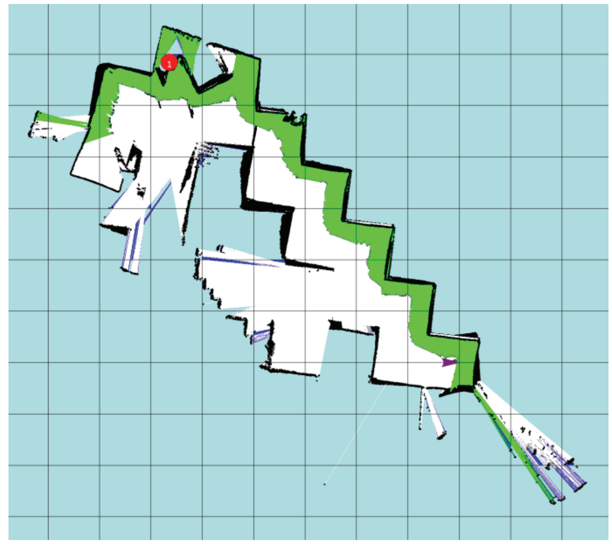

Fig. 10. Result of corner feature SLAM

VI. Conclusion

The superior speed of the split and merge method, makes it the best option for most of the real-time line extracting applications. However, the threshold values affect the algorithm performance in split and merge method. The conducted experiments revealed that a static threshold does not demonstrate a desirable accuracy and leads to a bad feature extraction and system divergence in the line based SLAM.

An Adaptive Line Extraction (ALE) is presented here for SLAM application. ALE is a modified version of split and merge method. It changes the threshold dynamically and finds the best line boundary. ALE is composed of the following steps: data smoothing to decrease the effect of noise, fitting a line to a data set using the least square method, applying RMSE criterion to evaluate the fitted line quality.

The strength of ALE is on the splitting method and the dynamic threshold. These two features enable ALE to identify line boundary fast and precisely.

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