SEGMENTATION AND GEOMETRIC PRIMITIVES EXTRACTION FROM 2D LASER RANGE DATA FOR MOBILE ROBOT APPLICATIONS

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Abstract: In this paper some algorithms for 2D segmentation, feature detection and fitting are presented. The features discussed here consist of three geometric primitives: lines, circles and ellipses. The segmentation process, whose objective is grouping segments that belong to the same object, is analysed using several kinds of algorithms. Results are presented using real data scanned by a laser range finder sensor.

Keywords: Segmentation; Feature extraction; Iterative methods; Kalman filters; Detection algorithms

1. INTRODUCTION

This paper summarizes some methods for data segmentation and feature extraction from range images generated by a single line Laser Range Finder (LRF). Most of these methods are valid for indoor and outdoor environments.

Segmentation process aims to identify and separate sets of segments related to targets detected by the LRF. The targets of interest are persons, posts, cars, walls and trees. On the other hand, feature extraction provides more condensed and feasible description of the objects in the environment. This arises with great advantage when performing mobile robotic tasks, such as object tracking, collision avoidance, etc.

Qualitative and quantitative comparisons are illustrated among the various methods discussed. Synthetic and real range data are used, concerned either with indoor and outdoor environments.

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1.1 Related works

Although some researches referred here stated works about object classification, SLAM, robot navigation, object tracking, and other related topics, this paper focuses just on the following processes: segmentation and feature extraction.

Segmentation methods are subdivided into two categories: the called Point-distance-based (PDBS) and the KF-based (KFBS) segmentation methods. Both of them related to 2D laser range data.

Examples of the PDBS approach are described in (Dietmayer, *et al.*, 2001; Lee, 2001; Borges and Aldon, 2004; Santos, *et al.*, 2003) and of the latter category are presented in (Borges and Aldon, 2004; Roumeliotis and Bekey, 2000; Adams, 2001; Zhang, *et al.*, 2003; Adams, *et al.*, 2004).

Feature extraction is analysed taking hand of several methods. For line fitting the methods exploited are mainly concerned to (Vandorpe, *et al.*, 1996; Siadat, *et al.*, 1997). For circle extraction we will base in (Gander, *et al.*, 1994; Guivant, *et al.*, 2000; Lee, 2001; Vandorpe, *et al.*, 1996) and, finally, for ellipses fitting an overview of the methods proposed by (Fitzgibbon, *et al.*, 1999; Gander, *et al.*, 1994) are described.
Moreover, feature matching is indeed achieved by

making use of some constraints assumptions about internal angles in arcs and lines presented in (Xavier, *et al.*, 2005).

1.2 Motivation and objectives

Examples of the utilization of a LRF in mobile robot applications appeared in many tasks: planning, localisation, SLAM, navigation, etc. Common issues present in those tasks are the processes related to segmentation and feature extraction. In this context, our motivation is to analyse and to compare several methods for segmentation and geometric primitive extraction, and hence to choose those that better accomplish the requirements related to our project (Bento and Nunes, 2005).

Due to the fact that we aim to implement a mobile robot system under real-time conditions, we have used a CAN (Controller Area Network) dedicated bus to forward the data from the LRF to the main CPU, mounted on a mobile robot, at the maximum Laser transfer rate. At that frequency, 500KBs, the amount of data from the Laser demands considerable capability of the CAN bus. To overcome this issue, and additionally to reduce the amount of data sent to the main CPU, a micro-controller based board will be used to perform a pre-processing stage using segmentation and feature extraction algorithms, outputting more relevant information from the raw laser data.

One of the contributions of this paper is the compilation of several methods commonly used for segmentation and feature extraction using data from a 2D laser sensor for the purpose of mobile robot tasks.

2. SEGMENTATION

Segmentation is the first step after the acquisition stage; however one could implement pre-processing techniques, e.g. median filter, before this step.

Consider a full scan of 180º as an ordered sequence of N measurements points (P), where each scanned point can be defined in Cartesian (x_n,y_n) or in polar coordinates (r_n,α_n), that is

$$P = \left\{ P_n = \begin{pmatrix} r_n \\ \alpha_n \end{pmatrix} \right\}, n \in [1, N] \quad (1)$$

Following the representation shown in Fig. 1, and in according to (1), a segment (S_i) can be expressed as

$$S_i = \{(r_i, \alpha_i); (x_i, y_i), : i = k : n\}, \ 1 \le k < n < N \quad (2)$$

Applying, as input, a complete sequence of scanned points (P) the segmentation algorithms output a pair of i^{th} values which represent the first and the final beam-point (r_n) in a detected segment.

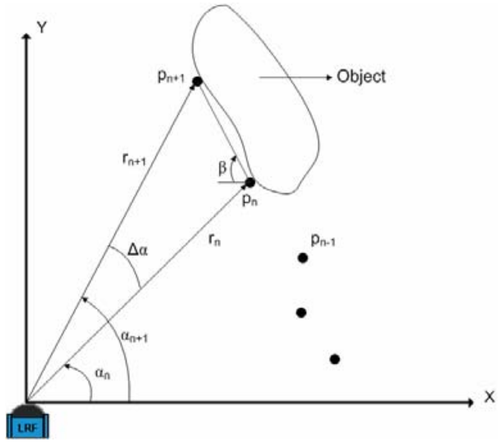

Fig. 1. Schematic representation of a hypothetical scan data and some involved parameters. Δα defines the sensor angular resolution.

2.1 Point-Distance-based methods (PDBS)

The algorithms concerned to this category have the general form:

If $D(r_i, r_{i+1}) > D_{thd}$ **then**, segments are separated **else** segments are not separated

where D_{thd} is the threshold condition and $D(r_i,r_{i+1})$ is the Euclidean distance between two consecutive scanned points

$$D(r_i, r_{i+1}) = \sqrt{r_i^2 + r_{i+1}^2 - 2r_i r_{i+1} \cos \Delta\alpha} \quad (3)$$

A well known approach (Dietmayer, *et al.*, 2001), uses the following threshold condition:

$$D_{thd} = C_0 + C_1 \min\{r_i, r_{i+1}\}, \quad (4)$$

where $C_1 = \sqrt{2(1 - \cos\Delta\alpha)} = D(r_i, r_{i+1}) / r_i$, and C_0 is a constant parameter used for noise reduction.

Based in the previous approach, (Santos, *et al.*, 2003) have included a new parameter (β) in the Eq. (4), aiming to reduce the dependence of the segmentation with respect to the distance between the LRF and the objects (see Fig. 1), resulting the threshold condition:

$$D_{thd} = C_0 + \frac{C_1 \min\{r_i, r_{i+1}\}}{\cot(\beta)[\cos(\Delta\alpha/2) - \sin(\Delta\alpha/2)]} \quad (5)$$

where C_0 and C_1 are the same as in (4).

A simple method for segmentation is presented in (Lee, 2001), where the threshold condition is given by:

$$D_{thd} = \left| \frac{r_i - r_{i+1}}{r_i + r_{i+1}} \right| \quad (6)$$

Another method, called *Adaptive Breakpoint Detector* (ABD) proposed by (Borges and Aldon, 2004), specifies a new equation for the threshold condition as

$$D_{thd} = r_i \frac{\sin \Delta\alpha}{\sin(\lambda - \Delta\alpha)} + \sigma_r \tag{7}$$

where λ is an auxiliary parameter and σ_r is a residual variance to encompass the stochastic behaviour of the sequence scanned points $\{P_n\}$ and the related noise associated to r_n.

2.2 KF-based methods (KFBS)

This category of segmentation is based on Kalman Filter (*KF*) and/or in Extended *KF* (*EKF*) approaches to detect, in the stochastic sense, the breakpoints. Let us assume that the dynamic process to be estimated is governed by the general discrete-time stochastic difference equations

$$\begin{aligned} \mathbf{x}_{k+1} &= \boldsymbol{f}(\mathbf{x}_k, \mathbf{w}_k) \\ \mathbf{z}_k &= \boldsymbol{h}(\mathbf{x}_k, \boldsymbol{\upsilon}_k) \end{aligned} \tag{8}$$

For the case where both f and h are linear functions, the state-space representation is

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{A}\mathbf{x}_k + \mathbf{w}_k \\ \mathbf{z}_{k+1} &= \mathbf{C}\mathbf{x}_k + \boldsymbol{\upsilon}_k \end{aligned} \tag{9}$$

An example of a KFBS method is described in (Borges, *et al.*, 2004). A discrete system model is proposed to describe the dynamic behaviour of adjacent points, having the following equations:

$$\begin{aligned} r_{k+1} &= r_k + \Delta\alpha \cdot \frac{dr_k}{d\alpha} \\ \frac{dr_{k+1}}{d\alpha} &= \frac{dr_k}{d\alpha} \end{aligned}, \tag{10}$$

choosing as state variables $x_k = \begin{bmatrix} r_k & \frac{dr_k}{d\alpha} \end{bmatrix}^T$.

Equation (10) in state-space form (9) yields

$$\mathbf{A} = \begin{bmatrix} 1 & \Delta\alpha \\ 0 & 1 \end{bmatrix}, \mathbf{C} = [1\ 0], \tag{11}$$

The general form of the algorithms using KF to detect breakpoints can be stated as:

```
Algorithm 1: KF-based Segmentation
FOR k=1:N, //N:= n° scanned points
- Initialize the filter //x=x0 and P=P0
- Calculate the filter prediction equations
- Test the gate-equation //χ² test
IF υk^T Sk^-1 υk ≥ Dthd //validation gate-equation
- Extract the break-point
- Reset the filter //x=x0 and P=P0
ELSE
- Perform the observation-update equations
END IF
END FOR
```

In the above algorithm the validation gate-equation ($\upsilon_k^T \mathbf{S}_k^{-1} \upsilon_k$) is formulated using the innovation and its covariance given by

$$\upsilon_k = z_n - \mathbf{C}\hat{\mathbf{x}}(k \mid k-1) \tag{12}$$
$$\mathbf{S}_k = \mathbf{C}_k \mathbf{P}(k \mid k-1)\mathbf{C}_k^T + \mathbf{R}$$

In treating with nonlinear process model and/or nonlinear observation model, an EKF can be employed. An EKF method to detect breakpoints, and indeed extract lines, is proposed by (Roumeliotis and Bekey, 2000), whose system equations, summarized in Table 1, were derived in according with Fig. 2.

Table 1 Line-segmentation approach using an EKF

System model	Relational matrices
$\phi_{k+1} = \phi_k + \Delta\alpha$	$\upsilon_{k+1} = z_{k+1} - \hat{z}_{k+1}$
$r_{k+1} = \frac{\sin(\phi_k)}{\sin(\phi_k + \Delta\alpha)} \cdot r_k$	$\mathbf{H}(k+1) = [1 \quad 0]$
$\hat{x}_k = [\hat{r}_k \quad \hat{\phi}_k]^T$	$\mathbf{F} = \begin{bmatrix} \frac{\sin(\phi_k)}{\sin(\phi_k + \Delta\alpha)} & \frac{\sin(\phi_k)}{\sin^2(\phi_k + \Delta\alpha)} r_k \\ 0 & 1 \end{bmatrix}$

where $\mathbf{F} = \nabla \boldsymbol{f}(x_k)$.

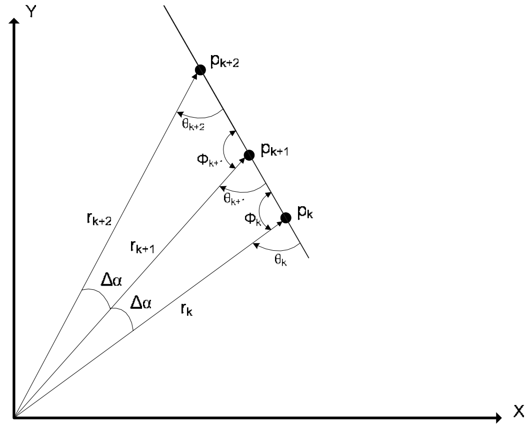

Fig. 2. Scan points from a flat (line) wall.

Another approach to breakpoint extraction (see Fig. 3) also based on an EKF is presented in (Adams, 2001), henceforth called ADA method.

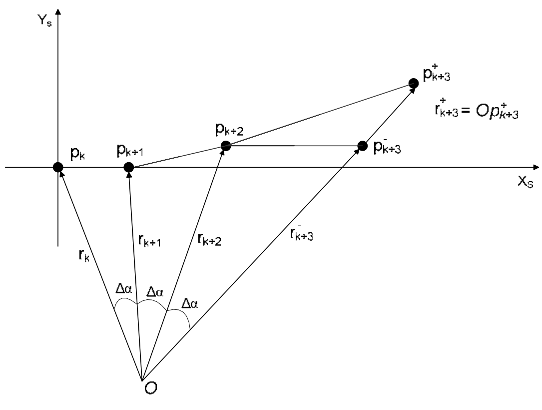

Fig. 3. ADA framework representation.

The ADA detection process validates regions, defined by a group of scanned points, and adapts its validation region according to the *spatial gradient*. Smoothness or, on the other hand, irregular behaviour are predicted by the EKF in order to detect breakpoints on that regions. The discrete system model has the following equations:

$$r_{k+2} = \frac{r_k \cdot r_{k+1}}{(2 \cdot r_k \cos\Delta\alpha) - r_{k+1}}$$

$$r^{-}_{k+3} = \frac{(2 \cdot r_k - r_{k+1}) r_{k+2}}{r_k - 2 \cdot r_{k+1}\cos\Delta\alpha + 2 \cdot r_k \cos 2\Delta\alpha}, \qquad (13)$$

$$r^{+}_{k+3} = r^{-}_{k+3} + \frac{N_1}{M} \cdot \frac{N_2}{R+S+T+U}$$

where,

$$\begin{aligned}
N_1 &= 2r_{k+2}(r_k^2 + r_{k+1}^2 - 2r_k r_{k+1}\cos\Delta\alpha) \\
N_2 &= 2r_k r_{k+2}\cos\Delta\alpha - r_k r_{k+1} - r_{k+1} r_{k+2} \\
M &= r_k - 2r_{k+1}\cos\Delta\alpha + 2r_k \cos 2\Delta\alpha \\
R &= -2r_k r_{k+1}^2 - r_k^2 r_{k+2} - r_{k+1}^2 r_{k+2} + 2r_k^2 r_{k+1}\cos\Delta\alpha + 2r_{k+1}^3 \cos\Delta\alpha \\
S &= r_k r_{k+1} r_{k+2}\cos\Delta\alpha - r_k r_{k+1}^2 \cos 2\Delta\alpha + r_k^2 r_{k+2}\cos 2\Delta\alpha \\
T &= r_{k+1}^2 r_{k+2}\cos 2\Delta\alpha - r_k^2 r_{k+1}\cos 3\Delta\alpha - 2r_k r_{k+1} r_{k+2}\cos 3\Delta\alpha \\
U &= r_k^2 r_{k+2}\cos 4\Delta\alpha
\end{aligned} \qquad (14)$$

The "*plus*" and "*minus*" in the previous expressions are related with a negative or positive spatial gradient (Adams, 2001).

Equations (13) in state-space form yields

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \\ x_3^-(k+1) \\ x_3^+(k+1) \end{bmatrix} = \begin{bmatrix} x_2(k) \\ x_3(k) \\ f^-(k)[x_1(k), x_2(k), x_3(k), \gamma] \\ f^+(k)[x_1(k), x_2(k), x_3(k), \gamma] \end{bmatrix} \qquad (15)$$

where $f^-[x_1, x_2, x_3, \Delta\alpha]$ and $f^+[x_1, x_2, x_3, \Delta\alpha]$ can be calculated from (13).

The corresponding innovation equation is given in Table 2:

Table 2 ADA Segmentation based on an EKF

Innovation	Relational Matrices
$\upsilon_{k+1} = \min\left\{\begin{array}{l} \mathbf{H}\hat{x}(k+1\|k) - z(k+1) \\ z(k+1) - \mathbf{H}\hat{x}(k+1\|k+1) \end{array}\right\}$	$\mathbf{H}(k+1) = [0 \quad 1 \quad 0]$ $\mathbf{F} = \nabla \boldsymbol{f}$

The general form of the EKF-algorithm using to detect breakpoints has a similar structure as the KF-based methods, taking the form below:

```
Algorithm 2: EKF-based Segmentation
FOR k=1:N,
- Initialize the filter //x=x0 and P=P0
- Calculate the filter prediction equations
- Test the gate-equation //χ2 test
IF υkT Sk-1 υk ≥ Dthd //validation gate-equation
- Extract the break-point
- Reset the filter
ELSE
- Performs the observation-update equations
END IF
END FOR
```

Variations of the ADA method for feature extraction are described in (Zhang, S., 2003) and (Adams, M., 2004).

3. FEATURE EXTRACTION

3.1 Introduction

The literature on primitives fitting can be dividing into two techniques: *clustering* (e.g. Hough-based approaches) and *least-squares* methods. In this paper only the second category will be reviewed.

Due to the fact that lines, circles and ellipses can be described like particular cases of *Conics*, let us formulate the extraction and fitting problem taking advantage of the conics formulation. The general form of the conic section equation in a plane is given by:

$$ax^2 + 2bxy + cy^2 + 2dx + 2ey + f = 0 \qquad (16)$$

where not both a and c are zero. The following assumptions are well known:
If $(b^2 - ac) < 0$, an ellipse is defined.
If $a = c$ and $b = 0$, a circle is defined.
If $a = b = c = 0$, a straight line is defined.

3.2 Line extraction

To further simplify the notation, the general form of a line is:
$$ax + by + c = 0, \qquad (17)$$
with the respective standard form
$$y = mx + q \qquad (18)$$

The basic concept in line extraction is to substitute a set of segments (S_i) by an ordered sequence of k lines, due to approximating the original run of the scan points. The first approach to be illustrated is the linear regression method (LRM). Probably it is one of most common and well known approach to line extraction, which objective is to solve the minimum error along the vertical axis.

The LRM is presented in (Vandorpe, *et al.*, 1996). Using a similar notation, let us define the following regression parameters:

$$S_x = \sum_{i=1}^{n} x_i,\ S_y = \sum_{i=1}^{n} y_i,\ S_{xx} = \sum_{i=1}^{n} x_i^2$$

$$S_{yy} = \sum_{i=1}^{n} y_i^2,\ S_{xy} = \sum_{i=1}^{n} x_i . y_i \qquad (19)$$

$$T_1 = S_{xy}.n - S_x S_y,\ T_2 = S_{xx}.n - S_{xx}^2$$

Yielding the line standard parameters:

$$m = \frac{T_1}{T_2} \text{ and } q = \frac{(S_y - m.S_x)}{n} \qquad (20)$$

Using (17), (Siadat, *et al.*, 1997) state the LRM problem as:

$$a = S_x S_{yy} - S_y S_{xy}$$
$$b = S_y S_{xx} - S_x S_{xy} \qquad (21)$$
$$c = S_{xy}^2 - S_{xx} S_{yy}$$

Thereby, the standard parameters yield: $m = -a/b$ and $q = -c/b$.

Considering again (17), a further mathematical development results in the matrix form

$$\mathbf{Bu} = \mathbf{0} \qquad (22)$$

$$B = \begin{bmatrix} x_1 & y_1 & 1 \\ x_2 & y_2 & 1 \\ \vdots & \vdots & \vdots \\ x_n & y_n & 1 \end{bmatrix}, \; u = [a \quad b \quad c]^T$$

The above expression relates to a classical problem to solve a linear over-determined system of equation $\mathbf{Bu} = \mathbf{0}$ for the coefficients $\mathbf{u}$, where $m = -a/b$ and $q = -c/b$.

In order to solve (22), a *LR factorization*, or a *svd* or *lsqr* algorithm can be used. The methods which solve (22) are in the sequel designated as LSM (Least Square Methods).

The well known IEPF (Iterative End-Point Fit) method (Duda and Hart, 1973) is a recursive algorithm, where a line is defined by the first and the last point of a given segment (S_i). Then, the point with the maximum distance to this line is detected. This point divides the segment in two intervals and the algorithm starts recursively again until the maximum distance is smaller than a certain threshold:

$$L_{thd} = \left| \frac{m\mathbf{x} - \mathbf{y} + q}{(m^2 + 1)^{1/2}} \right| \qquad (23)$$

Experiments of the IEPF are shown in Section 5, where this method is applied for line extraction.

3.3 Circle extraction

For the case of circles the general form is

$$(x - x_c)^2 + (y - y_c)^2 = r_c^2, \qquad (24)$$

with centre at (x_c, y_c) and radius

$$r_c = \sqrt{(x - x_c)^2 + (y - y_c)^2} \qquad (25)$$

From (19) the following expressions cab be applied to obtain the circle parameters (Vandorpe, *et al.*, 1996):

$$x_c = S_x / n$$
$$y_c = S_y / n \qquad (26)$$
$$r_c = \left(\rho_x^2 + \rho_y^2\right)^{1/2}$$

where $\rho_x^2 = \sum_{i=1}^{n} \frac{(x_i - x_c)^2}{n-1}$, $\rho_y^2 = \sum_{i=1}^{n} \frac{(y_i - y_c)^2}{n-1}$

Minimizing the sum of the square distances in some least square sense is one of the various methods of circle fitting presented in (Gander, *et al.*, 1994). Considering the general equation for conics in a 2D plane, the circle representation can be expressed as follows:

$$a(x^2 + y^2) + b_1 x + b_2 y + c = 0 \qquad (27)$$

Taking into account the linear system matrices

$$B = \begin{bmatrix} x_1^2 + y_1^2 & x_1 & y_1 & 1 \\ x_2^2 + y_2^2 & x_2 & y_2 & 1 \\ \vdots & \vdots & \vdots & \vdots \\ x_n^2 + y_n^2 & x_n & y_n & 1 \end{bmatrix}, \qquad (28)$$

$$u = [a \quad b_1 \quad b_2 \quad c]^T$$

The circle parameters calculation assumes the classical form:

$\|\mathbf{Bu}\| = \mathbf{0}$, subject to the constraint $\|\mathbf{u}\| = \mathbf{1}$. (29)

The centre and the radius of the circle, obtained from (29), are given by:

$$x_c = -b_1 / 2a$$
$$y_c = -b_2 / 2a \qquad (30)$$
$$r_c = \left(\frac{\|\mathbf{b}\|^2}{4a^2} - \frac{c}{a} \right)^{1/2}$$

where $\mathbf{b} = (b_1, b_2)^T$.

Again, a *svd* decomposition or a *lsqr* function can be employed to solve the related minimization problem (29).

A simple method was proposed by (Guivant, *et al.*, 2000) in order to approximate the radius and the centre of a circle-object. Using the average of the scanned range-points, that defines a segment, and the angular width (defined between the first and the last range bearing), the diameter of a circle-object is given by:

$$2 \cdot r_c = \sum_{i=k}^{n} \Delta\alpha \cdot \frac{1}{n-k+1} S_i, \qquad (31)$$

where S_i is given by (2).

Satisfying the assumptions that the centre of the circle is to be collinear with the median angular width, the coordinates that defines the centre (x_c, y_c) can be determined, in an approximation sense, considering two distinct assumptions:

1- The centre is assumed to be distant from the nearest laser scanned point by r_c. It is equivalent to:

$$x_c = (r_{\min} + r_c) \cdot \cos(\alpha_{\min}),$$
$$y_c = (r_{\min} + r_c) \cdot \sin(\alpha_{\min}) \qquad (32)$$

where $r_{\min} = \min(r_i), i \in [n, k]$

2- The centre is assumed to be distant from the average points ($mean(S_i)$) by a value of $r_c/2$. It is equivalent to:

$$\begin{aligned} x_c &= (r_{mean} + r_c/2) \cdot \cos(\alpha_{mean}) \\ y_c &= (r_{mean} + r_c/2) \cdot \sin(\alpha_{mean}) \end{aligned}, \quad (33)$$

where $r_{mean} = mean(r_i), i \in [n,k]$

3.4 *Ellipse extraction*

The standard form of the equation that defines an ellipse, with centre at (x_e,y_e), is

$$\frac{(x-x_e)^2}{a^2} + \frac{(y-y_e)^2}{b^2} = 1, \quad (34)$$

More specifically, the parameters to be found are the ellipse centre, the major and minor axes and the ellipses orientation.

An interesting method for ellipse fitting, which we designate by FITZ method, is described in (Fitzgibbon, *et al.*, 1999). This work presents an excellent analysis and comparison between the FITZ and others approaches of ellipse fitting. The (FITZ) method imposes the *equality* constraint:

$4ac - b^2 = 1$, (35)

which reduces the problem to minimizing the following expression:

$E = \|\mathbf{Da}\|^2$, subject to the constraint $\mathbf{a}^T\mathbf{C}\mathbf{a} = \mathbf{1}$,

where $\mathbf{D}$ = [x^2 xy y^2 x y ones(n,1)], is the *design matrix*, $\mathbf{C}$ is a 6x6 matrix that expresses the constraint (35) and $\mathbf{a}$ is the vector of the ellipse parameters.

4. SEGMENTS MATCHING

A fast and simple-to-use way of performing the segment-feature correspondence is proposed in (Xavier, *et al.*, 2005). Due to the fact that the angles of points inside an arc are congruent in respect to the extremes, the referred authors propose a technique called *Inscribed Angle Variance* (IAV). The segment-feature matching procedure involves two steps:
- Calculate the mean of the internal angles along the extremes points of S_i;
- Calculate the standard deviation of those values.

For circle correspondence empirical values of the average inscribed angle were found to lie between 90º to 135º and, in the case of lines this value is around 180º.

5. RESULTS

The laser used in this experiment is a SICK LMS200, configured with a field of view of 180º, range up to 8.0 m, N= 361 and angular resolution Δα = 0.5 º. All experiments were conducted using the Matlab software.

It should be pointed out that one of the objectives of this work is to identify feasible methods to be used in microcontroller based boards. In this context our experiments were focused in simple-to-use algorithms with low computation requirements.

5.1 *Segmentation experiments*

In this Section we present some results concerning those methods discussed before (PDBS and KFBS approaches). Two representative examples are shown in Fig. 4 and Fig. 5, related to an indoor and an outdoor environment, respectively. The numbers inside those figures represent the segments (S_i) identified by the algorithms. In the sequel we adopt the following abbreviations (some of them already mentioned in Section 2):

- DIET: (Dietmayer, *et al.*, 2001)
- LEE: (Lee, 2001)
- ABD: (Borgers and Aldon, 2004)
- KFBD: (Borgers and Aldon, 2004)
- SEGM: (Roumeliotis and Bekey, 2000)

The first three methods are of the PDBS category, and the others are classified as KFBS approaches (see Section 2). The main drawback of the PDBS methods is the necessity to adjust, in an *off-line* sense, some parameters accordingly with the distance from the LRF and the objects. Compared with these breakpoint methods, the KFBS algorithms have the advantage of treating the incoming data in an *on-line* nature, i.e. sequentially as the points appear. Furthermore, KFBS algorithms can give some insight of the feature type besides of performing the segmentation.

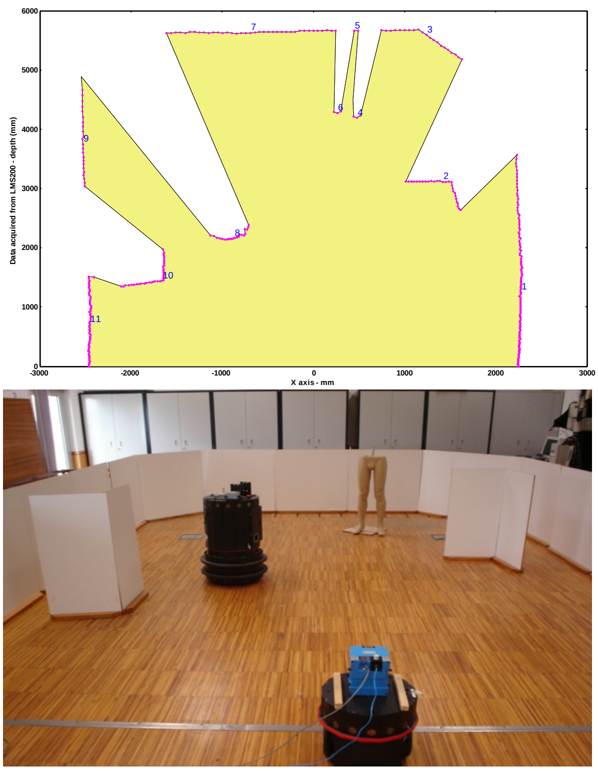

Fig. 4. Typical segmentation using DIET method. *Top*) Segmentation result; *Bottom*) A snapshot of an indoor scenario.

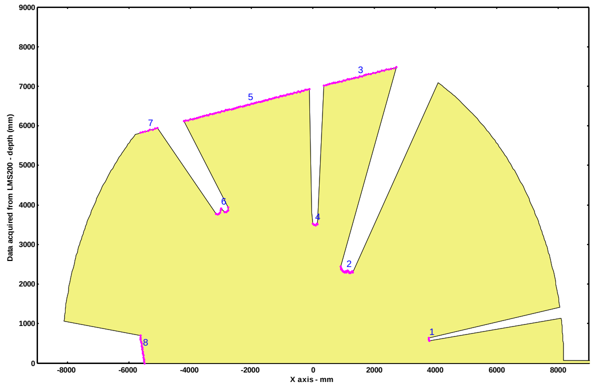

Fig. 5. Typical segmentation, using LEE, in an outdoor environment; where the segment 1 is related to a tree; segments 3, 5, 7 and 8 are related to walls and the others to persons (legs).

5.2 *Line extraction and fitting experiments*

All methods can extract a line even when the data has only two elements. Nevertheless, a constraint should be imposed when the lines are collinear with the y-axis (see Fig. 1) in respect with the laser reference frame. This problem is also discussed in (Vandorpe, *et al.*, 1996), where a condition was used to define how to make the regression, i.e. if the regression will be made of "y" to "x" or *vice-versa*.

Knowing that the LRM methods also implement a least square technique, it is not surprising that these algorithms have results similar to those designated LSM methods. More specifically, the results of the VAN method and of algorithms using *QR factorization* are quite identical; a similar conclusion is observed for the SIA method (Siadat, *et al.*, 1997) compared with the algorithms using *svd* decomposition. Some results of the LSM and LRM methods are illustrated in Fig. 6.

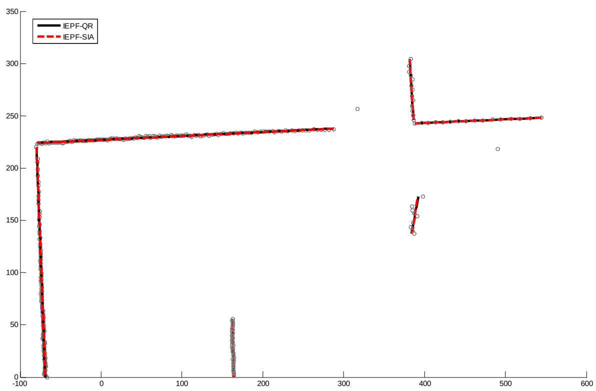

Fig. 6. Line fitting concerning an indoor environment using IEPF-LSM and IEPF-LRM methods.

The easiness and fast implementation of the LRM (VAN and SIA) algorithms justify the choice of one of these methods for implementation in microcontroller based boards to satisfy our requirements. The SEGM can also perform line extraction, like originally presented in (Roumeliotis, 2000).

5.3 *Circle extraction results*

Again we shall adopt some abbreviations to designate the methods illustrated in this Section:

- GAN1: algebraic form, (Gander, *et al.*, 1994)
- GAN2: parametric form, (Gander, *et al.*, 1994)
- VAN: (Vandorpe, *et al.*, 1996)
- GIV: (Guivant, *et al.*, 2000)

Some results are illustrated in Fig. 7. We can observe that the VAN method does not achieve a good estimation for the circle centre (x_c,y_c). To overcome this situation, for example, the GAN method can be used to estimate the centre of the circle.

However, VAN and GIV methods are very useful in approximating a circle where the segments have few points, which is a common case in outdoor scenarios. In cases where a reasonable amount of points define a segment, and more accurate results are required, GAN methods provide a good fitting.

Two variations of the GIV approach were presented in Section 3. Experiments with this method led us to conclude that the assumption where the centre of the circle is estimated considering the distance from the nearest point has better results in comparison with the other assumption.

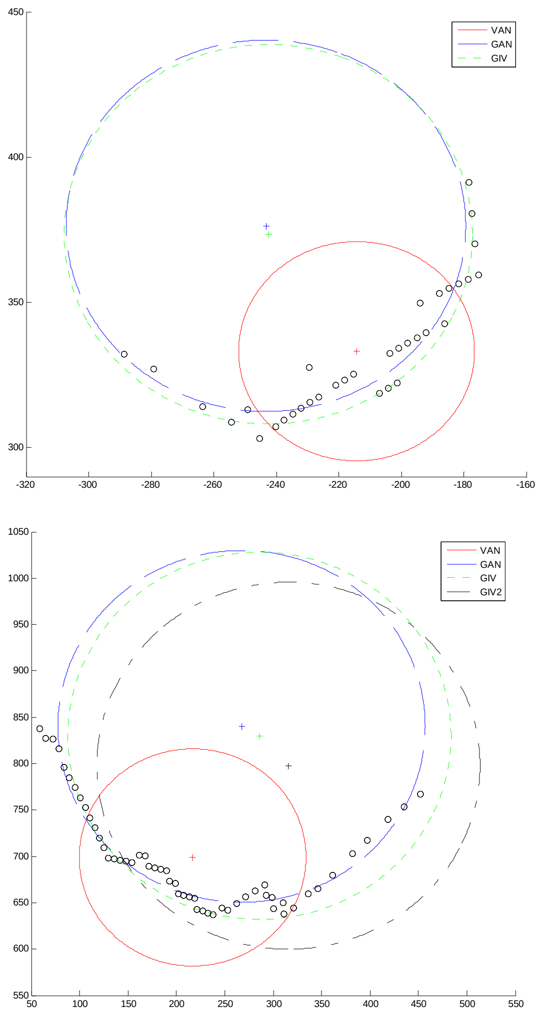

Fig. 7. Circle extraction using real scanned points using VAN, GAN, GIV and GIV2 methods.

Whereas the "original" GAN approach have been implemented based on various non-linear least square algorithms, in our experiments only the well known *svd* and *lsqr* Matlab functions were used.

The VAN and GIV are methods that, in despite of a low accuracy, have the advantages of being fast and easy to implement. These algorithms are a good choice for embedded controller implementation.

5.4 Ellipse fitting

Taking the advantage that the GAN and FITZ algorithms are available on public domain[2], these methods were experimented using the same data presented in Fig. 7. Illustrative results are shown in Fig. 8.

An important property is the simplicity of the FITZ algorithm, which can be encompassed in a six-line Matlab code, leading us to adopt this method for our future applications.

6. CONCLUSIONS AND FUTURE WORK

In this paper we have presented several methods to perform segmentation and feature extraction based on 2D scanned points from a LRF. Experiments were implemented in Matlab using real data collected in multiple situations.

The performance of the segmentation algorithms are substantially the same either for indoor as for outdoor environments, with some disadvantage for the PDBS methods due to the fact that those approaches, in contrast with the KFBS, do not adapt dynamically during the process.

Feature extraction was implemented with emphasis on algorithms being able to extract lines and circles. In despite of that ellipsis fitting methods were also discussed. As related in previous sections, line extraction should be performed under the constraint that the regression can be made of "y" to "x" ($y = mx + q$) or "x" to "y" ($x = sy + t$).

For circle extraction (approximation) VAN and GIV methods would be good choices. When more accuracy (better fitting) is required, one can use the GAN methods.

Further studies concerning with KF/EKF-based methods for feature extraction shall be required. Moreover the data association problem (feature matching) and the implementation of the algorithms in embedded systems are to be pursued as future work.

[2] ftp.inf.ethz.ch/pub/publications/tech-reports/2xx/217.ps
www.robots.ox.ac.uk/~awf/ellipse/fitellipse.html

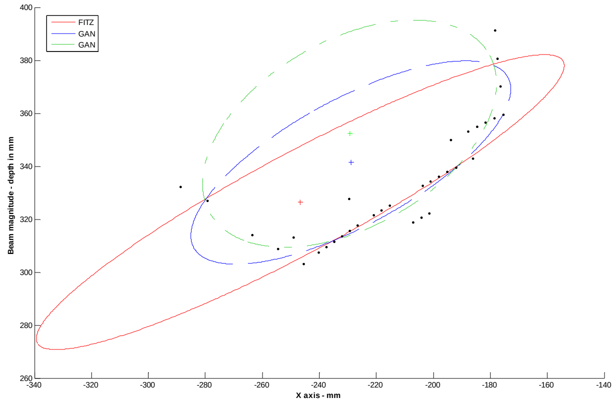

Fig. 8. Ellipses extraction using real scanned points, employing FITZ and GAN methods.

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