SLAM WITH CORNER FEATURES FROM A NOVEL CURVATURE-BASED LOCAL MAP REPRESENTATION

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This paper presents a solution to the Simultaneous Localization and Map Building (SLAM) problem for a mobile agent which navigates in an indoor environment and it is equipped with a conventional laser range finder. The approach is based on the stochastic paradigm and it employs a novel feature-based approach for the map representation. Stochastic SLAM is performed by storing the robot pose and landmark locations in a single state vector, and estimating it by means of a recursive process. In our case, this estimation process is based on an extended Kalman filter (EKF). The main novelty of the described system is the efficient approach for natural feature extraction. This approach employs the curvature information associated to every planar scan provided by the laser range finder. In this work, corner feature has been considered. Real experiments carried out with a mobile robot show that the proposed approach acquires corners of the environment in a fast and accurate way. These landmarks permit to simultaneously localize the robot and build a corner-based map of the environment.

1. Introduction

The difficulty of the simultaneous localization and map building (SLAM) problem lies in the fact that an accurate estimation of the robot trajectory is required to obtain a good map, and to minimize the unbounded growing odometry errors requires to associate sensor measurements with a precise map[5]. To increase the efficiency and robustness of the process, sensor data have to be transformed in a more compact form before attempting to compare them to the ones presented on a map or store them in the map that is being built. In either case, the chosen map representation heavily determines the precision and reliability of the whole task[4]. Typical choices for the map representation include occupancy grids, topological maps and feature maps[1].

In this paper, a feature based approach is employed to solve the SLAM problem. Feature maps are a suitable representation for long-term convergent SLAM in medium-scale environments[1]. It allows the use of multiple models to describe the measurement process for different parts of the environment and it avoids the data smearing effect[5]. In order to achieve consistent estimation of the robot pose, a basic stochastic SLAM algorithm is used. This algorithm stores robot and landmarks locations in a state vector and updates these estimates using an extended Kalman filter (EKF). This approach suffers from three main disadvantages: high computation and storage costs, fragile data association and inconsistent treatment of non-linearity[1,5,2]. In this work, we will demonstrate that all these weaknesses can be alleviated if a fast and reliable algorithm to extract landmarks for the large set of noisy and uncertain data is employed. The proposed landmark acquisition algorithm is based on the curvature information associated to every scan provided by the laser range finder. Particularly, in this work we only consider corner features. These corner features will permit to simultaneously localize the robot and build a map of the environment.

The rest of the paper is organized as follows: Section 2 describes the proposed EKF–SLAM algorithm, where the curvature-based corner acquisition algorithm is included. Section 3 presents experimental results and, finally, Section 4 summarizes conclusions and future work.

2. Description of the Proposed System

In the standard EKF-based approach to SLAM, the robot pose and landmark locations at time step k are represented by a stochastic state vector $\mathbf{x}_a^k$ with estimated mean $\hat{\mathbf{x}}_a^k$ and estimated error covariance $\mathbf{P}_a^k$. The mean vector $\hat{\mathbf{x}}_a^k$ contains the estimated robot pose, $\hat{\mathbf{x}}_v^k$, and the estimated environment landmarks positions, $\hat{\mathbf{x}}_m^k$, all with respect to a base reference W. This concatenation is necessary as consistent SLAM relies on the maintenance of correlations $\mathbf{P}_{vm}^k$ between the robot and the map[1]. In this work, we use the robot pose at step k=0 as the base reference ($W = \mathbf{x}_v^0$). Thus, the map can be initialized with zero covariance for the robot pose, $\hat{\mathbf{x}}_a^0 = (0,0,0)^T$, $\mathbf{P}_a^0 = 0$. Previous work has showed that this improves the consistency of the EKF–SLAM algorithm[2]. For convenience, the k notation can be dropped in this Section as the sequence of operations is apparent from its context. Then, the mean $\hat{\mathbf{x}}_a$ and covariance $\mathbf{P}_a$ of the state vector can be defined as

$$\hat{\mathbf{x}}_a = \begin{bmatrix} \hat{\mathbf{x}}_v \\ \hat{\mathbf{x}}_m \end{bmatrix} \qquad \mathbf{P}_a = \begin{bmatrix} \mathbf{P}_{vv} & \mathbf{P}_{vm} \\ \mathbf{P}_{mv} & \mathbf{P}_{mm} \end{bmatrix} = \begin{bmatrix} \mathbf{P}_{vv} & \mathbf{P}_{vm} \\ \mathbf{P}_{vm}^T & \mathbf{P}_{mm} \end{bmatrix} \tag{1}$$

When the robot pose and map landmarks are stored in a single state vector, stochastic SLAM[1,5,2] is performed by estimating the state parameters via a recursive process of prediction and correction. The prediction stage deals with robot motion based on incremental dead reckoning estimates, and increases the uncertainty of the robot pose estimate. Then, new landmarks are acquired from the environment. These landmarks are associated to the previously stored ones. The update stage employs this data association to improve the overall state estimate. Finally, if a landmark is observed for the first time, it is added to the state vector through an initialization process called state augmentation. Next subsections deal with the stages of the described EKF–SLAM algorithm. The proposed landmark acquisition stage will be explained in subsection 2.2.

2.1. *Prediction stage*

When the robot moves from pose at step $k-1$ to pose at step k, its motion is estimated by odometry. In our case, the system has been tested on a four wheeled robot, where left and right wheels are mechanically coupled and, thus, encoders only return right and left speeds. Assuming that the robot state is represented by its pose, $\hat{\mathbf{x}}_v = (\hat{x}_v \;\; \hat{y}_v \;\; \hat{\phi}_v)^T$, the prediction stage only changes the robot pose part of the state vector and the $\mathbf{P}_v$ and $\mathbf{P}_{vm}$ submatrices in the state covariance matrix. Map landmarks remain stationary. Therefore, the predicted state is given by

$$\hat{\mathbf{x}}_a^- = \begin{bmatrix} \hat{x}_v + D\cdot c \\ \hat{y}_v + D\cdot s \\ \hat{\phi}_v + \Delta\phi \\ \hat{\mathbf{x}}_m \end{bmatrix} = f(\hat{\mathbf{x}}_a, u) \qquad \mathbf{P}_a^- = \nabla f_{\mathbf{x}_a} \mathbf{P}_a \nabla f_{\mathbf{x}_a}^T + Q \tag{2}$$

$$c = \cos\hat{\phi}_v \qquad s = \sin\hat{\phi}_v$$

where $u = (D \quad \Delta\phi)^T$ defines the translation and angular difference with respect to the previous robot pose, and Q is the odometry covariance. The Jacobian $\nabla f_{\mathbf{x}_a}$ is defined as

$$\nabla f_{\mathbf{x}_a} = \left(\frac{\partial f}{\partial \mathbf{x}_a}\right)_{(\hat{\mathbf{x}}_a, u)} = \begin{bmatrix} \nabla g_{\mathbf{x}_v} & 0_{vm} \\ 0_{mv} & I_m \end{bmatrix} \qquad \nabla g_{\mathbf{x}_v} = \begin{bmatrix} 1 & 0 & -D\cdot s \\ 0 & 1 & D\cdot c \\ 0 & 0 & 1 \end{bmatrix} \tag{3}$$

2.2. *Curvature-based landmark acquisition stage*

In this work, we characterize each range reading of the laser scan by a curvature index. This index is adaptively filtered according to the distance between possible corners in the whole laser scan. This filtering permits to remove noise, but scan features are nevertheless detected despite their natural scale. For each range reading $i = (x_i, y_i)$ of a laser scan, the proposed method for corner acquisition consists of the following steps:

(1) Calculation of the maximum length of laser scan presenting no discontinuities on the right and left sides of the range reading i: $K_f(i)$ and $K_b(i)$, respectively. $K_f(i)$ is calculated by comparing the Euclidean distance from i to its $K_f(i)$-th neighbour $(d(i, i + K_f(i)))$ to the real length of the laser scan between both range readings$(l(i, i+K_f(i)))$. Both distance tend to be the same in absence of corners, even if laser scans are noisy. Otherwise, the Euclidean distance is quite shorter than the real length. Thus, $K_f(i)$ is the largest value that satisfies

$$d(i, i + K_f(i)) > l(i, i + K_f(i)) - U_k \tag{4}$$

where U_k is a constant value that depends on the noise level tolerated by the detector. $K_b(i)$ is also set according to Eq. (4), but using $i - K_b(i)$ instead of $i + K_f(i)$.

(2) Calculation of the local vectors $\overrightarrow{f_i}$ and $\overrightarrow{b_i}$ associated to each range reading i. These vectors represent the variation in the x and y axis between range readings i and $i+K_f(i)$ and between i and $i-K_b(i)$. They are defined as

$$\overrightarrow{f_i} = (x_{i+K_f(i)} - x_i, y_{i+K_f(i)} - y_i) \quad \overrightarrow{b_i} = (x_{i-K_b(i)} - x_i, y_{i-K_b(i)} - y_i) \tag{5}$$

(3) Calculation of the angle associated to i. According to previous works[3], the angle at range reading i can be estimated as follows

$$|K_\theta(i)| = \frac{1}{2} \cdot \left(1 + \frac{\overrightarrow{f_i} \cdot \overrightarrow{b_i}}{|\overrightarrow{f_i}| \cdot |\overrightarrow{b_i}|}\right) \tag{6}$$

(4) Detection of corners over $|K_\theta(i)|$. Corners are those range readings which satisfy the following conditions: i) they are local peaks of the curvature function and ii) their $|K_\theta(i)|$ values are over the minimum angle required to be considered a corner instead of a spurious peak due to remaining noise (θ_{min}).

2.3. *Data association stage*

Once corner features have been acquired, they must be associated to previously stored ones. Correct correspondence of observed landmarks to map ones is essential for consistent map building because a single failure may invalidate the whole process. In our case, landmarks are distinguishable only by their positions. Therefore, correspondences established by the data association stage are constrained by statistical geometric information. In this work, the normalised innovation squared (NIS) defines the validation gate or maximum discrepancy between a measurement $\mathbf{z}$ and a predicted observation $h(\hat{\mathbf{x}}_j)$ for target $\mathbf{x}_j$[1]. Given an observation innovation ν_{ij} with covariance $\mathbf{S}_{ij}$, the NIS forms a χ^2 distribution. The gate is applied as a maximum NIS threshold, γ_n. Then,

$$\nu_{ij} = \mathbf{z} - h(\hat{\mathbf{x}}_j) \qquad \mathbf{S}_{ij} = \nabla h_{\mathbf{x}_a} \mathbf{P}_a^- \nabla h_{\mathbf{x}_a}^T + \mathbf{R} \qquad NIS \equiv \nu_{ij}^T \mathbf{S}_{ij}^{-1} \nu_{ij} < \gamma_n \quad (7)$$

The integral of the χ^2 distribution from 0 to γ_n specifies the probability that, if $\mathbf{z}$ is a true observation of target $\mathbf{z}_j$, the association will be accepted. In our experiments, the innovation vector is of dimension 2, and the gate γ_2 equal to 6.0, if $\mathbf{z}_j$ is truely an observation of landmark $\mathbf{x}_j$ the association will be accepted with 90% of probability.

The validation gate defines an ellipsoid in the observation space centred about the predicted observation $h(\hat{\mathbf{x}}_j)$. Then, an acceptable observation must fall within this ellipse. Data association ambiguity occurs if either multiple observations fall within the validation gates of a particular target, or a single observation lies within the gates of multiple targets. The most common ambiguity resolution method is nearest neighbour data association. Given a set of observations, $\mathbf{Z}$, within the validation gate of target $\mathbf{x}$, a normalised distance ND_l can be calculated to each $\mathbf{z}_l \in \mathbf{Z}$

$$ND_l = \nu_l^T \mathbf{S}_l^{-1} \nu_l + log|\mathbf{S}_l| \quad (8)$$

Nearest neighbour data association then chooses the observation that minimizes ND_l. This is the simplest data association algorithm and it can only associate a single observation at each step k.

2.4. *Updating stage*

If an observation $\mathbf{z}$ is correctly associated to a map landmark estimate $(\hat{x}_i,\ \hat{y}_i)$, then the perceived information is related to the map by

$$\hat{\mathbf{z}}_i = h_i(\hat{\mathbf{x}}_a) = \begin{bmatrix} \Delta x \cdot c + \Delta y \cdot s \\ -\Delta x \cdot s + \Delta y \cdot c \end{bmatrix} \quad (9)$$
$$\Delta x = (\hat{x}_i - \hat{x}_v) \qquad \Delta y = (\hat{y}_i - \hat{y}_v)$$

The Kalman gain $\mathbf{K}_i$ can be obtained as

$$\nu_i = \mathbf{z} - h_i(\hat{\mathbf{x}}_a^-) \qquad \mathbf{S}_i = \nabla h_{\mathbf{x}_a} \mathbf{P}_a^- \nabla h_{\mathbf{x}_a}^T + \mathbf{R} \qquad \mathbf{K}_i = \mathbf{P}_a^- \nabla h_{\mathbf{x}_a}^T \mathbf{S}_i^{-1} \quad (10)$$

where $\mathbf{R}$ is the observation covariance and the Jacobian $\nabla h_{\mathbf{x}_a}$ is given by

$$\nabla h_{\mathbf{x}_a} = \left(\frac{\partial h_i}{\partial \mathbf{x}_a}\right)_{\hat{\mathbf{x}}_a^-} = \begin{bmatrix} -c & -s & -s\cdot\Delta x + c\cdot\Delta y & 0 \ldots & c & s \ldots 0 \\ s & -c & -c\cdot\Delta x - s\cdot\Delta y & 0 \ldots & -s & c \ldots 0 \end{bmatrix} \quad (11)$$

It can be noted that the Jacobian $\nabla h_{\mathbf{x}_a}$ only presents non-zero terms align with the positions of the robot states and the observed feature states in the augmented state vector. The posterior SLAM estimate is determined from

$$\hat{\mathbf{x}}_a^+ = \hat{\mathbf{x}}_a^- + \mathbf{K}_i \nu_i \qquad \mathbf{P}_a^+ = \mathbf{P}_a^- - \mathbf{K}_i \mathbf{S}_i \mathbf{K}_i^T \quad (12)$$

2.5. *State augmentation stage*

As the environment is explored, new landmarks are observed and must be added to the map. To initialise new landmarks, the state vector and covariance matrix are augmented with the values of the new observation, $\mathbf{z}$, and its covariance, $\mathbf{R}$, as measured relative to the observer.

$$\hat{\mathbf{x}}_{aug} = \begin{bmatrix} \hat{\mathbf{x}}_a \\ \mathbf{z} \end{bmatrix} \qquad \mathbf{P}_{aug} = \begin{bmatrix} \mathbf{P}_{vv} & \mathbf{P}_{vm} & 0 \\ \mathbf{P}_{vm}^T & \mathbf{P}_{mm} & 0 \\ 0 & 0 & \mathbf{R} \end{bmatrix} \quad (13)$$

A function g_i is employed to translate $\mathbf{z} = (x_c \quad y_c)^T$ to a global location. This transformation is defined as

$$g_i(\mathbf{x}_v, \mathbf{z}) = \begin{bmatrix} x_i \\ y_i \end{bmatrix} = \begin{bmatrix} x_v + x_c\cdot c - y_c\cdot s \\ y_v + x_c\cdot s + y_c\cdot c \end{bmatrix} \quad (14)$$

Then, the augmented state can be initialized by performing a transformation to global coordinates by the function f_i as follows

$$\hat{\mathbf{x}}_a^+ = f_i(\hat{x}_{aug}) = \begin{bmatrix} \hat{\mathbf{x}}_a \\ g_i(\mathbf{x}_v, \mathbf{z}) \end{bmatrix} \qquad \mathbf{P}_a^+ = \nabla f_{\mathbf{x}_{aug}} \mathbf{P}_{aug} \nabla f_{\mathbf{x}_{aug}}^T \quad (15)$$

The Jacobian $\nabla f_{\mathbf{x}_{aug}}$ can be derived as

$$\nabla f_{\mathbf{x}_{aug}} = \left(\frac{\partial f_i}{\partial \mathbf{x}_{aug}}\right)_{\hat{\mathbf{x}}_{aug}} = \begin{bmatrix} I_v & 0 & 0 \\ 0 & I_m & 0 \\ \nabla g_{\mathbf{x}_v} & 0 & \nabla g_{\mathbf{z}} \end{bmatrix} \quad (16)$$

where $\nabla g_{\mathbf{x}_v}$ and $\nabla g_{\mathbf{z}}$ are as follows

$$\nabla g_{\mathbf{x}_v} = \begin{bmatrix} 1 & 0 & -x_c\cdot s - y_c\cdot c \\ 0 & 1 & x_c\cdot c - y_c\cdot s \end{bmatrix} \qquad \nabla g_{\mathbf{z}} = \begin{bmatrix} c & -s \\ s & c \end{bmatrix} \quad (17)$$

The posterior SLAM covariance matrix, $\mathbf{P}_a^+$, is as follows

$$\mathbf{P}_a^+ = \begin{bmatrix} \mathbf{P}_v & \mathbf{P}_{vm} & \mathbf{P}_v \nabla g_{\mathbf{x}_v}^T \\ \mathbf{P}_{vm}^T & \mathbf{P}_m & \mathbf{P}_{vm} \nabla g_{\mathbf{x}_v}^T \\ \nabla g_{\mathbf{x}_v} \mathbf{P}_v & \nabla g_{\mathbf{x}_v} \mathbf{P}_{vm} & \nabla g_{\mathbf{x}_v} \mathbf{P}_v \nabla g_{\mathbf{x}_v}^T + \nabla g_{\mathbf{z}} \mathbf{R} \nabla g_{\mathbf{z}}^T \end{bmatrix} \quad (18)$$

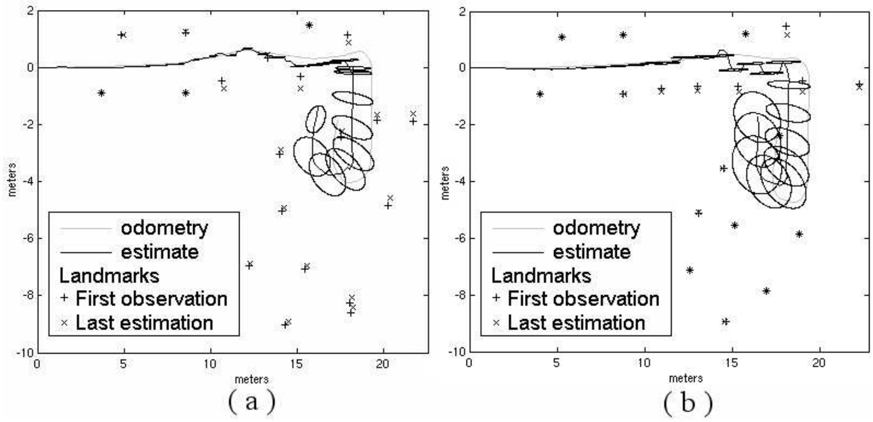

Figure 1. a) Estimated trajectory of the robot using the proposed landmark detection method; and b) Estimated trajectory of the robot using a slower landmark acquisition rate.

3. Experimental Results

Figs. 1.a and 1.b show the experimental results obtained by running two different landmark acquisition rates. Figures illustrate the estimated trajectory. The robot pose uncertainty has been drawn over the trajectory. Fig. 1.a has been generated using the proposed landmark acquisition algorithm. The whole EKF–SLAM algorithm runs every 200 ms on the 400MHz Versak6 PC 104+ embedded on our Pioneer 2AT mobile platform. The landmark acquisition algorithm only takes 25 ms including 180^o laser data acquisition. It can be noted that the robot pose uncertainty is bounded due to a more frequent updating. To obtain the estimated trajectory of Fig. 1.b, the robot has been moved through the same path. However, in this case the landmark acquisition algorithm is slower. Then, less landmarks are acquired and the updating rate decreases. It can be appreciated that the robot pose uncertainty is higher and its pose estimation is poorer than in Fig. 1.a.

4. Conclusions and Future Work

Experiments show that EKF–based SLAM problems can be alleviated when a fast and reliable landmark acquisition algorithm is employed. The proposed landmark extraction algorithm reduces the computational cost associated to the whole process. This fact is specially interesting because it avoids large periods without suitable update process. The increasing of the updating rate reduces the robot pose uncertainty and avoids that data association becomes very fragile[1].

On the other hand, it has been shown that in the basic EKF–SLAM framework, linearization errors produce inconsistency problems[1]. These problems can be reduced using local maps or robocentric mapping[2]. Future work will be focused on the combination of these techniques with the proposed fast landmark extraction approach in order to further improve map consistency. Besides, a batch data association method would improve the updating stage because it provides more information in the innovation[1].

Acknowledgments

This work has been partially supported by the Spanish Ministerio de Educación y Ciencia (MEC) project no. TIN2005-01349.

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