A Simple and Efficient Implementation of EKF-based SLAM Relying on Laser Scanner in Complex Indoor Environment

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Abstract:
Localization in an unknown environment is one of the major issues faced by autonomous vehicles. The solution to this problem is delivered by the Simultaneous Localization and Mapping techniques, commonly known as SLAM. SLAM is the category of algorithms allowing a robot to map the surroundings and to keep an estimate of its position. Nowadays several SLAM methods are widely used. Though, many issues arise when SLAM is applied in a complex and unstructured environment. This article details an implementation of SLAM using improved Extended Kalman Filter (EKF). The aim is to provide a simple but reliable SLAM technique. The work has been carried out on a robot Seekur Jr, the mapping has been realized with a laser scanner. The applied EKF model with its modifications is presented. The techniques used to observe the environment and to identify the landmarks are outlined. The robustness and consistency of introduced modifications were justified by experiments.

Keywords: *mobile robot, SLAM, environment recognition*

1. Introduction

1.1. Historical Context

It is often considered that the first publication about SLAM has been made by Durrant-Whyte and Leonard in 1991 [3]. Among the different possible methods of SLAM, the so-called stochastic mapping methods became very popular despite their heavy computational cost. They have been introduced by Smith, Self and Cheeseman in 1987 [15]. These methods rely on a probabilistic approach. They act upon strong theoretical basis and integrate many profitable concepts, this results in a good quality SLAM. The popular ones are the techniques using EKF based SLAM or the particle filter based SLAM. The EKF method is most widely used because its algorithm is simple and has relatively low computational cost. For the same reason the EKF based SLAM was considered in our study.

1.2. State of the Art of the EKF-based SLAM

There are many publications devoted to SLAM, the presented solutions depends on utilized sensors and on applied environment recognition and robot localization techniques. Here after are few examples. In paper [2] the vision based SLAM method is discussed, it is based on an estimated global map where a robot finds the path to the user defined goal. Publication [1] presents efficient method for building the 3D model of environment basis on 2D LIDAR information for the purpose of SLAM. In many SLAM applications EKF is utilized however it is not free of drawbacks. One of the serious disadvantages is its computational complexity growing unbounded with the number of landmarks [9]. The recent works on EKF based SLAM attempt to improve three aspects of this technique [6, 7, 10]. The first point is to reduce the computational cost what is crucial for real-time actions. The complexity of the basic EKF based SLAM is $O(n^2)$ where n is the size of the map. Some techniques like the Divide and Conquer SLAM [11] reduce it to $O(n)$. The second point is to optimize the data association for the recognition of the features of the environment. This point is critical because a single mismatch in association can cause a complete failure. The different methods available are generally trying to match several features at a time (batch validation) or to find patterns (especially visual signatures for visual SLAM). Then the third point is the consistency of robot localization. It is the ability to perform large trajectory loops in unknown areas while keeping all positions consistently estimated. Namely, the Hierarchical SLAM [4] is very consistent. Within this context, the purpose of our work is to deliver an EKF based SLAM solution for complex indoor environment. In basic EKF based SLAM algorithm some modifications coming from the nature of the considered landmarks and the environment were applied. It was aimed to obtain a satisfying technique, in terms of computational cost, data association and consistency. We consider the environment recognition using the laser scanner and the robot odometry basis on data delivered by wheel encoders and gyroscope. The robot positioning and mapping is performed concurrently in the real-time.

1.3. Problem Statement

SLAM is the problem faced by a robot in an unknown environment without absolute knowledge of its position. In such a situation, the robot has an estimation of its position provided by odometry but the error of this measure is increasing constantly during the movement. SLAM is a method combining the odometry's estimation and observations of the environment to keep the position error bounded.

Our purpose is to implement an accurate and robust SLAM method based on EKF [7,12], on a Seekur Jr robot. This work deals at the same time with the theoretical and the practical aspects of the problem. First it is necessary to master the localization and the recognition of the landmarks. Then models of the odometry and of the measurement have to be built. The overall method should naturally discard the disturbances from the environment and the noise of the measurements. The environment considered here is a laboratory classroom, it is a realistic and complex environment, with many obstacles like chairs, tables, equipment or people.

Fig. 1. The Seekur Jr from Adept MobileRobots [8]

The Seekur Jr (Fig.1) is one of the newest robots from the company Adept MobileRobots. It is dedicated to research and surveillance applications. Its overall kinematics can be approximated by the simple unicycle model.

The Seekur Jr has an odometry system relying on encoders on the wheel axis and a gyroscope. The gyroscope's measurement is merged with the encoders' data to have an optimized estimation of the position at every instant. This system provides position and heading measurement. This is the source of the odometry readings for the SLAM. Then a laser scanner is used to observe the environment. This sensor has the advantage to be accurate and fast. All sensory readings, from laser scanner and from odometry, are obtained every 100 ms (default period on this robot).

1.4. Main Steps

The EKF based SLAM relies on a mathematical model embedding the kinematics of the robot and the odometry's capabilities. This model is used for prediction of the future position with the current odometry's measurements. It is often called prediction model. Here it consists of the kinematic model, approximated by the unicycle model, and of an estimation of the odometry errors.

The environment is observed through some landmarks, other objects being ignored (feature based SLAM). The choice of the sensors and the type of landmarks used to observe and describe the environment is decisive for the overall SLAM process [13]. The chosen landmarks must be observable, recognizable, easy to observe and stationary. It appears that the best landmarks for the environment considered are the walls of the room and more generally every large vertical plane surface. They have all the qualities already mentioned. The walls appear as straight lines to the laser scanner. The step in SLAM which corresponds to the identification of a landmark from the sensory readings is called landmark extraction. The sensory reading from the laser scanner is a set of points in polar coordinates. First, it is necessary to obtain their Cartesian coordinates. Then the segments eventually formed by these points are identified as landmarks.

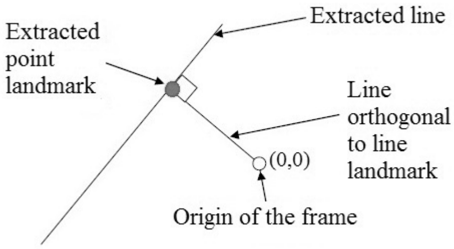

Fig. 2. Representation of landmarks

The landmarks will be treated as mathematical lines, supposedly infinite. The representation adopted for the map considers the initial position of the robot as the origin. Then the lines are represented by the projection of the origin on themselves. In this way, each landmark is represented by one single point in the map (Fig.2). For a meaningful map, the end points of the landmarks must be approximated but they are not used for localization purposes.

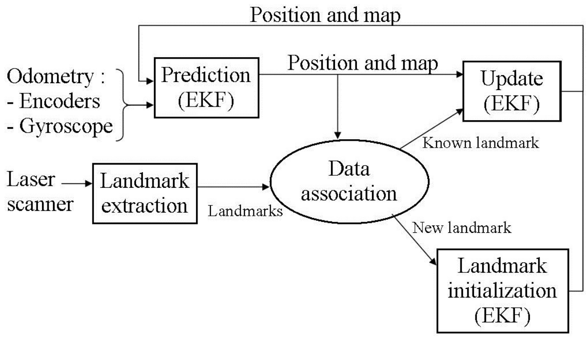

Fig. 3. Main steps in SLAM

The next step in SLAM is the data association. It is the most critical step in the process. Considering an observation of landmark from the landmark extraction, the data association has to identify whether a known landmark has been re-observed or whether a new landmark has been found. The data association tries to match the current observation with the known landmarks and if an observation does not match any landmark it is considered as a new landmark. Taking this into account, the EKF considers the re-observed landmark and updates the position and the map accordingly, or the EKF adds the new landmark to the map. The overall process is represented by the scheme shown in Fig.3.

2. Applied Solution

2.1. Identification of the Landmarks

The extraction of the landmarks and the data association are not complex but they must be realized with great care because the result strongly affects SLAM quality. In this study, it has been chosen to use few landmarks but very reliable ones. Therefore a harsh filtering process is used at all stages from the laser scanner reading to the acceptation of a landmark in the EKF state.

Initially, the laser scanner reading provides a set of points observed, in polar coordinates. In order to be processed, these points are converted to the Cartesian frame of the mobile robot. Then the line recognition algorithm identifies the line segments taking into account the obtained set of points. The RANSAC algorithm [5], simple and efficient, is a reasonable choice. This step belongs to the line extraction action mentioned in section 1.4.

The first filtering is applied here – only the lines satisfying a set of criteria are considered further. In this work, it has been decided to keep lines longer than 40 cm, with at least 6 points, with a maximal distance of a point to the line of 3 cm and a maximum average distance of the points to the line of 2 cm. These criteria have been chosen considering that the most reliable elements in a indoor environment are the walls and the furniture. The minimum length of 40 cm ensures that only these objects will be used to create landmarks, moving objects like human legs or chair legs are discarded. Only the lines of at least 6 aligned points are used because legs of chairs and table can create illusions of lines with 3 or 4 points aligned. Then the 2 last constraints mean that the point must be very well aligned, the line must be neat. This configuration is convenient for the measurement justification because it reduces the overall set of possible landmarks to the few very reliable landmarks. The length condition of the lines' segments and the requirement for minimum 6 points makes the landmarks localization precise. The main drawback of such choice is that some areas might not have observable landmarks because of blocked field of view, for example too many chairs or tables can hide the sight of the wall. Such situations occurred in our work, an introduced solution is described in section 2.3.

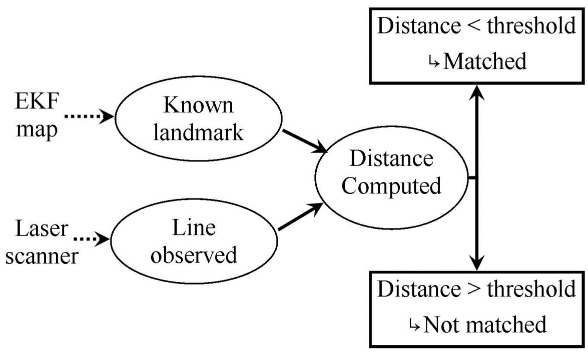

Fig. 4. Validation gate

In data association all new observed candidates for the line are analyzed one by one. The algorithm tries to match a line candidate with every known landmark. If a line does not match any landmark, it is considered as a potentially new landmark. The matching decision is issued by the so called validation gate. The validation gate considers the distance between the newly observed landmark and an already known landmark. If this distance is smaller than a given threshold, the match is valid otherwise it is not (Fig.4) and a new line (new landmark) is created. The innovation v is the difference between the observation realized and the expected position of the landmark (from the EKF), it can be computed for every pair line-landmark. In our case, the innovation is a 2 elements vector with the quantities representing difference in the distance from the robot to the lines, and the difference in angle between the lines. S given by the EKF (explained in section 2.2) is the innovation covariance matrix, it is computed for every landmark. Known from literature, the validation gate takes into account the value of $v^T S^{-1} v$. The boundary value equal to 9.0 defines the range that contains the measurement with a probability of 98.9% [17]. A line is considered as matching if it fulfills the inequality. This validation gate has the advantage to adapt the criterion to the uncertainties of the measure.

$$\begin{aligned} &S : \text{innovation covariance matrix} \\ &v : \text{innovation} \\ &v^T S^{-1} v < 9 \end{aligned} \tag{1}$$

This validation gate considers the theoretical infinite lines. If an observed line matches a landmark, it is necessary to check that the segments are also compatible and not only aligned. The segments are compatible if the observed segment is partly coinciding with the segment of the landmark. If the observed segment satisfies the validation gate without having a part coinciding with the landmark, it is considered as a new landmark (which is probably aligned with the first one). This situation happens often indoors. In order to make the distinction, one must keep an estimation of the end points of the landmarks and update it every time the data association is performed.

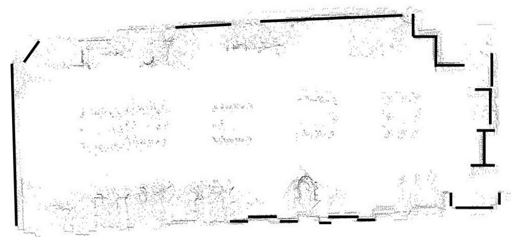

Fig. 5. Common landmarks in a 16 m×7 m room (map made by experiment)
points : laser scanner's observations
lines : SLAM landmarks

Every time a line is detected as a potential new landmark, it is safe to keep it in an intermediate state which is used for the data association but not including it yet in the Kalman filter. Such a landmark would be included in the EKF only if it is observed often enough in a short time period. In this work, relying on tests, we concluded that it must be at least observed 5 times (in the same place) over 15 iterations, otherwise it is deleted. The first practical aspect of this is that the robot must have a probability of $5/15 = 33\%$ to observe the landmark when it is near : it checks that the landmark is not affected by noise and is not hidden by obstacles. This means that the observation is repeatable. The second aspect is that the displacement of the landmark during 5 time steps (100 ms) must be below the matching criterion (8 cm and 1.25°). Therefore, with respect to a fixed frame, the linear speed of the landmark must be below 16 cm/s and its angular speed below 2.5°/s. So the landmark can be considered as fixed. These 2 points make sure that the SLAM discards irrelevant landmarks.

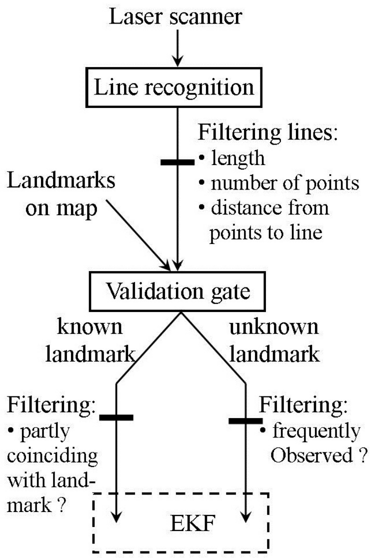

Fig. 6. Environment observation process

Thanks to what is explained above, the landmarks are only the most reliable elements (walls and furniture). Most of all, legs of tables, chairs and persons standing are discarded (because they do not contain straight lines). Moving objects are also discarded (opening doors, animals, other robots). The method can be executed in an office or a home environment without needing any special care or requirement. The Fig.5 illustrates which elements of a room are commonly extracted as landmarks. The Fig.6 displays the overall observation process.

2.2. Models for EKF

The EKF is the element of the method which realizes the fusion of the odometry's data and the observations resulting from the process described in section 2.1. It considers the landmarks as infinite lines, each line represented by a point (Fig.2). The state of the system consists in the position of the robot (x, y, θ) and the positions of the landmarks (x_i, y_i). At every iteration, the EKF computes the state and its covariance matrix. The covariance matrix holds the information about the uncertainty of every state component and also the correlations between components. Namely the i^th^ diagonal term of the matrix is the square of the estimated standard deviation of the i^th^ element of the state. Let X be the state and P its covariance matrix. Let n be the number of landmarks included in the state.

Whenever an odometry measurement is released, the EKF has to compute X_r and P_r, the parts of X and P related to the robot's position (first 3 components):

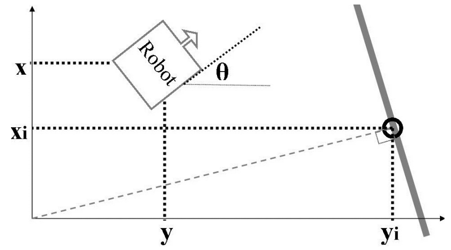

Fig. 7. State variables

this is the prediction step. Let A be the Jacobian matrix of the prediction model. The prediction model is represented by the function f delivering the expected state at the next iteration according to the kinematic model. The explicit argument of f is the current state, the current linear and angular speeds are also arguments of this function. A is the Jacobian matrix of f. In our notation the derivative is denoted by d.

$$\begin{aligned} X_{r,k+1} &\approx f(X_{r,k}) \\ A &= \frac{d(f(X_{r,k}))}{d(X_{r,k})} \end{aligned} \tag{2}$$

Let Q be the covariance matrix of the odometry's errors. The prediction step is globally defined by the set of equations (3).

$$\begin{aligned} X_{r,k+1} &= X_{r,k} + \Delta X_r \\ P_{r,k+1} &= A P_{r,k} A^T + Q \end{aligned} \tag{3}$$

Then the correlations with the landmarks also have to be updated. Let $P_{r|i}$ be the 3×2 block of correlation matrix between the robot and the i^th^ landmark.

$$\begin{aligned} P_{r|i,k+1} &= A P_{r|i,k} \\ P_{i|r,k+1} &= {P_{r|i,k+1}}^T \end{aligned} \tag{4}$$

In order to obtain the best performance for the SLAM, these updates have to be done adequately with the actual behavior of the robot and its odometry. The unicycle model leads to the definition of matrix A (5).

$$A = \frac{d(f(X_{r,k}))}{d(X_{r,k})} = \begin{bmatrix} 1 & 0 & -\Delta y \\ 0 & 1 & \Delta x \\ 0 & 0 & 1 \end{bmatrix} \tag{5}$$

The matrix Q in equations (3) represents the odometry errors and the un-modeled phenomena. Often only 2 kinds of inaccuracies are considered. There is the position (x, y) error increasing proportionally to the linear speed. Let q_t be its standard deviation per unit of displacement. Another is the heading (θ) error increasing proportionally to the angular speed. Let q_θ be its standard deviation per unit of rotation. The experimental observations with the Seekur Jr led to the addition of a third error in our implementation. It is the heading error increasing proportionally to the linear speed. Let $q_{t|\theta}$ be its standard deviation per unit of displacement. Introducing this additional error allows more realistic estimation of the robot performance. It seems that this uncommon kind of error is more important because the Seekur Jr is a skid-steering robot.

When the odometry delivers the displacement of $(\Delta x, \Delta y)$ and rotation of $\Delta\theta$ data, the equation (6) provides the definition of Q with the values used in this work. These values result from the robot features including frequency of the odometry readings. The parameters q were obtained experimentally. The global standard deviations (square roots of the 3 first components of the diagonal of Q) were obtained after several realizations of a same experiment (for example going straight forward for 20 m or rotating 10 times on its own). Then the q parameters $(q_t,\ q_{theta})$ were calculated from the global standard deviations. Matrix Q (6) provides good estimation of the uncertainties over short displacements but it is less accurate for larger displacements.

$$
\begin{aligned}
q_t &= 0.018\\
q_\theta &= 0.05\\
q_{t|\theta} &= 0.0045°/mm\\
\Delta t &= \sqrt{\Delta x^2 + \Delta y^2}\\
Q &=
\end{aligned}
$$
$$
\begin{bmatrix} (q_t\Delta x)^2 & {q_t}^2\Delta x\Delta y & q_t q_\theta \Delta x\Delta\theta + q_{t|\theta} q_t \Delta x\Delta t\\ \cdots & (q_t\Delta y)^2 & q_t q_\theta \Delta y\Delta\theta + q_{t|\theta} q_t \Delta y\Delta t\\ \text{symmetric} & \cdots & (q_\theta\Delta\theta)^2 + (q_{t|\theta}\Delta t)^2 \end{bmatrix} \tag{6}
$$

The EKF must also consider how to initialize and how to update the landmarks. This relies on the way the robot observes the landmarks and the accuracy of the measurement. The landmarks are considered as unlimited lines. Let ρ and α be the range and bearing from the robot to the projection of the robot on the landmark. In this section the observation of a line will always be expressed in such terms of a range and bearing.

The coordinates (x_i, y_i) refer to the representative point of the landmark (Fig.2). This point is convenient to deal with the line but it is has no physical meaning and can not be used directly. The points, O, P_R and P_L stand for the origin, the robot and the landmark. The reference frame is still defined by the initial position of the robot. The couple (ρ, α) is expressed by (7).

$$
\begin{aligned}
\rho &= \frac{|(x_i - x_r)x_i + (y_i - y_r)y_i|}{\sqrt{{x_i}^2 + {y_i}^2}}\\
\alpha &= \operatorname{atan2}(y_i, x_i) - \theta
\end{aligned} \tag{7}
$$

Let introduces, the side indicator, s is equal to 1 when O and P_R are on the same side of the line and -1 otherwise:

$$
s = \operatorname{sign}({x_i}^2 + {y_i}^2 - x_i x_r - y_i y_r) \tag{8}
$$

Let ρ_i denote the distance OP_L, H, the Jacobian matrix of the measurement is given by (9). When only the i$^{\text{th}}$ landmark is observed only the columns $1, 2, 3, 2+2i$ and $3 + 2i$ are non zero. H is the key matrix in the measurements' model, it holds the information about relation between the state variables and the measurements.

$$
\begin{aligned}
H &= \frac{d(\rho,\alpha)}{d(X)}\\
H^T &=
\end{aligned}
$$
$$
\begin{bmatrix}
-s\frac{x_i}{\rho_i} & 0\\
-s\frac{y_i}{\rho_i} & 0\\
0 & -1\\
0 & 0\\
\vdots & \vdots\\
0 & 0\\
s\frac{{x_i}^3 + x_i{y_i}^2 - x_r{y_i}^2 + x_i y_i y_r}{{\rho_i}^3} & -\frac{y_i}{{\rho_i}^2}\\
s\frac{{y_i}^3 + y_i{x_i}^2 - y_r{x_i}^2 + x_i y_i x_r}{{\rho_i}^3} & \frac{x_i}{{\rho_i}^2}\\
0 & 0\\
\vdots & \vdots
\end{bmatrix} \mapsto \text{line } 2+2i \tag{9}
$$

The coordinates of P_L are expressed by formula (10):

$$
\begin{aligned}
C &= \cos(\theta + \alpha)\\
S &= \sin(\theta + \alpha)\\
x_i &= x_r C^2 + y_r CS + s\rho C\\
y_i &= x_r CS + y_r S^2 + s\rho S
\end{aligned} \tag{10}
$$

From the derivation of (10), J_{xr} and J_z are obtained:

$$
\begin{aligned}
J_{xr} &= \frac{d(x_i,y_i)}{d(X_r)} =\\
&\begin{bmatrix} C^2 & CS & -y_r - 2x_r CS + 2y_r C^2 - s\rho S\\ CS & S^2 & -x_r + 2x_r C^2 + 2y_r CS + s\rho C \end{bmatrix}\\
J_z &= \frac{d(x_i,y_i)}{d(\rho,\alpha)}\\
&= \begin{bmatrix} sC & -y_r - 2x_r CS + 2y_r C^2 - s\rho S\\ sS & -x_r + 2x_r C^2 + 2y_r CS + s\rho C \end{bmatrix}
\end{aligned} \tag{11}
$$

These matrices are used for the initialization step, when a new landmark is found. At the initialization step the state X is expanded adding the position where the new landmark has been observed. Then the P is expanded adding 2 components: they are described by (12). This implementation considers the use of a complete P matrix (and not only its blocks). It has the advantage to allow the obtained landmark observation to introduce modification of the correlated landmarks. Due to that, this implementation does not any explicit feedback loop. However it results in bigger computation load – especially with plenty of landmarks. Therefore it might require a sub-mapping strategy [14] decreasing the calculations load.

$$
\begin{aligned}
&P_{n|n} = J_{xr} P_r {J_{xr}}^T + J_z R {J_z}^T\\
&P_{r|n} = {P_{n|r}}^T = P_r {J_{xr}}^T\\
&\forall i \le n-1,\ P_{n|i} = {P_{i|n}}^T = J_{xr} P_{r|i}
\end{aligned} \tag{12}
$$

The update step of the SLAM is realized when a landmark is re-observed. The innovation v (difference between the observation and expected landmark position) is here considered. The matrix R representing the measurement error in terms of range and bearing is also applied. R is given by (13). It is important to consider the uncertainty due to motion of the robot and due to laser scanner synchronization inaccuracy. So (q_ρ, q_α), the standard deviations of the measurement concerning the range and bearing, must be estimated experimentally, and if possible when the robot is in motion. Those quantities correspond to the accuracy in line extraction and the repeatability of the laser scanner positioning.

$$\begin{aligned} q_\rho &= 80\,mm \\ q_\alpha &= 1.25^\circ \\ R &= \begin{bmatrix} {q_\rho}^2 & 0 \\ 0 & {q_\alpha}^2 \end{bmatrix} \end{aligned} \tag{13}$$

The full update step is described by (14). It updates the state and its covariance using K – the Kalman gain. Note that S is the innovation covariance matrix given by (1). S sums up the uncertainties of the robot's position and the landmark's position expressed in terms of range and bearing, and adds the uncertainty of the measurement.

$$\begin{aligned} S &= HPH^T + R \\ K &= PH^T S^{-1} \\ X_{k+1} &= X_k + Kv \\ P_{k+1} &= (\mathbb{1} - KH)P_k \end{aligned} \tag{14}$$

2.3. Additional Improvements

The implementation with all the elements mentioned so far was leading to a successful mapping of areas with many landmarks, like the area on the right side of the map Fig.5. Though, in areas with fewer landmarks, the behavior was often diverging. This concerned, for example, the left side of the map shown in Fig.5. One of the hypothesis of the EKF based SLAM, is that the landmarks are equally distributed. This is not always true, especially when the robot is acting in not specially arranged environment like that one shown in Fig.5. Two novel modifications have been introduced in our work extending the EKF method for managing such situations.

The unstable situation in EKF based SLAM occurs due to the large variations of the uncertainties in the robot's position. The validation gate (inequality (1)) used in the data association is flexible. It considers a larger possible innovation when the uncertainties are high. Therefore the data association naturally adapts itself to the variations of uncertainty. But it relies on the EKF estimations. When the robot's position is uncertain, the EKF is very sensitive and the estimated position might be significantly affected by the landmarks. The area considered in the right side of the map Fig.5 contains only 2 landmarks. When the robot is focusing on this side, the EKF is strongly relying on those landmarks, especially if they are observed for the first time, due to the positioning errors, they can give a wrong reference for the whole procedure. We proposed a solution to this issue.

The idea is to detect such "dangerous" situation and to reduce the impact of observations of such landmarks. A dangerous landmark should be initialized and correlated with the others during first few observations and then it has to be progressively ignored preventing any damage of the EKF state. The idea is to prevent the dangerous landmarks to affect the EKF by the addition of a gain γ in the computation of the Kalman gain (15). γ is different for every landmark. This has been inspired by [6] discussing the problem of missed observations what is theoretically equivalent to our problem (some landmarks are observed too often and the others are absent).

$$K = \gamma PH^T S^{-1} \tag{15}$$

It has been observed that the problems occurs when the uncertainty of an observed landmark is much bigger that the uncertainty in the robot position. If the robot moves around such landmarks, their uncertainties are progressively decreasing, but the robot position and other landmarks' estimated position is negatively affected. In fact, the landmark uncertainties should not decrease because the robot's position is still uncertain; the observations are not bringing reliable information. To detect such situation a ratio φ is introduced and computed at every observation.

C_{ideal} is a covariance matrix which is sum of the uncertainties of the robot's position, the uncertainties of the measurement, and a minimal level of acceptable uncertainty of the landmark's position. This minimal level of acceptable uncertainty is defined as a fraction of R (term $(\beta - 1)R$ in (16)) it expresses the uncertainty of well known landmark. Thanks to H, the Jacobian matrix of the measurement, these uncertainties are expressed with respect to the measurement. C_{ideal} represents the minimum uncertainty in an observation, obtained when the landmark's position is very well known. $C_{landmark}$ is a covariance matrix which represents the uncertainties in the landmark's position, expressed with respect to the measurement. Finally φ is defined as the ratio of the trace of $C_{landmark}R^{-1}$ over the trace of $C_{ideal}R^{-1}$ (16).The multiplication by R^{-1} is used to allow the addition of the uncertainties in range and bearing, both expressed by the covariance matrices. φ increases when the landmark's position is uncertain and when the robot's position is certain.

$$\begin{aligned} \beta &= 2 \\ C_{landmark} &= H_i P_{i|i} {H_i}^T \\ C_{ideal} &= H_r P_{r|r} {H_r}^T + \beta R \\ \varphi &= \frac{\mathrm{Tr}(C_{landmark} R^{-1})}{\mathrm{Tr}(C_{ideal} R^{-1})} \end{aligned} \tag{16}$$

It has been considered that the minimum level of uncertainty reachable for a landmark is R itself. Therefore, according to its definition, β is equal to 2. Then it has been decided that, the uncertainties of the landmark and the uncertainties of the robot must become as low as R. So $C_{landmark} \approx R$ and $C_{ideal} \approx (1 + \beta)R$ then $\varphi \approx 1/3$. This reasoning gave the threshold value $\varphi_{threshold} = 1/3$. If $\varphi > \varphi_{threshold}$, the landmark is considered dangerous. During experiments it was detected that the criterion is rather conservative, it tends to consider many recent landmarks as dangerous, therefore $\varphi_{threshold}$ must be slightly increased in order to select only the most difficult situations. With this modification our innovation gives good results.

Initially γ is equal to 1 for every landmark. The ratio φ is computed after every landmark's observation once the update step is completed. For every dangerous landmark γ is decreased by a certain amount. In our study γ was decreased by 0.35. When γ reaches 0 it is locked for 5 s, every new dangerous observation of this landmark resets the time counter. When a landmark is not considered dangerous, its γ is increased in each step by small amount, for example 0.05. By this way the dangerous landmarks are progressively ignored and remain ignored until they disappear from a sight. After some time, they can be used again.

The result of the addition of this element in the EKF based SLAM is such:

- The new landmarks are not trusted immediately.
- The correlation between landmarks is more important during the exploration.
- The SLAM can stay stable longer without observations of previously known landmarks (better consistency).
- The complexity is not increased.
- The time needed to fully explore an area is slightly increased.

Due to the assumption about regularly spaced landmarks, the EKF based SLAM ignores another situation. The validation gate (Fig.4) uses a criterion based on the distance between the landmarks to distinguish them. This distance is compared with the uncertainties of the measurement, landmarks' positions and robot's position. When the uncertainties of the measurement are larger than the distance between 2 landmarks, the landmarks can be confused. This can cause severe damage to the SLAM process. Several techniques of data association, like the joint compatibility test [16], allow to reduce the risk of confusion. Though, in complex environments, the risk of data association error can not be fully eliminated. Instead of avoiding the confusion, the approach proposed in this paper tries to minimize the damageable effect of an association mistake. The method applied in this work relies in an elimination of the possible causes of confusions. It is done every 10 iterations (every 1 s). The validation gate is applied to all couples of landmarks which are likely to be observed (currently near to the robot). If 2 of such landmarks match together, it means that there is a danger of confusion. The SLAM could not distinguish these landmarks, therefore it is unsafe to keep both of them. The newest landmark is deleted. The uncertainty of the remaining landmark is increased by the distance between the 2 former landmarks. The addition (17) is performed on P_i – the part of the matrix P related to this landmark.

(Δ_x, Δ_y) : distance between the representative points of the landmarks along x and y

$$P_{i,k+1} = P_{i,k} + \begin{bmatrix} {\Delta_x}^2 & \Delta_x\Delta_y \\ \Delta_x\Delta_y & {\Delta_y}^2 \end{bmatrix} \tag{17}$$

This additional element acts like a local adjustment of the map resolution. In special situations with few landmarks, it maintains the covariance bound to a level of uncertainty which is actually reachable. In the beginning of the mapping, several landmarks can be ignored and only the main elements are placed on the map. Then, when an area starts to be better known, the uncertainty of the robot's position decreases and it allows mapping the details of the environment. Such approach has good stabilizing effect but it should not be used too often (it has been observed experimentally that it can cause a slight positioning drift).

The results are:

- The possibly confusing situations are secured.
- The behavior with high level of uncertainty is safe (when combined with the first additional module suggested).
- Data association mistakes causing the creation of new landmarks instead of re-observation of a known landmark are solved.
- Exploration is realized progressively, first a general map is built, then the details are added.
- Using this module too often will cause all uncertainties remaining on high level, this can cause an eventual slight drift of the map.

3. Results

3.1. Performance

In order to prove the efficiency, the described techniques have been implemented on a Seekur Jr robot. A test has been run in a classroom. The room was not tidy, there were many chairs and tables, and there were some persons walking. The robot was manually driven making loops at medium speed, the SLAM was active. Each experiment lasted 6 minutes.

Fig.8 shows a photo of the room and its map. This map is superposition of the reference map and the detected landmarks. The reference map shows the room plan with furniture elements. The landmarks found by SLAM are shown as obtained in the end of the experiment. The point (0,0) is the initial position of the robot. In ideal condition, the reference map and the detected landmarks coincide.

The superposition of reference and detected maps show that the landmarks are all relevant and each of them represents a significant element in the room. At least a section of each wall is represented by a landmark. Several elements or sections of walls were ignored either because they were too short or because they were hidden behind obstacles. The irrelevant elements have been filtered and all of the reliable ele-

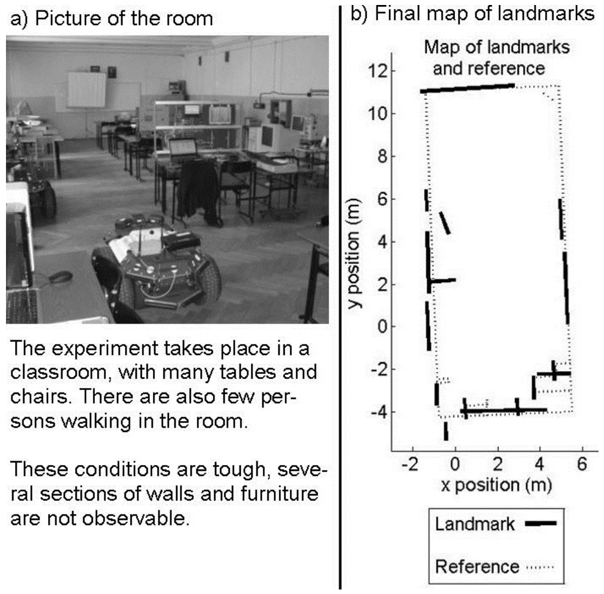

Fig. 8. Experiment on Seekur Jr:
a – room where the experiment took place.
b –position of the landmarks after exploration lasting 6 min.
The actual position of the walls and furniture is shown as the reference.

ments were used for the SLAM. The landmark extraction, data association and filtering was efficient.

The reference and the landmarks coincide well. The average mapping accuracy was 10 cm.

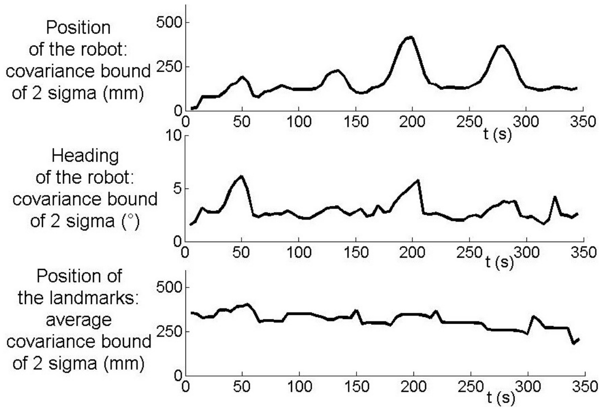

Fig. 9. Covariance bounds during the experiment

Fig.9 shows the 2σ covariance bound of the estimated robot's position, heading and the landmarks' position (averaged) during the experiment. It provides information of how the EKF is certain of the value.

These graphs show that the covariance bounds do not diverge and the average bound of the landmarks is slowly decreasing. It means that the SLAM is stable and the EKF is more and more confident in the landmarks. It can be observed that, locally, the covariance bounds of the position and the heading have some peak values. This happens when the robot explores not well known areas. In this case, the SLAM is less certain about the robot's position. An effect of the addition of the gain γ (described in 2.3) is that, that the local peaks are higher afterwards the bound decreases more quickly to its previous level. The consistency is increased but the exploration is slower.

The graphs in fig.9 show that the final value for the 2σ bounds are 12 cm for the position estimate, 2.2° for the heading estimate and 21 cm for the landmarks' positions estimates. The proof obtained by measurements showed that the robot localization error is about $\pm 10\ cm$ and $\pm 1°$ of heading. The estimated position accuracy is not far from what has been measured. It proves that the kinematic model of the robot (matrices (5) and (6)) is good and embeds properly the important factors.

During our experiments, the maximal computational time was 20 ms to perform landmarks' extraction, data association, prediction and update. It was with 25 landmarks in the state of the EKF and 3 landmarks observed at once. Therefore it can be concluded that the calculations time of the program is rather short, the algorithm is efficient.

3.2. SLAM Testing Using the Simulation

Besides of the experiments on the Seekur Jr, a simulation method has been used to test the SLAM method with the modifications we introduced. The simulation was found to be very useful because it allowed to test our algorithm with an ideal settings, with all elements fully mastered. This gave the opportunity to test more deeply our algorithm. The simulator MobileSim provided by Adept MobileRobots has been used for simulations.

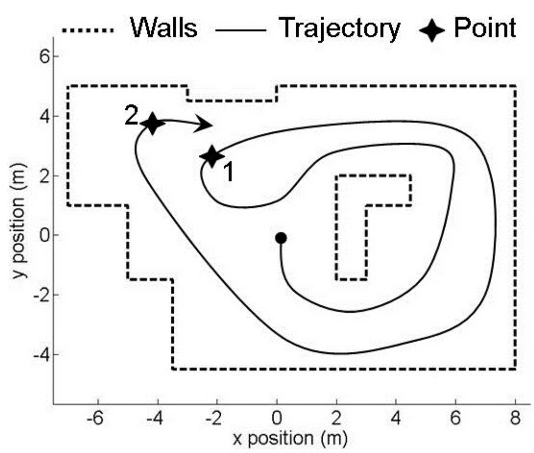

Fig. 10. Simulated room and trajectory of the robot

Fig.10 displays the virtual room considered in simulation. It shows also the trajectory followed by the virtual robot. Point 1 and point 2 in the trajectory are marking 2 situations that will be investigated later. The simulation lasted 2 minutes. The simulation considered the disturbances model matching the features observed in real conditions with the Seekur Jr concerning the laser measurements and the odometry results. The simulated experiment considered the same situation as in the actual experiment, the same SLAM program was used and with the same parameters. In simulated room was 1 obstacle (in the middle) blocking the sight of the laser scanner.

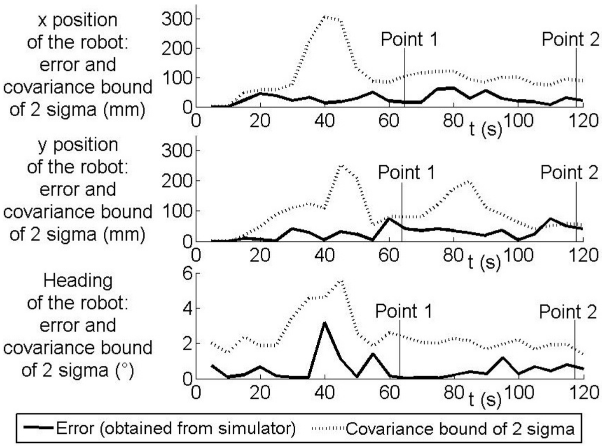

Fig. 11. Error and covariance bound during the simulation

The graphs in fig.11 display the actual localization error and the 2σ covariance bounds of estimated robot position. The actual error is obtained from the simulator. Even if this result is less meaningful than the experiment, it is worth to notice that the error remains below 2σ bound (except one very short time period for y coordinate). So the EKF provides good estimation. The robot made twice the loop around the central obstacle. When the robot was behind this obstacle it loosed the sight of its first landmarks, this caused a progressive increase of the position's covariance bound. When the robot passed the obstacle for the second time, the covariance bound increase was lower because the SLAM already knew these landmarks (the gain γ described in section 2.3 was equal to 1).

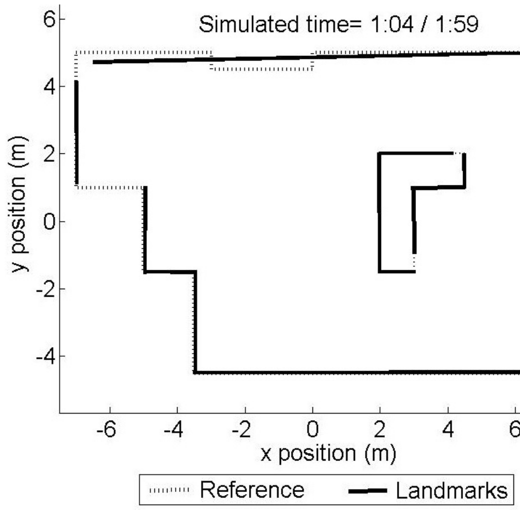

Fig. 12. Landmarks when the robot is at point 1

The figure 12 shows the landmarks identified by SLAM algorithm when the virtual robot reaches the point 1 (see on fig.10). For the reference the actual position of the walls is also shown. It can be noticed that the largest part of the identified landmarks coincides well with the real ones. Only the wall in upper part of drawing does not fully coincide with the landmarks. This is due to the fact that, in this wall, there is one section located 50 cm ahead of the rest of the wall. Because of that the wall should be represented by three landmarks while it is represented only by one landmark on the map in figure 12. The selection of only one landmark was controlled by our algorithm. Analyzing together the graphs in fig.11 and robot trajectory (fig.10) we learnt that before reaching point 1, the inaccuracy in robot's position estimate increases. Therefore, according to the technique explained in section 2.3, the SLAM was prevented from creating three landmarks for the upper wall. Creating three landmarks brings the risk of confusion between them. Therefore instead, the upper wall is represented by one landmark only, making a kind of compromise. This situation happened only once in this simulated environment but it is a common situation which happened much often in real experiments. Despite of the small inaccuracies possibly caused by the landmarks reduction the overall performance of algorithm can be concluded as being good, with decreased possibility of landmarks confusion.

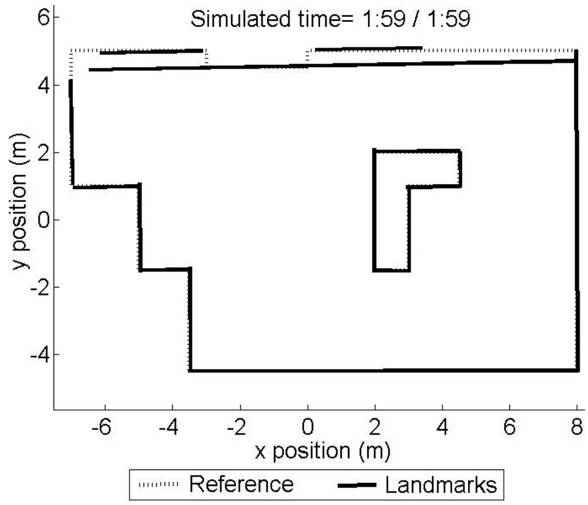

Fig. 13. Landmarks when the robot is at point 2

The figure 13 displays the map of the landmarks when the robot reaches point number 2. Then, the upper wall is represented by three distinct landmarks. The landmarks coincide well with the reference but the end points of the segments are mistaken. The distinction of the three landmarks is possible at this point because since passing the point 1 robot is in a known environment. So the estimated positioning error is smaller, therefore, the mapping can use a lower resolution (technique described in section 2.3). Then the first landmark is kept and the other two landmarks are added to comply with the new sections of observed walls. However, as it has been explained in section 2.1, it is not considered that the segment's size can be reduced. So the end points are not accurately placed. This is not a problem for robot localization but creates a limit for mapping purposes.

4. Conclusions

This paper presented a Kalman Filter based SLAM method. The method has been adapted to perform better in complex environment and it was tested on a skid-steering robot. The method succeeded to perform the SLAM in a complex environment, without being obstructed by common obstacles like chairs, tables and people. The method was implemented in the Seekur Jr robot. Tested mapping and the localization performance was found enough accurate. The algorithm is fast to execute. With the improvements, the algorithm is also consistent enough to achieve the satisfactory SLAM while the robot is moving along short loops, like those tested in the experiment and in the simulation. The method is consistent, fast and accurate while it is also rather simple. However for general exploration the method is slightly slow and not all landmarks can not be directly used for mapping purposes (due to the landmarks reduction the segments end points are not always accurate as it was explained).

The purpose of this work was to investigate the SLAM only in a single laboratory rooms but not outdoor. In order to extend this to larger areas, it would be needed to combine our method with more complex techniques like the Hierarchical SLAM [4]. This will improve the consistency of landmarks positioning with distributing the computational cost. Elaborated control program was sufficient for presented experiments, however for practical applications the failure recovery technique would be necessary to make sure that the SLAM remains stable with consistent information for long periods of time and over a long distances.

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