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A Comparison of SLAM Algorithms with Range Only Sensors

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Abstract— **Localization and mapping in indoor environments, such as airports and hospitals, are key tasks for almost every robotic platform. Some researchers suggest the use of RO (Range Only) sensors based on WiFi (Wireless Fidelity) technology with SLAM (Simultaneous Localization And Mapping) techniques. The current state of the art in RO SLAM is mainly focused on the filtering approach, while the study of smoothing approach with RO sensors is quite incomplete. This paper presents a comparison between a filtering algorithm, the EKF, and a smoothing algorithm, the SAM (Smoothing And Mapping). Experimental results are obtained, first in an outdoor environment using two types of RO sensors and then in an indoor environment with WiFi sensors. The results demonstrate the feasibility of the smoothing approach with WiFi sensors in indoors.**

I. INTRODUCTION

Wireless networks and specially WiFi have become widespread during the last years, especially in indoor environments. This makes WiFi a good choice to develop SLAM systems in indoors where GPS does not provide good results. In this work the SLAM systems are developed using only range measurements. The RO sensors provide the range measurements and a unique identifier per beacon, which helps the SLAM avoid data association problem. However, information about the angle is not obtained. So, with only one range sample it is impossible to estimate a position. The beacon could be anywhere within a ring of radius equal to the range measurement.

Typically, WiFi localization systems use different map representations of the environment. Most of them [1][2] use fingerprint maps based on the radiological patterns of the signal. In contrast, other authors [3] use maps containing the coordinates of all the beacons. In both cases building the maps is an expensive task therefore recent studies focus their efforts on SLAM techniques.

SLAM is considered to be a complex problem because a robot simultaneously needs a consistent map to localize itself, and an accurate estimate of its location to acquire the map. During the last years a number of solutions have been presented to solve the SLAM problem such as EKF [4], FastSLAM [5], GraphSLAM [6] and Smoothing approaches [7]. Although, SLAM is a well-studied problem with other sensors, the state of the art in RO SLAM is not fully explored. One of the most relevant works in RO SLAM is [8] which combines EKF with a Relative Over Parametrized (ROP) approach to solve the SLAM problem in outdoor environments. The use of that parametrization derives from the polar coordinate system where annuli, crescents and other ring-like shapes can be easily modeled. Furthermore, the authors have made public the dataset described in [9]. This dataset is one of their main contributions because it allows to test different algorithms with a common framework.

This paper focuses on a comparison of ROP-EKF with the Smoothing approach (SAM) presented in [7] to improve the state of the art in RO SLAM. Smoothing approaches for SLAM add the entire trajectory of the robot and the map in the estimation problem. While this seems counter-intuitive at first, because more variables are added to the problem, the simplification arises from the fact that the smoothing information matrix is naturally sparse. Therefore, smoothing approaches provide an exact and efficient solution of the problem.

Both algorithms are compared in the presented work by using the database described in [9]. The comparison demonstrates an improvement error rate of 20$\sim$40% for SAM with respect to ROP-EKF performance. Furthermore, an indoor WiFi setup is built to demonstrate the feasibility of the SAM approach in indoor environments. This setup consists of a large-scale building under real conditions, which means unexpected changes in the environment and people wandering around, and it is also a contribution of this work.

The following sections of this paper are organized as follows: section II describes the related work in this area; section III studies the algorithms that are compared in this work; section IV shows the datasets that have been used and the experimental results; and finally, in section V some conclusions and future work are presented.

II. RELATED WORK

Studies in RO SLAM identify two main problems to deal with. The first one consists in overcoming their lack of angle information while the second one is referred to the way the signal propagation is modeled. Both problems are specially significant in indoor environments, where the environment can change dynamically and the signal can be affected by several interferences like multipath effect.

In order to overcome the lack of angle information some works [10] use a two dimensional probability grid and a voting system to provide estimates of the beacon location. Other solutions [11] propose the use of FastSLAM to estimate the initial position of the beacon. They also replace the conventional EKFs for particle filters to avoid the need of angle measurements. The idea is extended in [12] maintaining independent Sum of Gaussians (SOGs) for each beacon.

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Other works are focused on modeling the signal propagation which is specially complex in the presence of obstacles such as buildings, walls or people. In [13] Ferris et. al. use GPLVM (Gaussian Process Latent Variable Model) to generate a likelihood model for signal strength measurements which, in combination with an appropriate motion dynamics model can be used to reconstruct a topological connectivity graph from those measurements performing efficient localization. However, it requires a large number of beacons to obtain good results. In [14] the authors show how wireless signal strength SLAM can be formulated as a GraphSLAM problem modeling the signal propagation by means of Gaussian interpolation weights to interpolate WiFi signal strengths. GraphSLAM is a commonly used technique in the robotics community for simultaneously estimating a trajectory and building a map. It shares many benefits of Gaussian processes, but can be applied to a broader range of environments, therefore improving the runtime complexity from $O(N^3)$ to $O(N^2)$, where N is the dimensionality of the state space.

III. RO SLAM COMPARISON

This section gives a brief description of the two SLAM algorithms that are compared in this work. Both algorithms are implemented following the original implementation by the authors [8][7]. The first, known as ROP-EKF [8], is an extension of the standard EKF to formulate the SLAM problem in polar coordinates. It has some drawbacks due to its computational complexity. The second, known as SAM [7], is based on smoothing approaches and factor graph representation. It successfully applies sparse least-square error minimization techniques to solve the so-called *full SLAM* problem i.e. the problem of estimating the entire trajectory of the robot with the map.

A. ROP-EKF

Typical EKF SLAM is based on an important characteristic which establishes that any information that helps to compute the posterior of the robot is also propagated through the map. As a result, it improves the localization of other landmarks in the map. In other words, observing a landmark improves the robots pose estimate decreasing some of the uncertainty of landmarks previously seen by the same robot. This dependence is captured in the Gaussian posterior, more specifically, in the off-diagonal covariance elements of the matrix Σ_t. This effect is one of the main advantages of EKF SLAM techniques, because this behavior is implicitly modeled in the EKF itself.

Since most of the uncertainty in earlier landmarks is related to the robot's pose, and this uncertainty persists over time, the location estimates of those landmarks are correlated. When gaining information on the robot's pose, this information spreads to previously observed landmarks.

However, it is well known that EKF becomes practically intractable when managing the covariance matrix Σ_t due to the fact that this matrix is non-sparse. The computational complexity is $O(N^2)$ where N is the number of landmark and grows quadratically. Moreover, EKF has been shown to be inconsistent when applied to non-linear problems as it is.

The basic formulation of EKF SLAM assumes that the location of features in the map is fully observable from a single position of the robot. The method has been extended to situations with partial observability like RO sensors [15]. Thus, the ROP-EKF extends the standard EKF to work with RO sensors by means of a Relative Over Parametrization. It formulates the problem in polar coordinates where ring-shapes can be easily modeled and parametrizes the state relative to an origin. The state vector is defined as (1) shows.

$$q_t = \left[q_t^r, q_t^1, q_t^2, \dots, q_t^N\right]^T \tag{1}$$

Where $q_t^r = \left[c_{x,t}^r, c_{y,t}^r, r_t^r, \theta_t^r, \phi_t^r\right]$ denotes the robot pose at time t being $(c_{x,t}^r, c_{y,t}^r)$ the origin of the polar coordinate frame, (r_t^r, θ_t^r) the range and angle values and ϕ_t^r the heading of the robot. $q_t^i = \left[c_{x,t}^i, c_{y,t}^i, r_t^i, \theta_t^i\right]$ corresponds to the position of the i-th landmark.

As RO sensors present multimodal distributions this approach uses a multi-hypothesis representation of the EKF to maintain those distributions. Hence, ROP-EKF is able to model the situations when the annulus-like prior distribution is split into separate modes because a second RO measurement is obtained.

B. Smoothing And Mapping (SAM)

Smoothing approaches are presented as efficient alternatives to the EKF framework for the SLAM problem. These methods propose the use of factor graphs [16] and optimization techniques to smooth the trajectory of the robot and the map. Thus, these approaches obtain the best possible trajectory and map for the given measurements.

One of the main characteristics of these approachs is to address the *full SLAM problem* so the complete trajectory of the robot is added into the estimation problem. From the point of view of the EKF this could seem as a disadvantage because more variables are added to the estimation problem. However, smoothing approaches take advantage of the fact that the smoothing information matrix I is naturally sparse in contrast to the covariance matrix of the EKF.

Moreover, smoothing deals with non-linear SLAM problems much better than filtering approaches by controlling in which region the linearization can be trusted while the linearization choices cannot be undone in filtering. Hence, the SLAM is solved as an optimization problem which is formulated in terms of sparse linear algebra, and becomes a fast alternative to EKF factorizing into square root form the matrix I and the measurement Jacobian A. So, this approach fully exploits the sparseness of both matrices being its computational complexity linear $O(M+N)$, which depends on the number of poses M and the number of landmarks N. Nevertheless, its performance depends on choosing a good variable reordering when factorizing the matrix.

The SAM approach recovers the maximum a posteriori (MAP) estimate for the entire tarjectory $X \triangleq \{x_i\}$ and the map $L \triangleq \{l_j\}$, given the measurements $Z \triangleq \{z_k\}$ and control inputs $U \triangleq \{u_i\}$ by solving the non-linear least-squares problem shown in (2)

$$\sum_{i=1}^{M} \|x_i - f_i(x_{i-1}, u_i)\|^2_{\Lambda_i} + \sum_{k=1}^{K} \|z_k - h_k(x_{i_k}, l_{jk})\|^2_{\Sigma_k} \quad (2)$$

If the process models f_i and the measurement equations h_k are non-linear, as they are in this work, and a good linearization point is not available, non-linear optimization methods are able to approach a minimum solving a succession of linear approximations to (2). Typically, Gauss-Newton iterations or Levenberg-Marquardt methods are used to solve the optimization problem.

Since SAM approach solves optimization problems, SAM is able to work with RO sensors without any modification. SAM only needs to define the RO measurements between the landmarks and the mobile as "range factors".

IV. EXPERIMENTAL RESULTS

This section presents an experimental validation of both algorithms for different types of RO sensors. First, it shows the results that are obtained using the public database of the Robotics Institute of Carnegie Mellon University [9], which can be downloaded from *www.frc.ri.cmu.edu/projects/emergencyresponse/RangeData/*. Second, it shows the results of a real WiFi indoor scenario that is set up at the University of Alcalá.

A. Carnegie Mellon RO sensors Database Results

The Carnegie Mellon database has several scenarios set up in an outdoor environment to validate the correct performance of both algorithms. Although the outdoor environment simplifies the problem because no external interferences appear, it provides a good test-bench to compare both algorithm. The SAM results are compared with respect to the results obtained by the ROP-EKF in [8] and [17].

The database consists of five different paths using two types of RO sensors (Pinpoint RF and ultra-wide band sensors). Table I shows the name of every experiment, the sensor that was used, the covered distance by the robot, the number of range samples that were collected and a brief description of the experiment.

The experiments were designed to test a wide number of possible situations such as long and short paths, different heading errors and random trials. Moreover, the use of two types of sensors allows the authors to test the algorithms with different noise configurations because RF sensor is noisier than the UWB (UltraWide Band) one.

Table II presents the results for both algorithms evaluating the path and map error, which are computed as the Euclidean distance between the estimated and groudtruth values. The ROP-EKF row shows the results presented in [8] for Gesling. The results for the Plaza dataset were published in [17] which only provides the error for the final 10% of the path. However, the SAM results that we have obtained provide the error for the complete path, which are more realistic results.

In terms of path error Table II demonstrates that SAM performs better than ROP-EKF for the whole dataset. It is shown that the SAM obtains an improvement error rate of 20∼40% with respect to ROP-EKF performance. Moreover, both algorithms are able to manage the Gaussian noise of the sensors. The results are not affected by the amount of Gaussian noise because the mean path error is similar in experiments with the same configuration (Gesling1 wrt Plaza2 and Gesling2 wrt Plaza1). However, the different path configurations affect directly to the performance of both algorithms. The paths that highlight the effect of heading error by turning in the same direction repeatedly get worse results than the other ones, which is intuitive.

In terms of map error, Table II shows that SAM performs better than ROP-EKF except when the path is not long enough to properly find a minimum in the optimization process.

To summarize, this section demonstrates the feasibility of the SAM algorithm when working with RO sensors in a controlled outdoor environment without external interferences. SAM can be considered as a better alternative than ROP-EKF for RO SLAM due to the fact that it obtains better results in most of the experiments.

B. Alcalá WiFi Database Results

The Alcalá WiFi database, which is available at *www.robesafe.es/repository/UAHWiFiDataset/*, has several scenarios set up to verify the feasibility of both algorithms in indoor environments. The experiments were tested at the University of Alcalá under real conditions which means people wandering around, small changes in the environment, small interferences due to portable devices, etc.

WiFi technology has been used in these experiments because most of the buildings provide this network. Since it is pre-installed there is no need to modify the environment and the use of WiFi frequency (2.4 GHz) is free. However, this technology is noisier than the previous ones because WiFi is affected by every object that contains water and the multipath effect. Hence, it can suffer variations in the power strength up to 10 dBm which means an error in the distance measurement up to 25 meters in some of the cases. Moreover, the non Gaussian noise presented in this technology makes it difficult to model these variations. Therefore, these conditions increase the difficulty of the experiments and it is a real challenge for both algorithms.

Figure 1 shows the environments that have been used in this dataset. Figure 1(a) shows the third floor of the building which has a size of 120x120 meters. This environment consists of four large corridors forming a square in which a landmark is placed in every corner. Figure 1(b) shows the west area of the second floor, the size of this area is 60x60 meters. There are four small corridors which are 18 meters long and a main corridor of 35 meters that finishes in a hall. The hall is an semi-empty space only occupied by two elevators. Although there is a large number of Access Points (up to 150) in the environments, which are used as landmarks, the experiments only take into account the most important ones for simplicity. The landmarks are considered to be important based on their spacial distribution. The

TABLE I

CARNEGIE MELLON DATASET DESCRIPTION

Name	Sensor	Distance (m)	# range samples	Description
Gesling1	RF	3700	2,565	Effect of heading error by turning in the same direction repeatedly.
Gesling2	RF	1360	1,416	Minimizes the effect of heading error by balancing the heading turns.
Gesling3	RF	6700	10,068	Long random trial.
Plaza1	UWB	1900	3,529	Minimizes the effect of heading error by balancing the heading turns.
Plaza2	UWB	6700	1,816	Effect of heading error by turning in the same direction repeatedly.

TABLE II

CARNEGIE MELLON RO SENSORS DATABASE RESULTS

Method	Gesling1		Gesling2		Gesling3		Plaza1		Plaza2	
	Path	Map	Path	Map	Path	Map	Path	Map	Path	Map
ROP EKF	0.97m	0.57m	0.78m	0.53m	0.83m	0.62m	0.65m[1]	0.48m [1]	0.87m [1]	0.48m [1]
SAM	0.59m	0.56m	0.47m	1.14m	0.66m	0.47m	0.51m	0.77m	0.61m	0.45m

data was collected with a Seekur Jr. of MobileRobot which provided the odometry measurements and an on board laptop to obtain the RO measurements.

Since the experiments were placed in indoor environments, a reliable groundtruth was not available. Hence, a visual inspection was chosen to evaluate the results. Figures 1(a) and 1(b) show the true trajectory of the robot (blue line) and where the landmarks were placed (blue stars).

Table III presents a brief description of the experiments. Two experiments have been designed in order to study the same cases that in the Carnegie Mellon ones. A new experiment also has been added to study the effect of high noise in the odometry measurements. Table III also shows that the covered distance by the robot is long enough to study that conditions in indoor environments. Alcala1 is performed at Environment1 (Figure 1(a)) while Alcala 2 and Alcala3 are performed at Environment2 (Figure 1(b)).

Figure 2 shows the results for Alcala1 dataset. The odometry path is shown in green, the estimated path is shown in red and the estimated landmarks are shown as black stars. This experiment studies the effect of heading error by turning in the same direction repeatedly. The ROP-EKF (Figure 2(a)) is not able to recover the square shape that the groundtruth draws and it fails to estimate the landmarks. The SAM (Figure 2(b)) recovers the square shape although it is affected by a rotation. The landmarks are well placed with respect to the estimated trajectory.

Figure 3 shows the results for Alcala2 dataset. The experiment minimizes the effect of heading error by balancing the heading turns. Both algorithms obtain similar results when the robot does not turn always in the same direction and the odometry is accurate enough.

Figure 4 shows the results for Alcala3 dataset. This experiment shows the effect of high noise in the odometry measurements. This is the worst possible scenario because none of the measurements (odometry and RO) are reliable enough. The ROP-EKF is not able to converge to any solution and the results are not valuable. The SAM is still able to estimate the trajectory of the robot and the map obtaining similar results to Alcala2 ones. This behavior is a consequence of the use of optimization techniques because they controls in which region the linearization is trusted. So, SAM can be considered as a more robust solution for this kind of environments.

Finally, it is important to remark that the performance of SAM with respect to ROP-EKF is much better in the Alcalá database than in the Carnegie Mellon one. This is due to the fact that in outdoor environments the noise of RO sensors are easily modeled while in indoor environments WiFi is affected by several variations. Hence, ROP-EKF finds it more difficult to obtain a good estimation in indoor environments. In addition, the performance of the SLAM algorithms can be compare with traditional WiFi localization methods such as the one presented in [18]. Where it is compare than both techniques obtain similar results.

V. CONCLUSIONS

In this work two different SLAM approaches have been compared, the ROP-EKF and the SAM, to solve the RO SLAM problem. The theoretical advantages of SAM with respect to EKF have been presented. Moreover, experimental results with real data demonstrate the effectiveness of SAM approach in outdoors. An improvement error rate of 20$\sim$40% with respect to ROP-EKF has been obtained. Furthermore, both algorithms have been tested in a real indoor environment with WiFi sensors. The feasibility of RO SLAM techniques in that environment has been demonstrated showing a remarkable improvement of the SAM approach with respect to the ROP-EKF one. In the near future we will use an incremental variant of SAM, known as iSAM, to solve the online SLAM problem.

ACKNOWLEDGMENT

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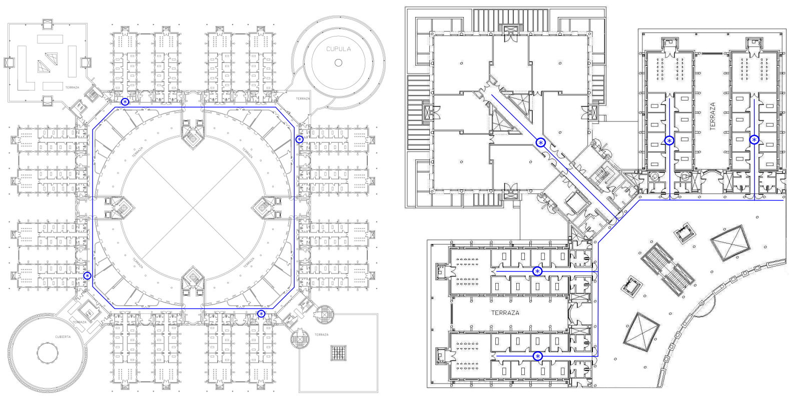
[1]These errors only take into account the final 10% of the path

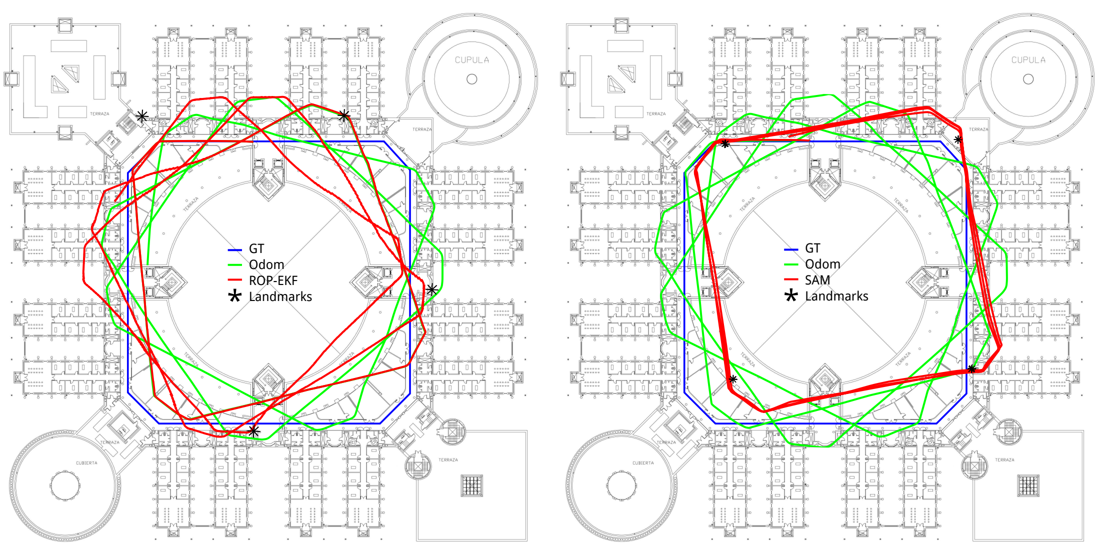


(a) Environment1 (b) Environment2

Fig. 1. Alcalá Environments

TABLE III
ALCALA DATASET DESCRIPTION

Name	Sensor	Distance (m)	# range samples	Description
Alcala1	WiFi	533	490	Effect of heading error by turning in the same direction repeatedly.
Alcala2	WiFi	821	568	Minimizes the effect of heading error by balancing the heading turns.
Alcala3	WiFi	937	785	Effect of high noise in the odometry measurements.



(a) Alcala1. ROP-EKF (b) Alcala1. SAM

Fig. 2. Alcala1 results

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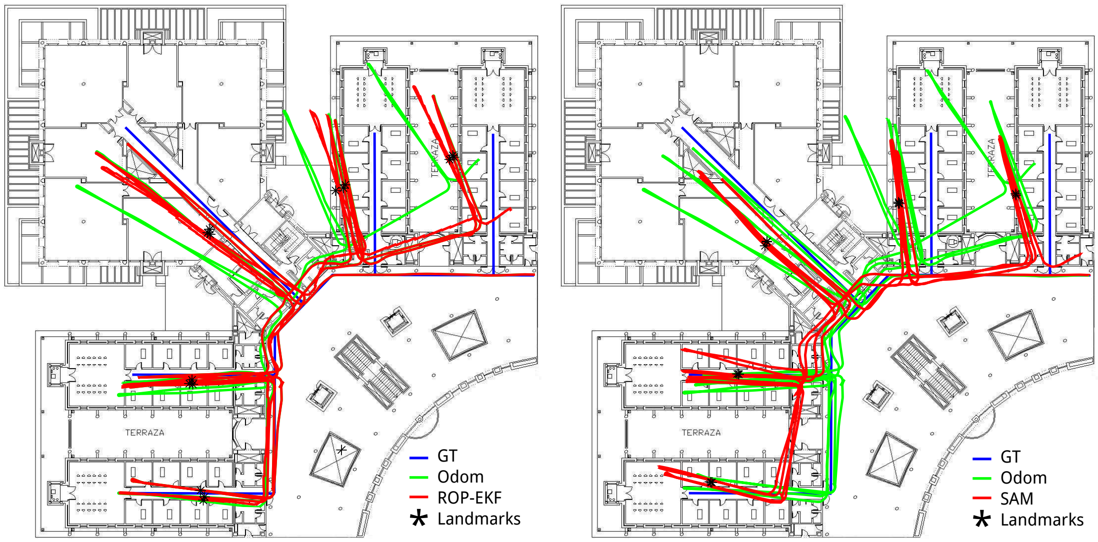

(a) Alcala2. ROP-EKF

(b) Alcala2. SAM

Fig. 3. Alcala2 results

(a) Alcala3. ROP-EKF

(b) Alcala3. SAM

Fig. 4. Alcala3 results

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