Radar Scan Matching SLAM Using the Fourier-Mellin Transform

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Abstract. This paper is concerned with the Simultaneous Localization And Mapping (SLAM) problem using data obtained from a microwave radar sensor. The radar scanner is based on Frequency Modulated Continuous Wave (FMCW) technology. In order to meet the needs of radar image analysis complexity, a trajectory-oriented EKF-SLAM technique using data from a 360° field of view radar sensor has been developed. This process makes no landmark assumptions and avoids the data association problem. The method of egomotion estimation makes use of the Fourier-Mellin Transform for registering radar images in a sequence, from which the rotation and translation of the sensor motion can be estimated. In the context of the scan-matching SLAM, the use of the Fourier-Mellin Transform is original and provides an accurate and efficient way of computing the rigid transformation between consecutive scans. Experimental results on real-world data are presented.

1 Introduction

Environment mapping models have been studied intensively over the past two decades. In the literature, this problem is often referred to as simultaneous localization and mapping (SLAM). For a broad and quick review of the different approaches developed to address this problem, one can consult [2], [8], [9] and [25]. Localization and mapping in large outdoor environments are applications related to the availability of efficient and robust perception sensors, particularly with regard to the problem of maximum range and the resistance to the environmental conditions. Most approaches to map learning generate 2D models from range sensor data. Even though lasers and cameras are well suited sensors for indoor environments, their

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strong sensitivity to atmospheric conditions has created an interest for doing SLAM with radars and sonars [21]. Microwave radar provides an alternative solution for environmental imaging and overcomes the shortcomings of laser, video and sonar sensors. In this paper, a trajectory-oriented SLAM technique is presented using data from a 360° field of view radar sensor. This radar is based on Frequency Modulated Continuous Wave (FMCW) technology [16].

In Section 2, a review of articles related to our research interests is carried out in order to position our work in relation to existing methods. Section 3 presents the microwave radar scanner developed by a Cemagref research team (in the field of agricultural and environmental engineering research) [22]. The way to obtain a radar image (i.e. the power spectra with polar coordinates) is briefly presented. Section 4 gives the SLAM formulation used in this paper. There, the Fourier-Mellin Transform is applied to register images in a sequence and to estimate the rotation and translation of the radar system (see Section 5). This process makes no landmark assumptions, and avoids the data association problem by storing a detailed map instead of sparse landmarks. Finally Section 6 shows experimental results of this work, which were implemented (and tested on recorded real data) in Matlab and C/C++. Section 7 concludes and introduces future work.

2 Related Work

2.1 In the Field of Radar Mapping

In order to perform outdoor SLAM, laser sensors have been widely used [19] [11] [4]. A recent application with Velodyne HDL-64 3D LIDAR is presented in [13]. To provide localization and map building, the input range data is processed using geometric feature extraction and scan correlation techniques. Less research exists using sensors such as underwater sonar [21] and Frequency Modulated Continuous Wave (FMCW) radar. Interestingly, this last kind of sensor was already used by Clark in [6] at the end of the last century. In an environment containing a small number of well separated, highly reflective beacons, experiments were led with this sensor to provide a solution to the SLAM problem [8] using an extended Kalman filter framework and a landmark based approach. Finally, in [17], methods were presented for building a map with sensors that return both range and received signal power information. An outdoor occupancy grid map related to a 30 m vehicle's trajectory is analyzed. So far, there seems to have been no trajectory-oriented SLAM work based on radar information over important distances. However, vision-based, large-area SLAM has already been carried out successfully for underwater missions, using information filters over long distances [10] [15].

2.2 In the Field of Scan Matching SLAM

Since Lu and Milios presented their article [14] in search of a globally consistent solution to the 2D-SLAM problem with three degrees of freedom poses, many techniques have been proposed in the literature concerning robotics as well as computer vision. A common method of pose estimation for mobile robots is scan matching. By solving the rigid transformation between consecutive scans from a range sensor, the robot's motion in the time period between the scans can be inferred. The sensor used is most often a scanning laser range finder. One of the most popular approaches for scan matching is the Iterative Closest Point (ICP) algorithm [3]. In ICP, the transformation between scans is found iteratively by assuming that every point in the first scan corresponds to its closest point in the second scan, and by calculating a closed form solution using these correspondences. However, sparse and noisy data, such as that from an imaging radar, can cause an ICP failure. A single noisy reading can significantly affect the computed transformation, causing the estimated robot pose to drift over time. Other recent trends in SLAM research are to apply probabilistic methods to 3D mapping. Cole et al. [7] use an extended Kalman filter on the mapping problem. Olson et al. [18] have presented a novel approach to solve the graph-based SLAM problem by applying stochastic gradient descent to minimize the error introduced by constraints.

In its current version, our algorithm is close to the method suggested by Cole et al. [7]. However, the Fourier-Mellin Transform for registering images in a sequence is used to estimate the rotation and translation of the radar sensor motion (see Section 5). In the context of scan-matching SLAM, the use of the Fourier-Mellin Transform is original and provides an accurate and efficient way of computing the rigid transformation between consecutive scans. It is a global method that takes into account the contributions of both range and power information of the radar image.

3 A Microwave Radar Scanner

The exploited radar uses the frequency modulation continuous wave (FMCW) technique which has been known for several decades [23][16]. Frequency modulation presents two advantages for mobile robotics application, where distances are hundreds of meters [22]. First, it permits a low transmission power, which is safer for the user (the mean power determines the range). Second, a transposition of temporal variables into the frequency domain allows to obtain the measure more easily (a very short delay time Δt is switched to a broad variation of frequency Δf).

The FMCW radar is called K2Pi (2π for panoramic - in K band). A general view of the radar is presented in Figure 1 and its main characteristics are listed in Table 1. The radar is equipped with a rotating antenna in order to achieve a complete 360° per second monitoring around the vehicle, with an angular resolution of 3°, in the 3-100 m range. The image construction is based on the classical Plan Position Indicator (PPI) representation, i.e. the power spectra with polar coordinates. An example of radar images is presented in Figure 1. Variations of shading indicate variations of amplitude in the power spectra. These images are "radar referenced": the heading indications are related to the internal encoder of the radar and not to the earth's magnetic field.

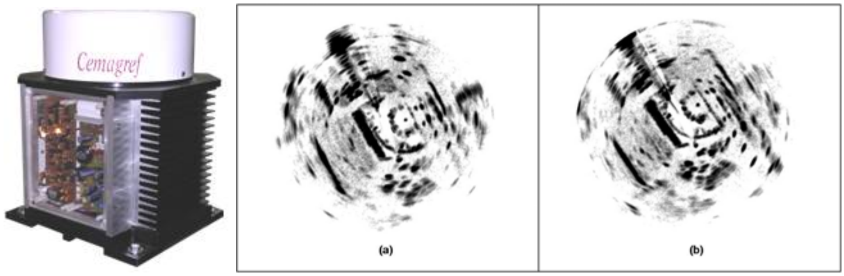

Fig. 1 Left side. The K2Pi FMCW radar. All the radar components are implemented in the same housing: microwave components, electronic devices for emission and reception, and the data acquisition and signal processing unit. The radar is mono-static: a single antenna, protected by a radome, is used for both transmitting and receiving. **Right side.** Two consecutive radar images ((a) & (b)) that are fairly similar.

Table 1 Characteristics of the K2Pi FMCW radar.

Carrier frequency $F0$	24 GHz
Transmitter power Pt	20 dBm
Antenna gain G	20 dB
Bandwidth	250 MHz
Angular resolution	3°
Angular precision	0.1°
Range Min/Max	3 m/100 m
Distance resolution	0.6 m
Distance precision (canonical target at 100 m)	0.05 m
Size (length-width-height)	27-24-30 cm
Weight	10 kg

4 Problem Formulation

4.1 SLAM Process

The used formulation of the SLAM problem is to estimate the vehicle trajectory defined by the estimated state $\mathbf{x}_k = \left[\mathbf{x}_{v_k}^T, \mathbf{x}_{v_{k-1}}^T, \ldots, \mathbf{x}_{v_1}^T\right]^T$. $\mathbf{x}_{v_i} = [x_i, y_i, \phi_i]^T$ is the state vector describing the location and orientation of the vehicle at time i. There is no explicit map; rather each pose estimate has an associated scan of raw sensed data that can be next aligned to form a global map.

4.2 Radar Scan Matching SLAM

The developed approach for a SLAM process is based on the following observation: two consecutive radar images are very similar to the "eye" point of view. For that reason a matching approach based on cross correlation function was selected [1].

Scan matching is the process of translating and rotating a radar scan such that a maximal overlap with another scan emerges. Assuming this alignment is approximately Gaussian, a new vehicle pose is added to the SLAM map by only adding the pose to the SLAM state vector. So, as described previously, observations are associated to each pose. They are compared and registered to offer potential constraints on the global map of vehicle poses. This is not only useful for odometry based state augmentation, but it is also an essential point for loop closing.

The estimator used here is the EKF, but it is not a limitation: algorithms like those presented in Section 2 could be tested too. Given a noisy control input $\mathbf{u}(k+1)$ at time $k+1$, upon calculation of the new vehicle pose, $\mathbf{x}_{v_{n+1}}(k+1|k)$, and a corresponding covariance matrix, $\mathbf{P}_{v_{n+1}}(k+1|k)$, the global state vector, $\mathbf{x}$, and corresponding covariance matrix, $\mathbf{P}$, can be augmented as follows:

$$\mathbf{x}(k+1|k) = \begin{bmatrix} \mathbf{x}(k|k) \\ \mathbf{x}_{v_n} \oplus \mathbf{u}(k+1) \end{bmatrix} \tag{1}$$

$$\mathbf{P}(k+1|k) = \begin{bmatrix} \mathbf{P}(k|k) & \mathbf{P}(k|k)\frac{\partial(\mathbf{x}_{v_n} \oplus \mathbf{u}(k+1))^T}{\partial \mathbf{x}_{v_n}} \\ \frac{\partial(\mathbf{x}_{v_n} \oplus \mathbf{u}(k+1))}{\partial \mathbf{x}_{v_n}}\mathbf{P}(k|k) & \mathbf{P}_{v_{n+1}}(k+1|k) \end{bmatrix}. \tag{2}$$

The operator $\oplus$ is the well-known displacement composition operator. $\mathbf{P}_{v_{n+1}}(k+1|k)$ is the covariance of the newly added vehicle state. Let us assume that two scans, $\mathbf{S}_i$, $\mathbf{S}_j$, have been registered. So, an observation $\mathbf{T}_{i,j}$ of the rigid transformation between poses in the state vector exists. Therefore a predicted transformation between the two poses can be found from the observation model as follows:

$$\mathbf{T}_{i,j}(k+1|k) = \mathbf{h}(\mathbf{x}(k+1|k)) = \ominus(\ominus\mathbf{x}_{vj}(k+1|k) \oplus \mathbf{x}_{vi}(k+1|k)) \tag{3}$$

where the operator $\ominus$ is the inverse transformation operator. This is then used as the initial estimate for our registration algorithm as follows:

$$\mathbf{T}_{i,j}(k+1) = \boldsymbol{\Psi}(\mathbf{T}_{i,j}(k+1|k), \mathbf{S}_i, \mathbf{S}_j) \tag{4}$$

where $\boldsymbol{\Psi}$ represents a registration algorithm. The state update equations are then the classical EKF update equations. The search for a transformation $\mathbf{T}_{i,j}$ is achieved by maximizing a cross correlation function [1].

5 Fourier-Mellin Transform for Automatic Image Registration

5.1 Principle

The problem of registering two scans in order to determine the relative positions from which the scans were obtained, has to be solved. The choice of an algorithm is strongly influenced by the need for real-time operation. A FFT-based algorithm was chosen to perform scan matching.

Algorithm 1. Steps of the Fourier-Mellin Transform algorithm applied to FMCW radar images

1. Get radar images I_k and I_{k-1}.
2. Apply thresholding filter to eliminate the speckle noise in both images.
3. Apply FFT to images $I_k \rightarrow \hat{I}_k$ and $I_{k-1} \rightarrow \hat{I}_{k-1}$.
4. Compute the magnitudes $M_k = \left|\hat{I}_k\right|$, $M_{k-1} = \left|\hat{I}_{k-1}\right|$
5. Transform the resulting values from rectangular to polar coordinates. $M() \rightarrow MP()$.
6. Apply the FFT to polar images, a bilinear interpolation is used. $MP() \rightarrow \widehat{MP}()$.
7. Compute $\widehat{Corr}(w_\rho, w_\theta)$ between $\widehat{MP}_k(w_\rho, w_\theta)$ and $\widehat{MP}_{k-1}(w_\rho, w_\theta)$ using Eq. 6.
8. Compute the inverse FFT $Corr(\rho, \theta)$ of $\widehat{Corr}(w_\rho, w_\theta)$.
9. Find the location of the maximum of $Corr()$ and obtain the rotation value.
10. Construct a new image Ir by applying reverse rotation to I_{k-1}.
11. Apply FFT to image Ir_{k-1}.
12. Compute the correlation $\widehat{Corr}(w_x, w_y)$ using Eq. 6.
13. Take inverse FFT $Corr(x,y)$ of $\widehat{Corr}(w_x, w_y)$.
14. Obtain the values $(\Delta x, \Delta y)$ of the shift.

Fourier-based schemes are able to estimate large rotations, scalings, and translations. Let us note that the scale factor is irrelevant in our case. Most of the DFT-based approaches use the shift property [20] [12] [24] of the Fourier transform. To match two scans which are translated and rotated with respect to each other, the phase correlation method is used, stating that a shift in the coordinate frames of two functions is transformed in the Fourier domain as a linear phase difference. To deal with the rotation as a translational displacement, the images are previously transformed into an uniform polar Fourier representation.

It is known that if two images I_1 and I_2 differ only by a shift, $(\Delta x, \Delta y)$, (i.e., $I_2(x,y) = I_1(x - \Delta x, y - \Delta y)$), then their Fourier transforms are related by:

$$\hat{I}_1(w_x, w_y).e^{-i(w_x \Delta x + w_y \Delta y)} = \hat{I}_2(w_x, w_y). \tag{5}$$

Hence the normalized cross power spectrum is given by

$$\widehat{Corr}(w_x, w_y) = \frac{\hat{I}_2(w_x, w_y)}{\hat{I}_1(w_x, w_y)} = \frac{\hat{I}_2(w_x, w_y)\hat{I}_1(w_x, w_y)^*}{\left|\hat{I}_1(w_x, w_y)\hat{I}_1(w_x, w_y)^*\right|} = e^{-i(w_x \Delta x + w_y \Delta y)} \tag{6}$$

where $*$ indicates the complex conjugate. Taking the inverse Fourier transform $Corr(x,y) = F^{-1}(\widehat{Corr}(w_x, w_y)) = \delta(x - \Delta x, y - \Delta y)$, which means that $Corr(x,y)$ is nonzero only at $(\Delta x, \Delta y) = \arg\max_{(x,y)}\{Corr(x,y)\}$. If the two images differ by rotational movement (θ_0) with translation $(\Delta x, \Delta y)$, then

$$I_2(x,y) = I_1(x\cos\theta_0 + y\sin\theta_0 - \Delta x, -x\sin\theta_0 + y\cos\theta_0 - \Delta y). \tag{7}$$

Converting from rectangular coordinates to polar coordinates makes it possible to represent rotation as shift: The Fourier Transform in polar coordinates is $\hat{I}_2(\rho, \theta) = e^{-i(w_x \Delta x + w_y \Delta y)}\hat{I}_1(\rho, \theta - \theta_0)$. Let M_1 and M_2 denote the magnitudes of $\hat{I}_1$ and $\hat{I}_2$

($M_1 = \left|\hat{I}_1\right|$, $M_2 = \left|\hat{I}_2\right|$). So, M_1 and M_2 are related by $M_1(\rho,\theta) = M_2(\rho,\theta-\theta_0)$. The shift between the two images can now be resolved using Eq. 6.

5.2 Scan Registration

In order to perform a scan registration algorithm, the Fourier-Mellin Transform (FMT) has been chosen [5] [20]. The FMT is a global method that takes the contributions from all points in the images into account in order to provide a way to recover all rigid transformation parameters, i.e. rotation, translation. It is an efficient and accurate method to process a couple of images that are fairly similar (see Fig. 1). The steps of the scan registration algorithm are described in Alg. 1.

6 Experimental Results

This section provides experimental results of the Scan SLAM application using the radar sensor previously described. The radar and the proprioceptive sensors were mounted on a utility car moving at a speed ranging from 0 to 25 km/h. Here, two experimental runs are presented. They were performed in an outdoor field, Blaise Pascal University campus, with a complex environment (buildings, cars, trees, roads, road signs, etc.). The radar was on top of the vehicle, 3 meters above the ground. The estimated trajectories obtained with the Scan SLAM process are presented in Figures 2 and 5. The successive positions of the radar are separated by an interval of one second. The photograph (see Fig. 2) is an aerial image of the experimental zone. The trajectory of the vehicle simultaneously measured with a centimetrically-precise GPS is overlayed. For these experiments, all data acquisitions have been realized in real time but SLAM processing has been realized off-line. One step of the process (scan registration, prediction and update) is achieved in less than one

Fig. 2 Overlay of the estimated trajectory and the aerial image of Blaise Pascal University campus. The total traveled distance is around 1,135 m. The thin red line shows the trajectory of the vehicle measured with a centimetrically-precise GPS. The vehicle estimates are in thick white dashes.

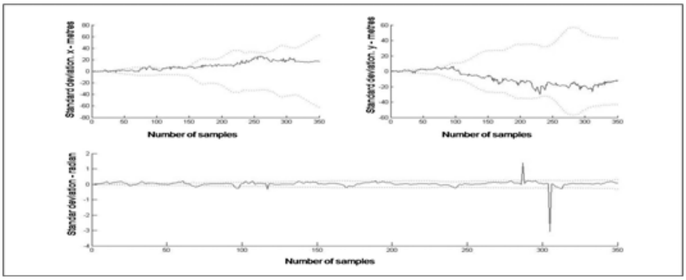

Fig. 3 Error and standard deviation (lower and upper bounds) related to the trajectory depicted in Fig. 2. Near sample 300, there is a GPS loss.

Fig. 4 Global map related to the trajectory depicted in Fig. 2.

Fig. 5 The total traveled distance is around 700 m. The thin red line shows the trajectory of the vehicle measured with a centimetrically-precise GPS. The vehicle estimates after the loop closing are in thick white dashes.

second with Matlab on a dual-core 2 GHz laptop. A quantitative evaluation of the localization performances of the implemented process has been achieved. The position errors are calculated using the estimates and GPS data, assumed to be the ground truth (see Fig. 3 and Fig. 6). The first experiment was made on a distance

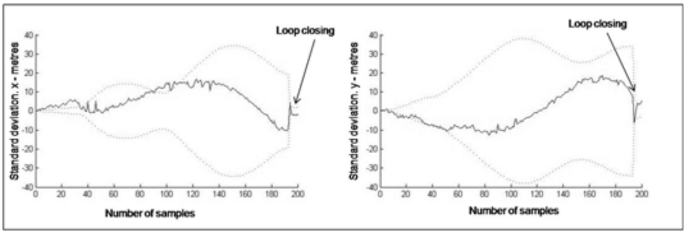

Fig. 6 Standard deviation along the north (x) and west (y) axes between pose estimation and GPS and influence of the loop closing.

of 1,135 m without loop closing. Figure 2 shows the trajectory of the vehicle. In Figure 3, error and standard deviation (lower and upper bounds) are presented. The global map that is obtained is shown in Figure 4. The second experiment was made on a distance of 700 m with loop closing (a circular trajectory around the campus sports-ground). In Figure 5, the corrected trajectory after loop closing is presented. In Figure 6, error and standard deviation (lower and upper bound) are presented.

7 Conclusion and Future Work

This paper presented results of SLAM using a microwave radar sensor. Due to the complexity of radar target detection, identification, tracking and association, a trajectory-oriented SLAM process based on the Fourier-Mellin Transform was developed; in this way, target assumptions about their position and nature were avoided.

Currently, this work considers only a static environment, assuming that there are no mobile elements around the radar. However, in order to develop a perception solution for high velocity robotics applications, future work will be devoted to the enhancement of the global map using methods such as the one described in [18]. Once the sensor delivers the measurement of Doppler frequency to take the relative velocity of mobile targets into account, integration of SLAM with Mobile Object Tracking (SLAMMOT) will be considered [25].

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