GLRT PARTICLE FILTER FOR TRACKING NLOS TARGET IN AROUND-THE-CORNER RADAR

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ABSTRACT

This article examines the problem of tracking NLOS targets by exploiting multipath information measured by an urban around-the-corner radar. Due to the non linearity relationship between target position and multipath delays and the complexity of the multipath measurement model, a particle filter is considered. It samples separately the target state (position and velocities) and the multipath amplitudes thanks to an appropriate importance density function. GLRT particle filter, a special case of the proposed particle filter, is shown to provide the most efficient localization results. Simulations demonstrate the ability of the particle filter to correctly estimate the target location and the improvement of localization performance compared to a multipath localization algorithm without tracking.

***Index Terms*—** around-the-corner radar, multipath exploitation, NLOS target, particle filter, urban radar

1. INTRODUCTION

Locating targets in urban environments is a quite recent topic in radar applications. The presence of buildings creates shadow areas in which targets are not in direct line of sight (NLOS) of the radar. However, targets in these NLOS areas can be reached by different paths produced by reflections on surrounding surfaces. These multipaths generally present a challenge in classic applications. For instance, they produce frequency selective channels in telecommunication applications. However, in urban radar application, these multipaths represent an opportunity as they may be exploited to locate and track NLOS targets.

This around-the-corner radar application has been studied only since a few years, first papers focusing on the applicability of such a detection behind corners [1, 2, 3]. Then, in [4], the authors proposed a detection and localization algorithm and applied it to experimental data obtained by a portable radar. They developed a multipath subspace matched filter based on a propagation model enabling to predict the multipath delays for any considered position. The algorithm was shown to provide promising results in single target localization. Most of the time, the maximum likelihood (ML) estimator of the target position is indeed close to the real target position. However, the main problem of the algorithm was the appearance of high ambiguities which could generate ghosts or strong biases affecting localization performance. This phenomena can be observed in other works dealing with multipath exploitation. For example, in [5], where an urban Synthetic Aperture Radar is studied, the two proposed multipath exploitation techniques also provided ambiguous images; and in [6], for the purpose of tracking targets in range-time domain with multipath exploitation, the proposed approach was not able to disambiguate two multipath tracks with similar range. The ambiguities presented in several works due to multiplicity of urban scenes motivated us to develop a tracking algorithm to mitigate them and thus improve target localization. Note that if tracking in urban environment has been investigated in [7] with an airborne radar, thus with a radar located far away and above the urban scene, or in [8] using multisensors in the urban scene, their purpose was not to mitigate the ambiguities inherent to the multipath propagation.

In the present article, we deal with the problem of tracking target in NLOS by exploiting multipaths in urban environment with a single radar. Our purpose is to exploit the dynamics of the target to alleviate localization ambiguities. In this context, Kalman type filters cannot be considered since the measurement equation is non linear. In particular, we will see here that the measurement equation depends on the target state itself in a very complex ways as the number of paths depends on the location of the target! We thus propose to use a particle filter to deal with the non linearity of the measurement model and to handle the multipath propagation model. Another challenge raised by the localization problem in urban environment is the modelization of the measurement itself. First, to easily take into account the information provided by the different multipaths, the proposed particle filter considers raw radar data, as in Track-Before-Detect settings [9]. Second, due to the complexity of the propagation in this environment, it is not realistic to suppose that the complex amplitudes of the different paths are known or can be simply modeled. To

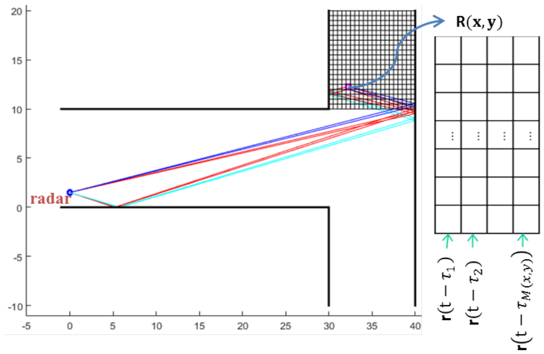


Fig. 1: Simulated urban intersection. The target position can be located anywhere in the hatched area.

solve this problem, we propose a particle filter that samples separately the target state (position and velocities) and these amplitudes thanks to an appropriate importance density function. Simulations will show that the proposed particle filter improves the localization performance compared to the localization algorithm proposed in [4]. Furthermore, thanks to a particular way of sampling the multipath amplitudes, we obtain a particle filter which provides the most efficient result of localization. We call this filter GLRT (Generalized Likelihood Ratio Test) particle filter.

The article is organized as follows. In section 2, state and measurement models will be presented. In section 3, we will describe the proposed particle filters. Finally, in section 4, simulations will be carried out and then, results from this simulation will be presented and analyzed.

2. MODELING

2.1. State model

Let us denote by $\mathbf{x}_k$ the target state composed of its positions (x_k, y_k) and its velocities $(\dot{x}_k, \dot{y}_k)$. The target trajectory can be described by a classic linear equation:

$$\mathbf{x}_k = \begin{bmatrix} 1 & 0 & T_r & 0 \\ 0 & 1 & 0 & T_r \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{x}_{k-1} + \mathbf{b}_k,$$

where $\mathbf{b}_k$ is the state noise assumed to be white gaussian with known covariance matrix.

2.2. Measurement model

In the following, we assume that all reflections are specular, and that diffraction effects can be neglected. We also assume that strong fixed echoes produced by the surrounding buildings and objects have already been removed, for instance by using [10], so that the only received echoes are backscattered by nearby moving targets.

After cancellation of fixed echoes and taking into account the multipath propagation, the signal $\zeta_k(t)$ at discrete time k received by the radar can be written as:

$$\zeta_k(t) = \sum_{j=1}^{M(x_k,y_k)} \alpha_j(x_k, y_k) s(t - \tau_j(x_k, y_k)) + n_k^{'}(t),$$

where $M(x_k, y_k)$ is the number of multipath returns for a target located at (x, y), $\tau_j(x, y)$ is the delay of the j-th return for this target and $\alpha_j(x_k, y_k)$ is its complex amplitude. Note that for the purpose of simplicity, we will not exploit here Doppler-shifts of the different multipaths. Letting $z(t)$ denote the output of the matched filter applied to $\zeta(t)$, we have:

$$z_k(t) = \sum_{j=1}^{M(x_k,y_k)} \alpha_j(x_k, y_k) r(t - \tau_j(x_k, y_k)) + n_k(t),$$

where $r(t)$ is the autocorrelation of $s(t)$. Taking N snapshots ($t_i = iT_s = i/f_s$, where f_s is the sample frequency), the previous equation can then be written as

$$\mathbf{z}_k = \mathbf{R}(x_k, y_k)\boldsymbol{\alpha}(x_k, y_k) + \mathbf{n}_k, \qquad (1)$$

where

$$\mathbf{z} = [z(t_1) \quad z(t_2) \quad \ldots \quad z(t_N)]^T,$$

$$\mathbf{n} = [n(t_1) \quad n(t_2) \quad \ldots \quad n(t_N)]^T,$$

$$\boldsymbol{\alpha} = [\alpha_1 \quad \alpha_2 \quad \ldots \quad \alpha_{M(x,y)}]^T,$$

$$\mathbf{r}(t - \tau) = [r(t_1 - \tau) \quad r(t_2 - \tau) \quad \ldots \quad r(t_N - \tau)]^T,$$

$$\mathbf{R}(x, y) = [\mathbf{r}(t-\tau_1(x, y)) \quad r(t-\tau_2(x, y))\ldots \quad \mathbf{r}(t-\tau_{M(x,y)}(x, y))].$$

The matrix $\mathbf{R}(x_k, y_k)$ depends on the position of the target and is provided by a simple ray tracing model using an approximate knowledge of the scene. The amplitudes $\boldsymbol{\alpha}(x_k, y_k)$ also depend on the position of the target. We assume here that these amplitudes are unknown and deterministic. For the purpose of simplicity, $\mathbf{R}(x_k, y_k)$ is replaced by $\mathbf{R}_k$ and $\boldsymbol{\alpha}(x_k, y_k)$ by $\boldsymbol{\alpha}_k$ for the rest of the article but we shall not forget that they depend on the target state. The observation model can thus be provided by:

$$\mathbf{z}_k = \mathbf{R}_k\boldsymbol{\alpha}_k + \mathbf{n}_k,$$

where the sizes of $\mathbf{R}_k$ and $\boldsymbol{\alpha}_k$ depend on the state $\mathbf{x}_k$.

3. GLRT PARTICLE FILTER

The amplitudes $\boldsymbol{\alpha}_k$ depend on the target position at the instant k (x_k, y_k) and are normally difficult to model because of unknown environment parameters such as propagation losses, reflection on target/walls coefficients, etc. Thus, we propose to integrate these amplitudes in the particle state in order to sample them as well as the target state, following a classic particle filter strategy [11]. Let us denote by $\mathbf{X}_k^i$ the state of particle i composed of its positions and velocities $\mathbf{x}_k^i$ and the amplitudes $\boldsymbol{\alpha}_k^i$ of the different multipaths coressponding to the particle position:

$$\mathbf{X}_k^i = \left[\mathbf{x}_k^{iT}, (\boldsymbol{\alpha}_k^i)^T\right]^T = \left[x_k^i, y_k^i, \dot{x}_k^i, \dot{y}_k^i, (\boldsymbol{\alpha}_k^i)^T\right]^T.$$

Following the classic particle filter framework, particles are propagated from the instant $k-1$ to the instant k in two steps. First, the state of the particles at the instant k are drawn from the importance density $q(\mathbf{X}_k^i|\mathbf{X}_{k-1}^i, \mathbf{z}_{1:k})$. Then the unnormalized weights $\tilde{\omega}_k^i$ for the particle i can be calculated according to:

$$\tilde{\omega}_k^i \propto \omega_{k-1}^i \frac{p(\mathbf{z}_k|\mathbf{X}_k^i)p(\mathbf{X}_k^i|\mathbf{X}_{k-1}^i)}{q(\mathbf{X}_k^i|\mathbf{X}_{k-1}^i, \mathbf{z}_{1:k})},$$

where $\tilde{\omega}_{k-1}^i$ are the particle weights at instant $k-1$ and the likelihood function $p(\mathbf{z}_k|\mathbf{X}_k^i)$ is provided by:

$$p(\mathbf{z}_k|\mathbf{X}_k^i) \propto \exp\left(-\frac{\left\|\mathbf{z}_k - \mathbf{R}_k^i\boldsymbol{\alpha}_k^i\right\|^2}{\sigma^2}\right),$$

supposing that the noise vector $\mathbf{n}_k$ is complex circular white gaussian with covariance matrix $\sigma^2\mathbf{I}$.

A classic particle filter would sample the target amplitude according to the prior model. However, this strategy presents two drawbacks: first it assumes a coherent behavior of the amplitude along time enabling to describe it via a Markov chain model. We rather propose here to consider that the prior model for the amplitudes is $\alpha_k^i = \rho_k^i e^{j\phi_k^i}$ with $\rho_k^i \sim \mathrm{U}_{[0,\rho_{max}]}$ and $\phi_k^i \sim \mathrm{U}_{[0,2\pi]}$, where $\mathrm{U}_{[a,b]}$ is the uniform distribution over the interval $[a,b]$, thus accepting no coherence of the amplitude along times. Second, it does not enable to retrieve information from the current measurement, although it is well known that the optimal importance density is $p(X_k|X_{k-1}, z_k)$ [12] . Here, we propose to factorize the importance density in the following way:

$$q(\mathbf{X}_k^i|\mathbf{X}_{k-1}^i, \mathbf{z}_{1:k}) = q(\boldsymbol{\alpha}_k^i|\mathbf{x}_k^i, \mathbf{z}_k)p(\mathbf{x}_k^i|\mathbf{X}_{k-1}^i).$$

This means that the position and velocity of the target are sampled according to the state equation, while the amplitudes of different paths are sampled conditionally to the target position and velocities at the instant k and the measurement at the instant k. This allows to retrieve some information from the current measurement. A possible choice for $q(\boldsymbol{\alpha}_k^i|\mathbf{x}_k^i, \mathbf{z}_k)$ is:

$$q(\boldsymbol{\alpha}_k^i|\mathbf{x}_k^i, \mathbf{z}_k) \sim \mathcal{N}(\hat{\boldsymbol{\alpha}}_k^i, \sigma_{\boldsymbol{\alpha}}^2\mathbf{I}_{[M(x_k^i, y_k^i)]}), \quad (2)$$

where $\hat{\boldsymbol{\alpha}}_k$ is the ML estimation of $\boldsymbol{\alpha}_k$ from the measurement $\mathbf{z}_k$ conditional to x_k, which is given by:

$$\hat{\boldsymbol{\alpha}}_k = (\mathbf{R}_k^H\mathbf{R}_k)^{-1}\mathbf{R}_k^H\mathbf{z}_k,$$

and $\sigma_{\boldsymbol{\alpha}}^2$ is an adjustable parameter. Under these prior hypotheses and choice of the importance density, the unnormalized weight of particles i at instant k can be found as:

$$\tilde{\omega}_k^i \propto \frac{\omega_{k-1}^i}{q(\boldsymbol{\alpha}_k^i|\mathbf{x}_k^i, \mathbf{z}_k)} \exp\left(-\frac{\left\|\mathbf{z}_k - \mathbf{R}_k^i\boldsymbol{\alpha}_k^i\right\|^2}{\sigma^2}\right) \quad (3)$$

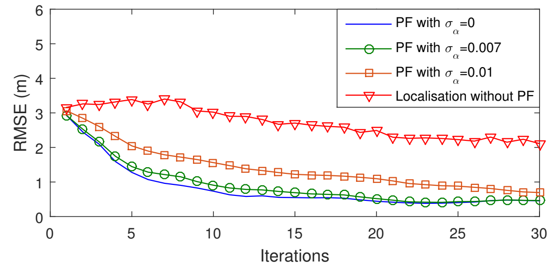


Fig. 2: Comparison of particle filters (PF) with different $\sigma_{\boldsymbol{\alpha}}$ and the localization algorithm without tracking algorithm.

where $\boldsymbol{\alpha}_k^i$ is sampled from the distribution $\mathcal{N}(\hat{\boldsymbol{\alpha}}_k^i, \sigma_{\boldsymbol{\alpha}}^2 \mathbf{I}_{[M(x_k^i, y_k^i)]})$ and $q(\boldsymbol{\alpha}_k^i|\mathbf{x}_k^i, \mathbf{z}_k)$ is calculated from (2). In the extreme case when $\sigma_{\boldsymbol{\alpha}}$ tends to 0, $\boldsymbol{\alpha}_k^i$ is directly given by the ML estimator of $\boldsymbol{\alpha}_k$. Then dividing Eq.(3) by the likelihood of the measurement under hypothesis that no target is present in the scene, which is the same constant for all particles, we obtain a GLRT particle filter [13]. Eq.(3) becomes:

$$\tilde{\omega}_k^i \propto \omega_{k-1}^i L(\mathbf{z}_k|\mathbf{X}_k^i), \quad (4)$$

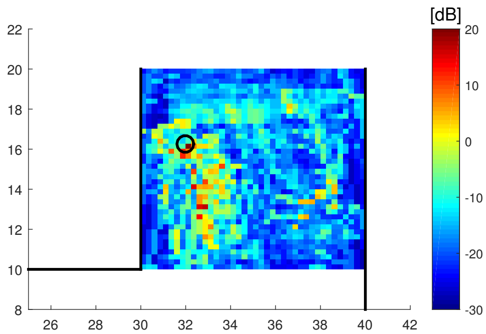
where $L(\mathbf{z}_k|\mathbf{X}_k^i)$ is the likelihood ratio for the detection test testing the presence of a target with state $\mathbf{X}_k^i$.

Finally, the classic estimator of the target position is provided by: $\hat{x}_k = \dfrac{1}{N_p}\displaystyle\sum_{i=1}^{Np} w_k^i x_k^i$ and $\hat{y}_k = \dfrac{1}{N_p}\displaystyle\sum_{i=1}^{Np} w_k^i y_k^i$.

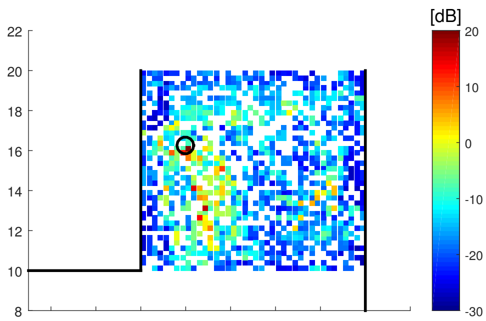
4. SIMULATION

The particle filter localization performance is evaluated by simulations for the simple urban intersection scenario shown in Fig. 1. The radar is placed at location (0,2). The bandwidth of the signal $s(t)$ transmitted by the radar is 300 MHz, giving a range resolution of 0.5 m. For each $N_{MC} = 1000$ Monte Carlo simulations performed, $N_p = 1600$ particles are uniformly initialized in the area of interest (hatched area in Fig. 1). The matrix $\mathbf{R}$ corresponding to each particle at the instant k can be found by a ray tracing model. However, computing matrices $\mathbf{R}$ for all the particles for each instant is very costly. Then, in order to accelerate the process, we propose to precompute the matrices $\mathbf{R}$ for small cells discretized from the area of interest. A particle in a cell is assumed to have the matrix $\mathbf{R}$ computed at the center this cell. In the simulation, we discretize the area into 0.25 mx0.25 m cells, which is equal to half of the radar range resolution. The target moves from $(32, 16.25)$ to $(35; 16.25)$ at constant velocity: $\dot{x}_k = 2$ m/s and $\dot{y}_k = 0$. The sample rate for the particle filter is set to 50 ms, so 30 iterations are executed along the target trajectory. To evaluate the particle filter performance, the signal-to-noise ratio (SNR) of the target is set to 10 dB for all positions of its trajectory.

Fig. 2 shows the Root-Mean-Square Error (RMSE) obtained for the proposed particle filter with different values of

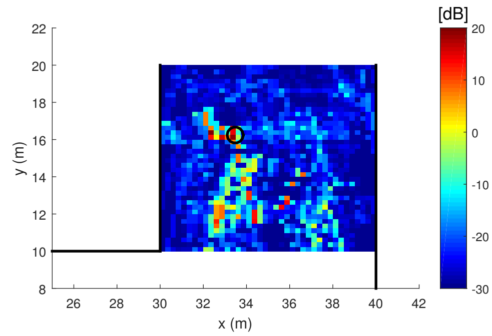


(a) Localization result

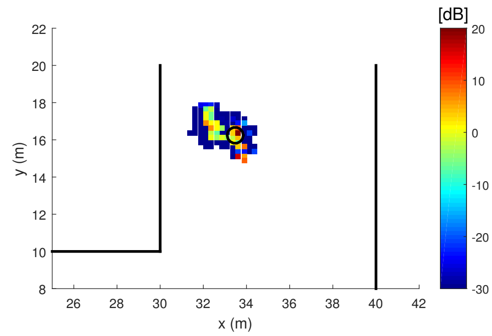


(b) Particle filter result

Fig. 3: Localization and particle filter results when the target is at $(32, 16.25)$ (first iteration). The black circles indicate the true target position.



(a) Localization result



(b) Particle filter result

Fig. 4: Localization and particle filter results when the target is at $(33.5, 16.25)$ (16th iteration). The black circles indicate the true target position.

σ_α. From this figure, it appears that the smallest values for σ_α provide the best performances. As expected, the GLRT particle filter described by Eq. (4) is the most efficient. These curves are also compared to the result of the localization algorithm proposed in [4]. As mentioned in [4], the localization algorithm could rise strong ambiguities because of the geometry of the scene. Especially in this simulation, when the SNR of the target is low, these ambiguities can easily yield a strong bias and generate large errors in localization. This explains why the RMSE of the localization algorithm is quite significant, between 2 and 4 m. When applying the proposed particle filter, we observe a considerable improvement of RMSE after only a few iterations. This improvement proves that the particle filter succeeds to take into account the dynamics of the target to alleviate the ambiguities.

To illustrate this ambiguity alleviation, we show in Fig. 3(a) the output image of the localization algorithm, and in Fig. 3(b) the weighted particles before the resampling step when the target is at location $(32, 16.25)$, the first position of its trajectory. At the first iteration, the particle filter provides a similar ambiguity image as the localization algorithm because at this time, the particle filter shares the same information with the localization algorithm. Fig. 4 shows a similar comparison when the target is in the midpoint of its trajectory. The localization algorithm still shows high ambiguities while the particle filter provides a remarkable ambiguity reduction. Most particles are concentrated around the true target position.

5. CONCLUSION

In this article, we proposed a particle filter for the problem of tracking a single NLOS target in around-the-corner radar. A specific urban signal model was provided in order to take into account multipath propagation. In this model, due to the complexity of the propagation environment, it was assumed that the multipath amplitudes could not be simply inferred from any available information. To resolve this problem of complex measurement modelization, the importance density was decomposed in two parts: the first part enabled to resample the target position and velocity by the state equation; and the second allowed to take into account the current measurement to sample the unknown multipath amplitudes. For the limiting choice of importance density where the multipath amplitude variance tends to 0, we obtained the GLRT particle filter that was shown by simulation to provide the most efficient localization results. Simulations also showed that applying the particle filter decreased ambiguities arising in urban multipath localization, and thus improved localization performance compared to the localization algorithm without filtering.

6. REFERENCES

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