Around-the-Corner Radar: Detection and Localization of a Target in Non-Line of Sight

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Abstract—This paper examines the problem of detecting and locating an NLOS target in an urban environment by exploiting multipath radar returns. We propose a detection-localization algorithm based on a matched subspace filter approach that works in the target state space directly. A real experimentation was carried out to show that a portable radar can provide images of multipath returns in NLOS cases that can be clearly interpreted thanks to a simple ray tracing model. The application of the detection-localization algorithm on experimental radar measurements shows that the target can be detected and located but that the mitigation of strong ambiguities inherent to the multipath detection-localization problem remains a challenging problem for the application at hand.

I. INTRODUCTION

In conventional radar applications, targets are in the direct line of sight (LOS) of the radar. On the contrary, in recently emerging urban radar applications, the presence of buildings surrounding the radar generates multiple challenges. For example, these buildings create shadow areas within which a target is not in direct line of sight (NLOS) of the radar and many multipaths are produced by reflection and diffraction on surrounding surfaces. Fortunately these multiple paths can be exploited by the radar to detect and locate targets in shadow areas. It may then become possible to look around corners of walls using a single portable radar. Such a radar can be called “around-the-corner” radar (ACR) [1].

Recently, some articles related to the subject investigated the theoretical and experimental aspects of the ACR. Theoretical works with the purpose of exploiting multipath information are presented in [2][3] using airborne radar technologies and in [4] using a SAR technology. Experimental works were also handled to test the feasibility of detection and localization in the absence of LOS with real measurements [1][5][6][7].

Some very recent works treat the problem in both experimental and theoretical aspects. Signal processing algorithms were developed and applied to experimental measurements. In [8], the authors proposed a multipath tracking algorithm and a location estimation based on only one reflection path, one diffraction path and their combinations. The authors did not take into account two or more-bounce reflection paths or more mirroring walls. In [9], the authors carried out several measures in NLOS situations but focused only on the micro-doppler signature of the imaged target for the purpose of classifying objects. In [10], detection of movements in a realistic scene was investigated. In this study, the authors applied an adaptive threshold level to the measured impulse response in order to find exceeding points. After a posterior processing, these points were considered as a detection. No propagation model was given. The method is relatively simple and easy to implement but informations provided by different paths were processed separately.

In this article, we consider the problem of detecting and locating a target in NLOS with a small portable radar located in an adjacent street, as illustrated in Figure 1. To the best of our knowledge, the problem of around-the-corner radar has not been treated with a dedicated multipath matched filter approach. In the present article, we fill this gap by proposing a multipath propagation based matched filter derived from a simple model. Thus, the developed detection-localization algorithm jointly handles the information provided by different multipath returns to estimate the NLOS target position. Note that since the scene geometry should be extracted from rough map information and only a rough propagation model can be used in the radar device for computational cost purpose, the proposed detection localization algorithm should be robust to
some misknowledge of the exact geometry of the scene and of the exact wave propagation.

This proposed solution has been applied to real data. The real experimentation carried out showed that a simple propagation model can explain clearly most of the multipath return images provided by a portable radar in an NLOS case. Then, results of the algorithm applied to these experimental data were analyzed.

The article is organized as follows. In section II, the signal model and the problem formulation are introduced, and the detection-localization algorithm is then proposed. In section III, an experimentation in a T-junction scene with a portable radar is presented. Finally, results of measurements and of the detection-localization algorithm on experimental signals are shown and analyzed in section IV.

II. SIGNAL MODEL AND PROBLEM FORMULATION

A. Signal model

In this article, it is assumed that all reflections are specular, that diffraction effects can be neglected, and that a rough knowledge of the geometry of the scene is available, that could for instance be extracted from free available street maps, knowing the GPS position of the radar. The problem of detecting and locating a single target in a 2D-surface problem is considered. An example of a typical considered scenario is provided in Figure 1 that represents a simple urban setting, where the radar located in the main street is looking for targets located in the adjacent perpendicular street.

The signal \( y(t) \) received by the radar in the urban environment can be written, taking into account the multipath propagation, as

\[
y(t) = \sum_{k=1}^{M(x,y)} \alpha_k s(t-\tau_k(x,y))e^{j2\pi v_k t} + n(t), \tag{1}
\]

where \( s(t) \) is the signal transmitted by the radar, \( M(x,y) \) is the number of multipath returns for a target located at \((x,y)\), \( \tau_k(x,y) \) is the delay of the return \( k \) for this target, \( \alpha_k \) is the amplitude of the multipath return \( k \) and \( v_k \) is the Doppler speed of the target following the return \( k \). Taking \( N \) snapshots, we define:

\[
s(t-\tau) = [s(t_1-\tau_1) \ s(t_2-\tau_1) \ ... \ s(t_N-\tau_1)]^T,
\]

\[
n = [n(t_1) \ n(t_2) \ ... \ n(t_N)]^T,
\]

\[
y = [y(t_1) \ y(t_2) \ ... \ y(t_N)]^T,
\]

\[
\alpha = [\alpha_1 \ \alpha_2 \ ... \ \alpha_{M(x,y)}]^T,
\]

\[
S(x,y) = [s(t-\tau_1(x,y)) \ s(t-\tau_2(x,y)) \ ... \ s(t-\tau_{M(x,y)}(x,y))].
\]

For the purpose of simplicity, in the present article, we will not take into account possible Doppler-shifts of the different multipaths in the detection-localization algorithm, although such information may be of interest to improve the localization performance of the proposed solution. Thus, the equation (1) can be written as:

\[
y = S(x,y)\alpha + n, \tag{2}
\]

where \( n \) is supposed to be a circular complex white Gaussian noise with covariance matrix \( \sigma^2I \).

We also assume here that strong fixed echoes produced by the surrounding buildings and objects have already been removed, for instance by applying a zero-Doppler rejection method based on [11], so that the only received echoes are backscattered by nearby moving targets.

B. Detection-localization algorithm

A natural idea in radar to detect and localize a target is to perform a single target based Maximum Likelihood (ML) estimation or Generalised Likelihood Ratio Test (GLRT) detection, both known as matched filter detection/estimation. In the particular problem at hand here, the NLOS propagation should be exploited in order to detect and localize the target in NLOS. Indeed, a classic matched filter that does not exploit multipath propagation would only consider one single delay, that is insufficient information to locate the target in an adjacent street, due to strong spatial ambiguities. Taking into account multiple reflected paths should enable to extract several delays information and thus reduce location ambiguities and increase detection performance.

Following the Direct Position Determination (DPD) approach [12], we will work in the target space \((x,y)\) directly. This seems particularly relevant in our context where the range in itself does not carry much information on the location, as we are prone to multipath propagation.

For a fixed position \((x,y)\), the hypothesis testing problem to be considered is the following one:

\[
\begin{cases}
H_0 : y = n, \\
H_1 : y = S(x,y)\alpha + n.
\end{cases}
\]

Exploiting prior information on the path amplitudes \( \alpha_k \) stacked in vector \( \alpha \) is not trivial, since this would require a good knowledge of the wall materials and reflectivities, as well as the good knowledge of the target radar cross section for all presentation angle; we rather assume here that these amplitudes are unknown and deterministic. Classically, in such a setting, the ML estimation of the amplitude vector \( \alpha \) is provided by

\[
\hat{\alpha} = (S^H(x,y)S(x,y))^{-1}S^H(x,y)y.
\]

Injecting this expression into the likelihood ratio corresponding to the above hypothesis testing problem then provides the following GLRT for our detection problem:

\[
T(x,y) = \left| \left| P(x,y)y \right| \right|^2 \tag{4}
\]

and

\[
P(x,y) = S(x,y)(S^H(x,y)S(x,y))^{-1}S^H(x,y). \tag{5}
\]

For a fixed position \((x,y)\), this GLRT solution is known as the matched subspace detector [13]. It aims at detecting signals belonging to the subspace spanned by matrix \( S(x,y) \).
The probability law of $T'(x, y) = T(x, y)/\sigma^2$ under $H_0$ hypothesis is a $\chi^2$ central distribution with $2M(x, y)$ degrees of freedom. Thus the threshold level $\lambda$ can be calculated as a function of the number of multiple paths $M(x, y)$, the noise variance and the false alarm probability $P_{FA}$, as:

$$\lambda = 2\sigma^2\gamma^{-1}(M(x, y), \Gamma(M(x, y))(1 - P_{FA})),$$

where $\Gamma(N)$ and $\gamma(N, x)$ are the gamma and the incomplete gamma functions respectively [13].

For the problem of localization, considering also that $\alpha$ is an unknown deterministic vector, the ML estimator of $(x, y)$ in (2) is given by the maximum of $T(x, y)$. Like in a classical LOS radar, the single target ML cost function is used both for detection and localization. The value $T(x, y)$ (called T-level) for the detection test at each position $(x, y)$ in the considered zone is calculated and shown as an image. The cells with high T-level are more likely to correspond to the position of the target.

In order to apply this detector to our particular problem, the zone considered for target detection and localization is divided into small cells as seen in Figure 2.

For each cell $(i, j)$, the matrix $S_{ij}$ with $M_{ij}$ columns is generated, where $M_{ij}$ is the number of multiple paths for this cell. As the scene geometry is roughly known, multipath delays $\tau_k$ ($k = 1, ..., M_{ij}$) for a target located in a given cell $(i, j)$ can be obtained by a simple ray tracing simulation. Since many multiple paths may be simulated with a large number of reflections, it is possible to consider only a reduced number of multipaths for the detection-localization algorithm, thus assuming that paths presenting too many reflections will be too weak to provide exploitable information. Then, once the multipath delays are obtained by simulation, and since the signal $s$ transmitted by the radar is known, the matrix $S_{ij}$ corresponding to cell $(i, j)$ can be easily found.

III. EXPERIMENTATION

In order to test the ACR problematic and the proposed solution, an experimentation was set up in a real urban environment, using a small existing commercial radar that was not initially devoted to such an application.

A. Radar description

A small portable 24GHz radar was used for all measurements. The signal transmitted by this radar consisted of a coherent train of LFM pulses. The signal bandwidth was 800MHz, thus corresponding to a range resolution of 0.1875m. The choice of such a quite large bandwidth was motivated by the need to be able to separate close paths, due to the reduced size of the urban scenario. The duration of each LFM pulse was equal to $T = 8$ms, and the pulse repetition period (PRP) was set to $T_r = 60$ms. This very long PRP, that could not be chosen smaller due to the specific hardware configuration, unfortunately provided a very small Doppler ambiguity (about 0.1m/s). For such a small Doppler ambiguity, any not perfectly zero-Doppler backscatter is immediately spread over the whole Doppler ambiguity domain and in particular the target whose energy is thus diluted. Thus, Doppler processing could not be fully exploited in this setting, and the Doppler processing consisted here in applying a zero-Doppler rejection to remove strong energy at zero Doppler, and then to incoherently integrate the residual energy in all Doppler cells for each range cell, in order to gather all the energy diluted over the Doppler dimension. The total duration of each measurement was about 15s. Finally the radar was placed at 1.2m height from the ground, the horizontal aperture of the radar antenna was 60°, and the signal was transmitted with a vertical polarization.

B. Scenario description

A T-junction quite representative of a typical urban intersection was selected for the real measurement campaign (Figure 3). The NLOS target scenario considered in this T-junction scenario is presented in Figure 4. The scale is in meters.
Any possible return path (radar-target-radar) is obtained as a combination of two simple paths (radar-target).

At the beginning of its trajectory, the target is in NLOS. From the position \( y_t = 19.1 \) up to \( C \), the target is in LOS but multipaths are still also present. This choice of target trajectory enables us to consider and compare two different multipath propagation scenarios: when the target is in NLOS and when the target is in LOS.

IV. RESULTS

A. Measurement results

In the scenario described above, the pedestrian target moved from \( D \) to \( C \) for 15 seconds. The output of the range matched filter before rejection of the fixed echoes is presented in Figure 5. It appears that the fixed echoes are strong, thus motivating the rejection procedure explained in section III-A. Measured range profiles after zero-Doppler filtering are presented in Figure 6. In the NLOS phase (the first 8.2 seconds), range profiles contain only echoes due to paths reflected at least by one wall. In the LOS phase (after 8.2s), the nearest strong echo results from the direct path (without any reflection on surrounding walls).

In order to interpret the measurement, a simulation was carried out with a rough geometrical model of the real scene (in particular doors, windows and other possible backscattering elements present in the scene were not modeled) and a simple ray tracing simulator (see Figure 7).

Comparing the simulation result in Figure 7 and the measure in Figure 6, we can observe that a quite good agreement is achieved between the echoes generated by the simulation and the echoes observed on the real measurement. In the NLOS phase, the first three strongest echoes are indicated as 1, 2 and 3 in Figure 6. The echo 1 corresponds to a two-bounce reflection following the path radar-W5-target-W5-radar. When the target moves away from the radar, the length of this path...
increases. Inversely, the echo 3 whose length decreases over time corresponds to the path radar-W1-target-W1-radar. The echo 2 combines these two paths, i.e. radar-W1-target-W5-radar and inversely. The energy difference seen in Figure 6 can be explained by the reflection coefficients of the different walls, the loss due to the different scattering angles, and the radar antenna mainlobe.

Also in this phase, apart from the three apparent echoes, a fuzzy zone can be observed at far ranges. This fuzzy zone is quite well explained by the simulation since, as can be seen in Figure 7, after a range of 35m, many mutipath returns can be observed.

In the LOS phase, the direct return is clearly observed, which is coherent with the red echo in the simulation. The two orange simulated echoes can also be observed. However, some additional echoes can be seen in Figure 6, which are not explained by the simple propagation result of Figure 7. These echoes are however less energetic and parallel to the first echo in the LOS phase. The most likely explanation is the simplicity of the geometry used in the simulation. In reality, there was also a fix metal post present in the scene that was not modelled in the rough geometry. It was close to the wall W5 and relatively small. So, when the target was in NLOS, the echoes generated could not be seen in the range profiles because of their relatively low energy level. However, when the target was in LOS, the combined returns with the direct path and a reflection path in the cylinder appeared clearly in the range profiles.

B. Detection and localization result

The algorithm described in section II was applied to the experimental data. We present in Figure 8 the result of the detection-localization algorithm when the pedestrian target was located at coordinates (15.5; 16.2). The algorithm was applied in a specific zone discretized in a certain number of location cells. With a simple ray tracing simulation, matrices $S_{ij}$ are constructed from the multipath returns which have less than three reflections on surrounding walls. Then, for each cell, the T-level was calculated and is presented in Figure 8. It appears that the maximum of the test output indeed corresponds to the real position of the target. This means that, as for the localization, the proposed test may indeed provide some information about the target position by exploiting several multipaths. Nevertheless, the presence of the target in the scene also created a lot of perturbations, and in many cells the T-level obtained is also relatively high. These high-level cells can be called spatial ambiguities and in fact correspond to high sidelobes of the proposed spatial multipath matched filter. This is due to the fact that depending on the scene geometry, there can be several cells whose multipath delay response is similar to the delays expected for the real target position; in particular, many different locations may share at least one or two similar delays. These spatial ambiguities are susceptible to generate local maxima that will not only create ghosts but may also generate a strong bias for the localization performance. Note however that these ambiguities are due to the geometry of the scene and cannot be avoided.

These spatial ambiguities, or high sidelobes, may be problematic for the detection test itself: the T-level output was compared to the threshold level provided by equation (6), where the noise variance $\sigma^2$ was experimentally calculated under hypothesis $H_0$, i.e. from a noise-only measurement. Figure 9 shows the result of the detection test with a false alarm probability of $10^{-6}$ for the considered zone. The red cells correspond to positions where the output T-level exceeds the detection threshold. Clearly from this figure, although the target is well detected at its real position, many other points are also detected as ghosts or false alarms.

The proposed detection-localization test was applied to another scenario measured during the real measurements, where the pedestrian target moves from point A(25; 19.5) to point B(10; 19.5). We present in Figure 10 the result of the detection-localization algorithm when the target was located at coordinates (18.0; 19.5) in this scenario, and in Figure 11 the corresponding detection test output. For the localization, we can observe here even stronger ambiguities, with high level points not corresponding to the target position. However, when looking at the ambiguity figure, it appears that it mainly consists in three circular arcs that intersect at the real target position. For the detection output, as previously these strong ambiguities lead to many detections.
Another possibility would be to exploit the movement of the target over time with a tracking algorithm to alleviate the spatial ambiguities.

REFERENCES


