Development of a High Resolution Imaging Radar for Automotive Applications in Critical Visibility Conditions

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Abstract

There is increasing interest in automotive sensor monitoring systems as a means to enhance safety by providing reliable assistance in hazardous situations. These systems are commonly based on video cameras; however, their effectiveness is significantly reduced in adverse weather conditions such as fog, rain, or in the presence of smoke. To address this limitation, radar sensors—particularly imaging radars—are gaining prominence within the context of Driver Assistance Systems. A key challenge in current radar signal processing techniques is their limited ability to distinguish multiple targets along the same line of sight. In this paper, we propose a novel radar signal processing approach based on Deep Learning, capable of detecting and differentiating two or more targets aligned on the same line of sight, while also estimating the position and speed of vehicles ahead. Specifically, we adapt techniques originally developed for civil and military tracking radar applications to the automotive context, taking into account the higher spatial resolution and lower signal-to-noise ratio (SNR) characteristic of automotive radars. The proposed system integrates target detection, tracking, recognition, classification, and analysis, with a particular focus on the accurate identification of close-range targets.

1. Introduction

The sale of passenger vehicles has been steadily increasing, playing an essential role in the global economy. With this growth and the continuous advancement in automation technology, there is rising demand from consumers, governments, and society for improved road safety and a reduction in traffic-related fatalities and injuries. In response, automobile manufacturers have integrated Driver Assistance Systems (DAS) into production models. These systems include stability control, anti-collision features, Antilock Braking Systems (ABS), traction control, Electronic Brakeforce Distribution (EBD), seat belts, airbags, impact-absorbing bumpers, anti-intrusion bars, and various visual driver assistance systems (VDAS) [1].
Many VDAS rely on video cameras, which are commonly used for parking assistance, front or rear vision enhancement, and lane monitoring [2],[3],[4]. However, these cameras depend on external light sources and can be ineffective in conditions with poor visibility, such as fog, heavy rain, or smoke. To address these limitations, radar-based technology has emerged as a viable alternative [5]. Unlike cameras, radar systems can detect objects at significant distances, often extending hundreds of meters, with minimal interference from adverse weather conditions [6]. These systems use a variety of sensing and processing techniques to determine the position and speed of surrounding vehicles [7],[8],[9].
A key challenge in the automotive industry is the reluctance of manufacturers to modify vehicle designs to accommodate sensors. As a result, engineers must develop compact systems that fit within existing structures, such as the car's front grille. To achieve a balance between size and functionality, high-frequency signals are often employed. Specifically, radar systems operating in the 76–77 GHz range offer a practical compromise between performance and cost-effectiveness. Developing a high-resolution radar imaging system for vehicles involves multiple factors, including selecting the most suitable radar architecture, designing an efficient antenna, and implementing a system simulator to evaluate performance. Additionally, once radar images are obtained, post-processing techniques such as target detection and tracking are essential for refining the data.
Currently, various automotive radar imaging solutions exist, employing either analogic or digital beam synthesis to scan areas of interest and identify objects [5]. Different beam synthesis techniques include phased arrays, traveling wave antennas, and lens antennas, with phased arrays offering the best resolution and scanning range. However, due to their high cost, a balance must be struck between affordability and performance. One approach is to process signals from multiple antennas to create a larger synthetic array [6]. Another method involves a modular design, in which the array is divided into identical sub-arrays with independently controlled feeds.
For post-processing, modern automotive radar systems typically use an Ultra-Wideband (UWB) structure [5],[9]. Algorithms designed for noise reduction and target classification rely on statistical analysis of radar backscatter, followed by classification techniques that determine the category of detected objects. Statistical models are applied to the data to assess the likelihood of an object belonging to a particular classification. While this analysis is often performed on a single frame, improvements can be made by extending the approach to multi-frame data for enhanced accuracy.
Certain signal processing techniques utilize Compressive Sensing (CS) theory to detect and generate 3D images of objects, even when multiple scatterers align along the same Line of Sight (LoS) [10],[11],[12]. This is achieved by identifying targets within the observed space, estimating their positions, and determining their reflectivity properties.
In this manuscript, a first step towards a deep learning based radar imaging solution is proposed. More precisely, the detection of targets sharing the same LoS has been exploited by definition of a deep learning (DL) based method. In particular, an unsupervised fully connected neural network is proposed for

predicting the vector of target positions by Euclidian distance minimization between estimated and actual measured signal from a radar antenna. The vector of target positions is representative of different scatterers of one or more vehicles in the same LoS by processing the echo back-scatterers towards a radar antenna specifically designed [13]. The paper is organized as in the following: in Section 2, the following the radar antenna design, the simulation approach and deep learning methods are described. The experimental results are carried out in Section 3. Section 4 is reserved for the conclusion.

2. Methodology

In this section the methodology of the proposal is described.
The radar antenna system is described with its configuration.
The signal acquisition model and simulated scenario together with the deep learning solution is presented.

2.1 Radar Antenna Design

For the antenna design, we refer to the method proposed in [13] where the system characterized by a planar antenna is simplified by the use of two linear arrays.
The view of the considered planar antenna located at the front of the car, standing on the (x, y) plane, is reported in Figure 1. The planar antenna array is composed of $K_N \times K_M$ elements, where each one transmits and receives the signal.

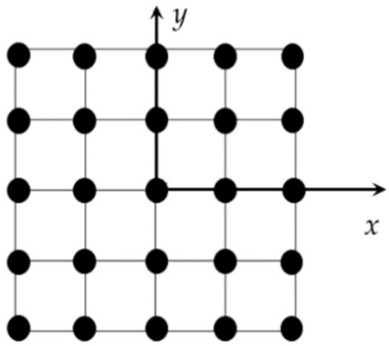

Figure 1. Planar antenna and 3D Cartesian reference system x, y with origin in the center of the antenna. Black dots highlight the positions of antenna elements (x_i, y_j).

The assumption is to transmit a monochromatic signal S_T at frequency f_0. The model of the received antenna at the position (x_i, y_j)., considering the noise free-case and neglecting constants, can be modeled as [13]:

$$S_R(x_i, y_j) = \iiint_V \gamma(x, y, z) \frac{G}{[R(x_i - x, y_j - y, z)]^2} \cdot exp\left(i4\pi \frac{f_0}{c} R(x_i - x, y_j - y, z)\right) dxdydz \quad (1)$$

where x_i, i=[1,…, K_N] and y_j, j=[1,…, K_N], $z=0$, are the coordinates of antenna elements, G is the antenna gain and $R(x_i - x, y_j - y, z)$ is the distance between each antenna element, with coordinates (x_i, y_j, 0), and a target placed in (x, y, z) with reflectivity $\gamma(x, y, z)$. In this model for the received signal S_R there have been conducted the following assumptions: all scatterers are point scatterers, there is no multipath effect and that the superposition principle stands. Moreover, the signal S_R is the result of the coherent interference from all the echoes deriving from the illuminated volume V, with proper attenuation and phase. These assumptions represent a good trade-off between complexity and handling and therefore is widely accepted.

In this manuscript we consider the simplification of the system proposed in [13] where the planar antenna is synthetized with the combination of two linear arrays, one horizontal and one vertical with a spacing of is $\lambda/2$ between each element, as show in Figure 2. Beside the number of the antennas, also the transmitting and receiving configuration is simplified: the horizontal array is composed by only K_M receiving antennas (red dots in the Figure 2); the vertical array contains only K_N the transmitting elements (blue dots in Figure 2). Therefore, the total array is composed by $K_N + K_M$ elements in place of the $K_N x K_M$ of the planar one.

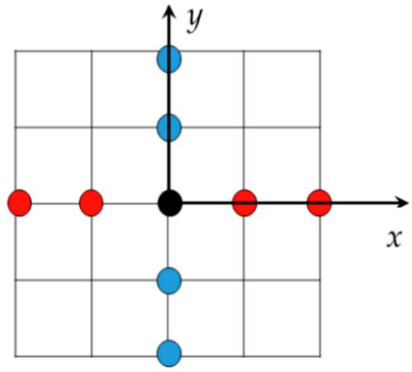

Figure 2. Two linear arrays in cross configuration that synthetize a planar antenna. In this case $K_N + K_M$ elements are considered instead of $K_N x K_M$.

In [12] the 3D distribution of scatterers is decomposed in detection of targets along the LoS. In this manuscript the same approach is followed. Therefore, some pre-processing steps (i.e. 2D focusing and deramping) for the focusing of the received signal in on a vertical plane at a fixed distance z_0 lead to

$$S_{dr}(x_i, y_j) = \iint \gamma(x, y, z_0) \exp(i\phi) \; exp\left(-\frac{i2\pi}{\lambda}\frac{xx_i}{z_0}\right) exp\left(-\frac{i2\pi}{\lambda}\frac{yy_j}{z_0}\right) dxdy \quad (2)$$

please, refer to [13] for more details.

2.2 Signal Acquisition Model

Considering the previous antenna configuration and the multi-frequency operative approach, it is expected that a single complex value is obtained for each of the N working frequency. Our aim is, once focused on a line of sight, to detect one or multiple targets and estimate their range distance based on N acquisitions. The acquisition model can be written as:

$$q = Ah + w \quad (3)$$

where q is the N×1 data vector collecting the focused signals at the different frequencies for the direction (θ, φ), A is the transformation matrix and h is a vector of the reflectivity at different distances. The vector h contains the complex reflectivity values for different range distances ε_κ, uniformly sampled in the interval [ε_{min} , ε_{max}].
h is supposed to be a sparse vector with majority of elements equal to zero with few targets are expected to be for each line of sight. Discretising the acquisition model of Equation (1) the generic element of matrix A can be defined as

$$a_{i,j} = \frac{1}{\varepsilon_j^2} \cdot exp\left(i4\pi \frac{f_i}{c} \varepsilon_j\right) \quad (4)$$

where f_i is one of the frequencies within the bandwidth and ε_j is a discretized range distance.
Given the previously reported model, our aim is to estimate the number of non-zero elements of h, i.e. how many targets are present in the selected line of sight, their position within vector h, i.e. the range distances of the detected targets, and their values, i.e. the reflectivity of the targets. We could refer to the estimation of vector h as an "in depth" focusing. The radar imaging situation for two scatterers in a line of sight is reported in Figure 3: in a single line of sight more than one scatterer may be present and the vector h contains the reflectivity of each scatterer. The final aim is to recover the target for each line of sight and therefore reconstructing the whole scenario. In this manuscript the focus is on the target detection on the single line of sight.

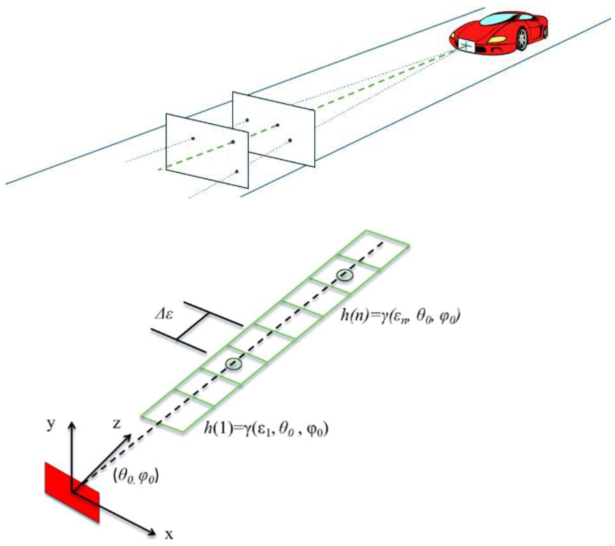

Figure 3. Figure placement and numbering.

2.3 Deep Learning based solution

The problem of scatterer detection and elevation estimation can be framed as an optimization problem. Considering the discretized acquisition model of Equation (3), the proposed method is designed as an unsupervised fully connected network that predict the vector of target position h. In particular, the proposed method does not rely on any reference data, and starting from a random reflection vector h_0 produce an estimate $\hat{h}$ of the real reflection vector by minimizing the distance between the estimated $\hat{q} = A\hat{h}$ and the measured one q. The workflow of the proposed method is illustrated in Figure 4, consisting of two key components: the training process and the simulation process.
The training dataset construction relies on a simulation process where the h reflection vector is simulated with one or more targets present in discretized position in a fixed range. Considering a multi-frequency system in a fixed bandwidth, the reference measured signal q is computed following the acquisition model of Equation (3).
In summary, the proposed DL solution is trained to reconstruct the reflection vector, without the need of a reference one, such that $\hat{q}$ aligns with the measured q. The architecture of the solution consists of a single complex fully connected layer.

Since the reflection vector h is typically sparse vector, inspired by compressive sensing techniques, the optimization problem is defined as combination of two minimization terms (see Equation 5): the mean squared error between between $\hat{q}$ and q for correct prediction, and the L_1 norm regularization term on the estimated reflection vector $\hat{h}$ for promoting the sparsity of the estimated result.

$$\arg\min_{\hat{h}} \|\hat{h}\|_1 + \psi \|Ah - \hat{q}\|_2 \tag{5}$$

3. Experimental Part

In this section the experimental settings and results are presented.

3.1 Experiment settings

Given the previously reported model, our aim is to estimate the number of non-zero elements of h, i.e. how many targets are present in the selected line of sight, their position within vector h, i.e. the range distances of the detected targets, and their values, i.e. the reflectivity of the targets. We could refer to the estimation of vector h as an "in depth" focusing.
In the realistic case, measurements are corrupted by noise, leading to:

$$q = Ah + w \tag{8}$$

where w is the noise vector, whose element are circular complex Gaussian distributed.
In order to evaluate the performances of the proposed method, different simulated case studies have been implemented. We simulated, in Matlab® environment, the received signal in case of difference scenarios, corrupting data with circular complex Gaussian distributed random noise.
A cross antenna composed of two linear arrays of 111 (horizontal, Rx) and 141 (vertical, Tx) elements has been considered. The system band, between 77 GHz and 77.5 GHz, has been sampled following a stepped approach. Complete system details are reported in Table 1.

Table 1. Imaging antenna features.

Antenna Features	Values
Antenna type	Cross antenna
Central Frequency	77,25 GHz
Bandwidth	500 MHz
Gain	21.7609
Number of elements of antenna	111 x 141
Distance among the elements	1.9 mm (λ/2)
Antenna dimensions	21x27 cm

For the reported simulations, different number of targets have been simulated in front of the antenna, i.e. $(\theta, \varphi) = (0,0)$, with the same reflectivity. Different SNR for a target at a distance of 20 m from the antenna have been taking into account. Considering a multi-frequency scenarios, different frequency samples have been considered for the reconstruction. In particular, the reconstruction of targets positions has been performed considering four different frequency sampling: 500, 200, 100, 50; two different SNR: 30dB, 10dB, and five different distances among targets: 10cm, 30cm, 50cm, 2m, 10m.

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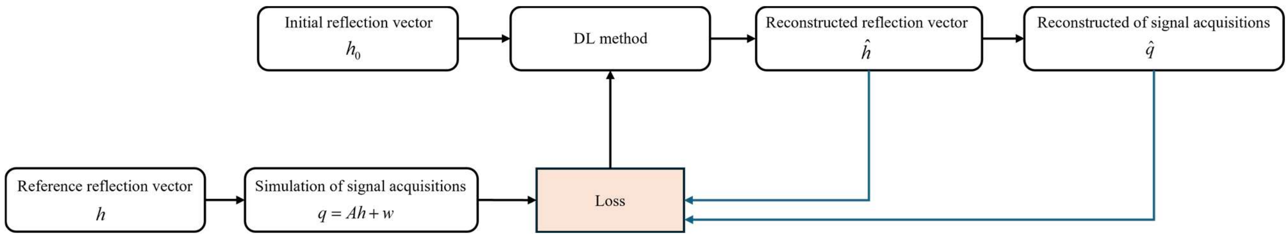

Figure 4. Workflow of proposed method

3.2 Results

In order to evaluate the robustness of the proposed method, a traditional inversion based on L_2minimization is carried out.
For all the experiments, reconstruction results from different number of frequency samples within the considered bandwidth are reported. In particular, the bandwidth has been samples with fixed number of frequency: 500, 200, 100 and 50.

3.3 Two Target Configuration

Results for two targets configurations with SNR equal to 30dB are reported in Figure 5.
The first target has been placed at 20m of distance from the radar antenna and, considering the range resolution of the system being 30cm, the second target has been places at 10cm, 30cm, 50cm, 2m, 10m of distance from the previous one. The results are shown from top to bottom of the figure. The results are reported in terms of distance (x-axis) and target intensity (y-axis).
As expected, in the case of 10cm (below the resolution of the system) both solution are not able to discriminate the two targets, no matter the number of frequency samples. The DL one solution show a narrower main lob, characteristic that can be seen also for the other results shown in figure. Beside this case (first row), in case of 500 frequencies (Figure 5a), both techniques are able to detect the presence of two different targets (side lobes are strongly lowered), their reflectivities and distances. Both solutions detect the two targets in the exact location with the L2-norm approach characterized by a coarser resolution with respect to proposed DL based methodology, as the impulses are larger. Indeed, the DL solutions shows a more direct and clear-cut detection both in terms of target position both in terms of side lobes. This behaviour is confirmed lowering the number of frequency samples to 200 and to 100 (Figures 5b and 5c). Instead with 50 samples, when the two target are at 10m (bottom of Figure 5d,), the DL solution find difficulties in recovering both targets. This suggest that further analysis should be carried out in the architecture design for making the solution more robust to the noise. When lowering the SNR to 10dB, similar comments can be drawn out with the DL solution showing a good robustness with respect the level of noise.
From this analysis, it looks that the considered unsupervised method finds challenging the case of a predominant backscatterer: when targets are close each other, and therefore with similar backscattering intensity to the radar antenna the detection ability is evident. When there is a target much closer to the antenna with respect to the other one, according to the model of Equation 4, the first backscattering is much strong than the second one that risk to not be recovered by the DL solution.

4. Conclusion

In this manuscript an unsupervised deep learning solution for target detection in automotive environment is proposed. Simulated scenarios of line of sight targets illuminated by cross radar antenna is performed and a the potential of an unsupervised fully connected network is exploited in the estimation of the targets position vector. The solution is trained without the need of a reference by minimizing the estimated signal with the measured one. Results in different configuration highlights the ability of clear detection provided by the Dl solution and its robustness to the noise level. At the same time, the proposal find difficulties in the detection of multiple target when the scenarios is characterized by a dominant one. Further investigation on this aspect will be carried out in the future works.

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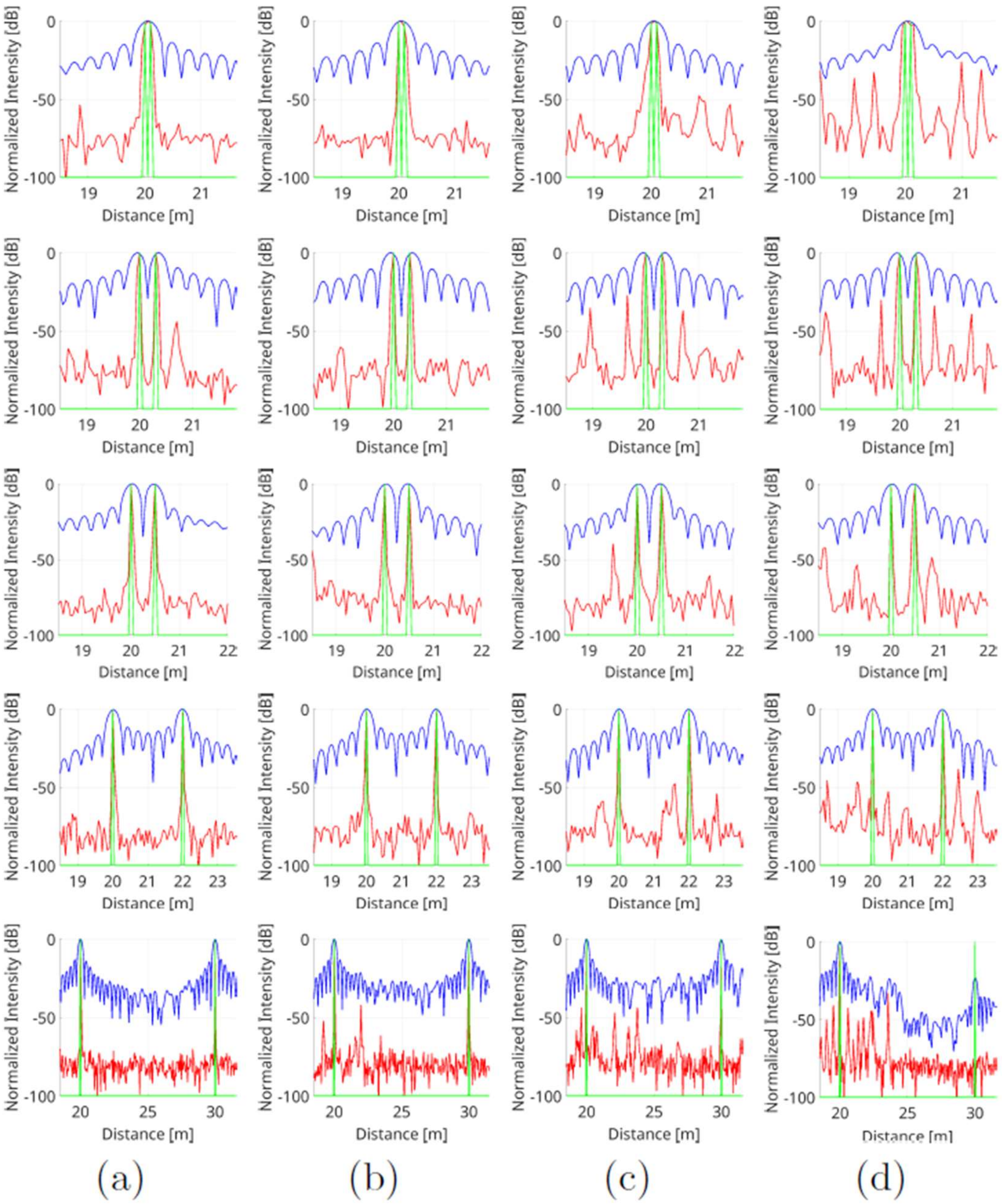

Figure 5. Detection results for two targets for SNR 30dB. From left to right (a-e): results for different samples of frequencies (500, 200, 100, 50. From top to bottom, results at different distance among targets at 10cm, 30cm, 50cm, 2m and 10 m of distance Traditional inversion method in blue line, proposed solution in red, reference target position in green.

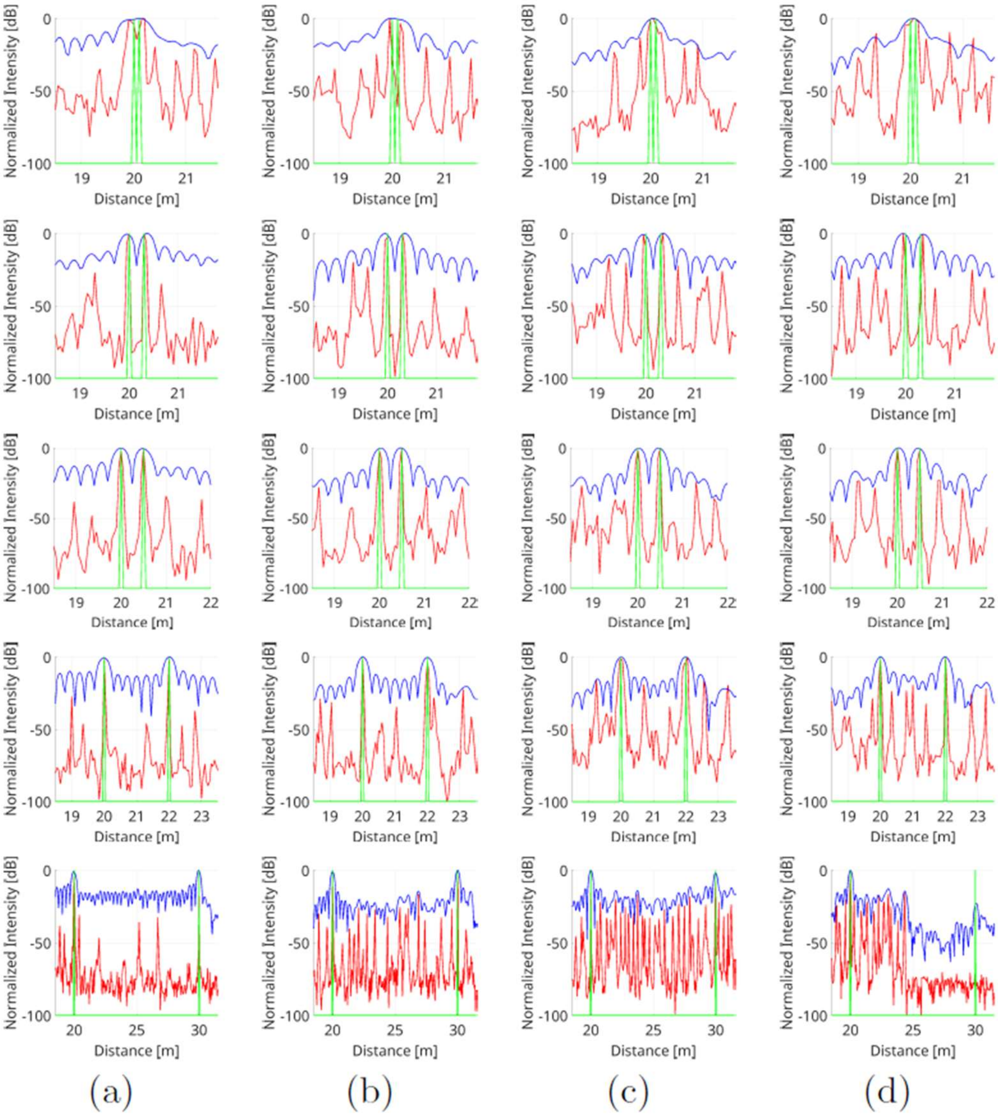

Figure 6. Detection results for two targets for SNR 10dB. From left to right (a-e): results for different samples of frequencies (500, 200, 100, 50). From top to bottom, results at different distance among targets at 10cm, 30cm, 50cm, 2m and 10 m of distance Traditional inversion method in blue line, proposed solution in red, reference target position in green.

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