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Enhancing Angular Resolution Using Neural Networks in Automotive Radars

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***Abstract* — Poor angular resolution is one of the main disadvantages of automotive radars, and the reason why lidar technology is widely used in the automotive industry. For a fixed frequency, the angular resolution of a conventional Multiple-Input Multiple-Output (MIMO) radar is limited by the number of physical antennas, and therefore improve the resolution involves increasing the size and the cost of the system, critical constraints in the automotive industry. In this work, a novel approach is presented to overcome this limitation, where a Neural Network (NN) is used to enhance the angle resolution of a MIMO radar without increasing the number of physical elements, but extrapolating the antennas signals in a teacher-student fashion. The method was validated using real data of stationary pedestrians captured outdoors, demonstrating an effective increase of three times the antenna array size. To the best knowledge of the authors, this is the first method that includes an evaluation metric in the final stages of the processing pipeline, enforcing the conservation of the target's angular shape, key for subsequent object classification.**

***Keywords* — automotive radar, MIMO, angular resolution, neural networks.**

I. INTRODUCTION

Autonomous driving is one of the biggest trends in the automotive industry, and a race for reaching driver-assistance level 5 has begun between all the major car manufacturers. To achieve this, the sensing suite in autonomous vehicles needs to provide the most trustworthy and dense information on the surroundings. Therefore, reliable detection and classification of very different objects such as pedestrians, cars, potholes, or speed bumps should be performed in real-time. Moreover, the system must understand which objects can be driven-over, such as small debris on the road or speed bumps, which objects can be driven-under, such as bridges or tunnel entrances, and which objects should be safely avoided as significant obstacles on the road for the vehicles.

This difficult task cannot be done successfully by any single sensor, and a combination of radars, cameras, and lidar is the most used formula. However, radars have an advantage with regards to the other sensors: they work in adverse weather conditions, are insensitive to lighting variations, provide direct range, azimuth, and speed measurements, and can be mounted under the vehicle chassis. On the other hand, radars have a weak point that must be solved before they can become the primary sensor of an autonomous car: they suffer from poor angle resolution.

The basic principle for angle estimation in MIMO radars relies on the extra distance that a signal travels to reach the different antennas in the system. The easiest way to exploit this, known as Digital Beam Forming (DBF), applies a Fourier transform to translate the phase shifts, which are proportional to the time delays due to extra distances, into the angle of arrival of the signal. There are more advanced algorithms such as MVDR [1], MIMO-Monopulse [2], or subspace methods such as MUSIC [3] or ESPRIT [4]. However, the angular resolution achieved with all of them is still proportional to the number of virtual antennas of the system [5].

This work presents a novel method that exploits the constant phase difference between antennas to extrapolate new elements and enhance angular resolution in MIMO systems. To achieve this, a back-and-forth estimation approach is used, where each extrapolated element is a linear combination of the previous ones. A linear one-layer Neural Network (NN) is trained for this purpose, where the input is a subsampled antenna array and the ground-truth for training is the full antenna array. Although the NN is generating samples in the time domain, the optimization metric can be evaluated in the spectral domain, resulting in a more accurate angle profile reconstruction. This method opens the possibility of enhancing the angle resolution of a compact and cheap low-resolution radar on autonomous vehicles by using a simple NN previously pre-trained with a single larger high-resolution system.

The rest of this paper is organised as follows. In Section II, an overview of the related works is presented. Section III presents the proposed method, with results in Section IV. Finally, some conclusions and future work are discussed in Section V.

II. RELATED WORK

Recently several extrapolation methods for improving angle resolution in automotive radars have been published. A method for angle enhancement using piecewise cubic extrapolation is presented in [6]. The results show an increase of 37,5% in the array size given an original antenna array of 32 virtual elements. However, the undesirable effects of this method in a more complex environment (e.g., creation of ghost targets, loss or artefacts on real targets) are not analysed.

In [7], the authors propose a Generative Adversarial Network (GAN) to generate a super-resolution range-angle map. This family of super-resolution methods has been proved very effective in the image processing field [8, 9], but they do not apply any radar "expert knowledge" and treat the range-angle maps as images. Thus, the data is enhanced after the angular Fourier transform, and no complex-valued data is used.

On the other hand, Auto-Regressive (AR) models have been used in the past for extrapolating the range and Doppler dimensions with good results. In [10], the authors proved that it is possible to enhance the velocity resolution of a Frequency Modulated Continuous Wave (FMCW) radar using AR models to generate artificial chirps. Similarly, they artificially increased the sweep bandwidth to enhance the range resolution. Their results show that this method can double the range resolution and triple the speed resolution. Moreover, AR model-based extrapolation has been used in airborne devices to improve angle resolution in Front-Looking Synthetic Aperture Array (FL-SAR) radars [11].

Having in mind all this previous research, the main contributions of this work are:

- A novel method for extrapolating MIMO antenna arrays, which surpasses the limitations of AR models.
- A methodology for enhancing angle resolution which uses a teacher-student fashion between two radar systems.
- The introduction of a new tuneable metric used for evaluating the performance of the NN, which considers undesirable effects of the extrapolation. It also enforces the preservation of the object shape, needed for subsequent classification purposes.

III. Proposed Method

The proposed method aims to enhance the angle resolution of a low-resolution radar using a NN trained with data from a high-resolution radar. The first step, which can be seen in Fig.1, is to process the radar data cube using a 2D FFT and later apply a detector in each range-Doppler map to select those cells that contain at least one detection. With this step, it is ensured that the channel vectors which will be used to train the NN are not only noise. Hereafter, the channel vectors are pre and post trimmed, keeping the number of central elements the same as the low-resolution radar has.

Now, using the full array as the ground-truth, the trimmed vector must be reconstructed. This could be done by fitting the data into an AR model, finding the model parameters with the Burg or Yule-Walker method, and then forecasting the missing samples, such as in [10] and [11]. However, as can be seen in the AR model equation (1), this will limit the reconstructed channels to simple linear relationships of the previous samples. Moreover, finding a common model order p, and common coefficients a_n that yield good performance for all the test cases is not trivial.

$$X_n = a_0 + \sum_{i=1}^{p} a_i X_{n-i} \tag{1}$$

To overcome these limitations a one-layer NN is used, where the real and imaginary components of the signal are concatenated before inputting them to the network. It uses a linear activation function, and therefore the output can be understood as a Vector Autoregressive Model (VAR) in which the complex signal is a multivariate time series. The function the NN is applying can be seen in (2).

$$Re(X_n) = c_0 + \sum_{i=1}^{k} a_i Re(X_{n-i}) + b_i Im(X_{n-i})$$
$$Im(X_n) = c_1 + \sum_{i=1}^{k} d_i Re(X_{n-i}) + e_i Im(X_{n-i}) \tag{2}$$

The coefficients a_i, b_i, c_i, d_i and e_i are optimized on a custom loss function. Since the main goal of this algorithm is to reconstruct the spectral characteristics of the signal, the loss function is computed in the frequency domain according to the equation

$$L(\hat{y}, y) = \frac{1}{n} \sum_{i=1}^{n} (FFT(\hat{y})_i - FFT(y)_i)^2. \tag{3}$$

This loss function enforces the reconstructed spectrum (where ^ represents reconstructed) to be as similar as possible to the original one, maintaining the angular shape of the observed objects, crucial for later classification processing. However, this metric does not directly reflect how well the position and extent of the targets are reconstructed. For this reason, a tuneable cost function to assess the performance at the user level (i.e., the latest stage of the signal processing, where the detection list is reported) of different algorithms has been implemented. This metric, shown in (4), is composed of two terms. The first term, A, evaluates if the algorithm has erased a target or has created a new one. Moreover, a second term, B, is included for considering the error in the angle of the targets as well as their angle extension. A weighting parameter p is included to balance their contributions, allowing flexibility in which error is more important for the specific application.

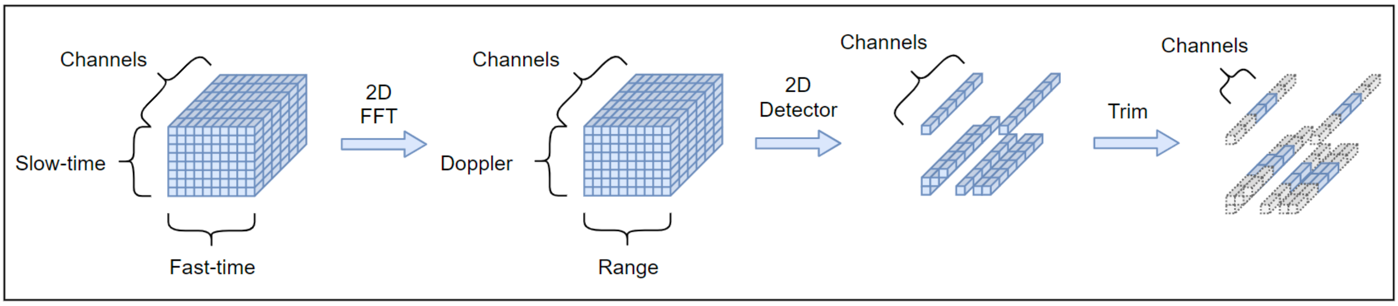


Fig. 1. Method pre-processing pipeline: 2D FFT followed by a detection stage; then the output is trimmed to the desired length.

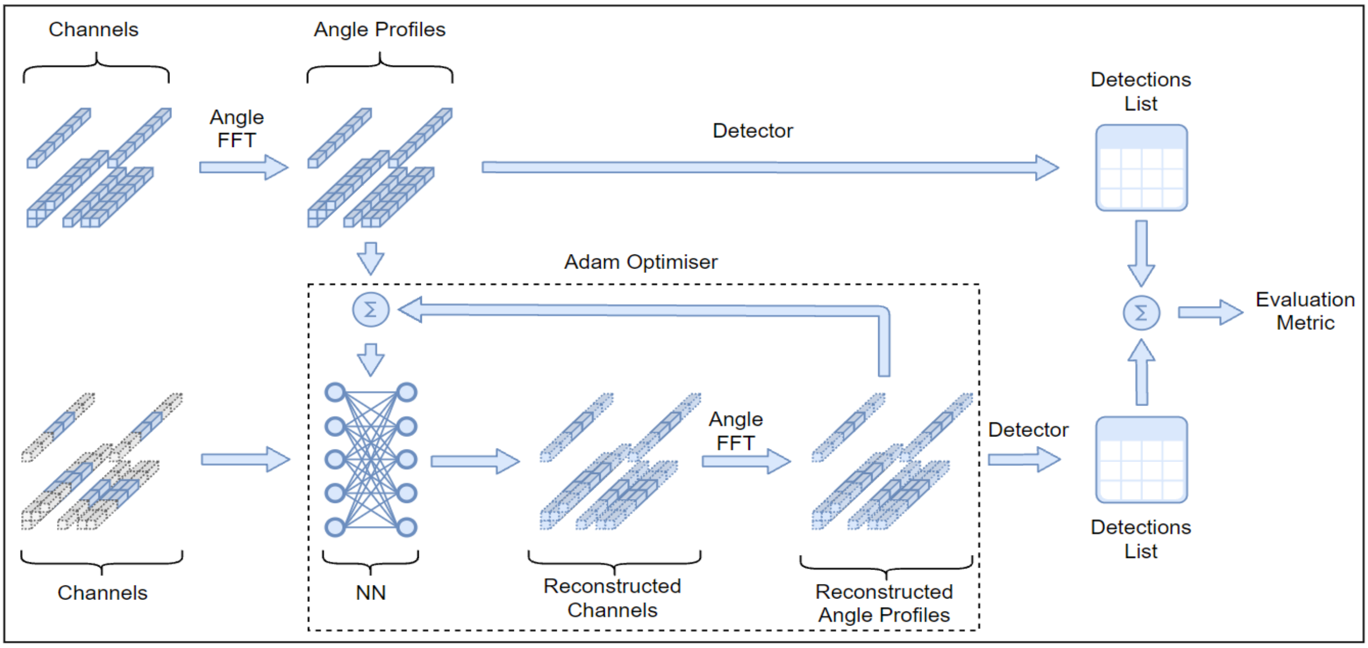


Fig. 2. Block diagram of the proposed method. The NN is fed with the trimmed vectors, and the output is processed with an FFT to compute the loss in the angle domain. After the NN is trained, an evaluation metric is computed using the processed detection points.

$$A = (\widehat{N}_{targets} - N_{targets})^2$$
$$B = p\,RMSE(\widehat{ang}, ang) + (1-p)RMSE(\widehat{ext}, ext)$$
$$Loss = A + B \tag{4}$$

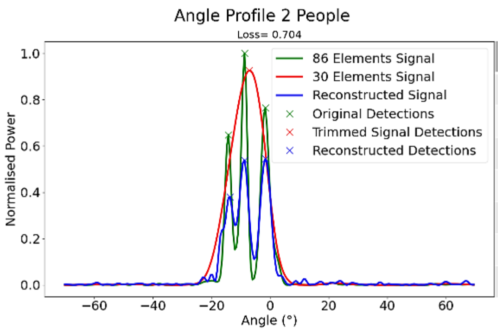
A visual representation of the full pipeline can be seen in Fig.2. The proposed method is considered as the baseline implementation of more complex algorithms for angular resolution enhancement. Since targets are not point-like in the range and Doppler spectrum, more advanced network architectures, such as Convolution Neural Networks (CNN), can be used to exploit the spatial relationship between angular profiles. Also, it is important to notice that this is a single-frame method, and therefore using several frames with a Recurrent Neural Network can be beneficial as future work stemming from these initial results.

IV. Results

To validate the proposed method, data from two different scenarios have been captured with an 86 virtual non-overlapping channel FMCW radar board, operating at 78 GHz. Firstly, the system was set-up in a laboratory environment, and scene captures from different perspectives were done using small reflectors in different positions as targets. After the pre-processing, 1345 angle profiles were obtained. Moreover, another 1000 angle profiles of point targets were synthetically generated and added to the dataset. The data were then trimmed to a length corresponding to only 30 channels, around 35% of the original length of 86 channels. Therefore, the network must extrapolate 56 elements, 28 at the beginning and 28 at the end of the array, enhancing the angular resolution of the system by a factor of 3. Different trimming lengths have been tested, but the 30-channel configuration was selected as a trade-off between performance and resolution improvement.

The network was trained with the 2345 time-series of 30 complex numbers (i.e., the response of the virtual antennas). It is important to note that only synthetic data and data from the laboratory environment with static reflectors were used to train the network. The Adam optimization algorithm was used using the default hyperparameters (η=0.001, β_1=0.9, β_2=0.999, ε=1e-7).

To test the trained network, more meaningful data for an automotive radar perspective were collected. A second batch of captures was performed outdoors involving several people. This resulted in 1262 times-series that were used for testing, acquired in a very different environment from the one where the training dataset was collected. Fig. 3 shows the result of the network for an angle profile where two people were standing at 5m range and with an air gap of approximately 25cm between them to simulate standing pedestrians.



Centroids (°)	Extents (°)
-14,22	3,28
-8,75	3,28
-1,64	4,38
-7,11	14,22
-13,67	5,47
-8,27	4,38
-1,64	5,47

Fig. 3. Angle profile of two standing people captured outdoors. In green, the angle profile obtained with the original 86 channels; in red the angle profile generated with the trimmed signal; in blue the angle profile generated with the reconstructed samples.

Three different signals are presented in Fig. 3. In green, the angle profile obtained with the full capabilities of the radar, i.e., all 86 channels, where three main peaks can be seen (probably the two peaks in the left are scattered from the same person or multipath due to multiple scattering between them). In red, the response that would have been obtained with a 30 virtual antenna system is shown, where only one lobe is perceived for both targets. Finally, in blue, the reconstructed signal using the proposed method is shown. As it can be seen, the shape is close to the original one, preserving the three main peaks. Using the equation (4) and a p=0.75, a loss of 0.704 is obtained. Several tests with other types of objects in different ranges and angles have been performed with a successful result, but this scene has been presented because being the most representative for an automotive scenario point of view.

The method reconstructs simultaneously all angular profiles of the scene. Fig. 4 shows a cartesian projection of the static component of a full-frame of the scene, where the two people are standing still, and some other opportunity targets are present.

Fig. 5 shows the same scene but computing the angular FFT only with the 30 middle elements, displaying how the scene would be perceived by a low-resolution radar. It is clear that the angular resolution has been severely decreased, and the targets cannot be split anymore.

Finally, Fig. 6 presents the output of the proposed method. It can be seen how it represents the scene in a more accurate way, being very similar to the one captured with the high-resolution radar system.

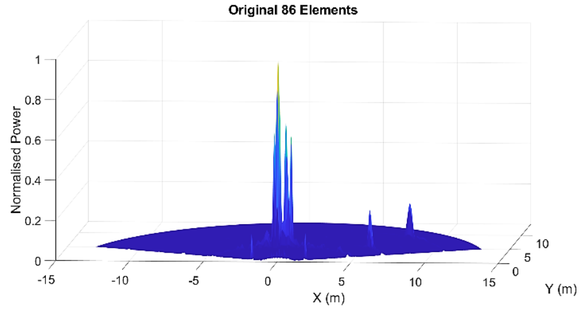


Fig. 4. The static part of a full-frame with two people, generated with the original experimental 86 virtual antennas.

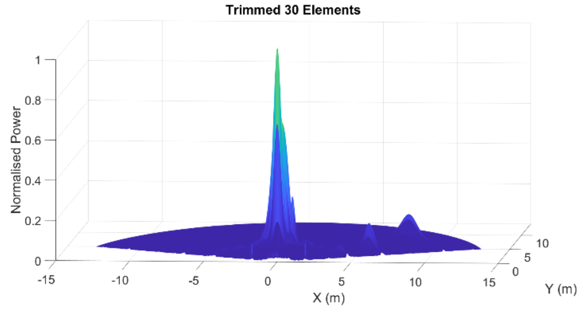


Fig. 5. The static part of a full-frame with two people, generated with the trimmed 30 middle virtual antennas.

V. Conclusions

This paper presents a novel method to increase the angular resolution of a low-resolution MIMO radar using a Neural Network trained with data from a high-resolution radar. A metric to assess the quality of the output is also introduced, reducing the undesirable effects while trying to preserve the shape of the targets. The method has been validated with meaningful experimental data from an automotive scenario (two pedestrians standing close to each other) with a very successful result.

The proposed approach can be used to increase the angular resolution of MIMO radars without including extra physical antennas and their respective analogue hardware. In future, more complex neural networks to exploit the space and temporal relationships of the signals will be developed, and the method will be validated in denser and dynamic scenarios. Also, efforts in including the evaluation metric inside the learning/optimization loop of the NN will be considered.

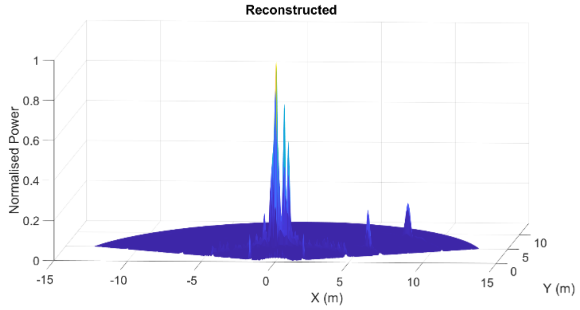


Fig. 6. The static part of a full-frame with two people, generated with the reconstructed signal from the method proposed in this paper.

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