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Fusion of Data from Multiple Automotive Radars for High-Resolution DoA Estimation

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***Abstract*—High angular resolution is in high demand in automotive radar. To achieve a high azimuth resolution a large aperture antenna array is required. Although MIMO technique can be used to form larger virtual apertures, a large number of transmitter-receiver channels are needed, which is still technologically challenging and costly. To circumvent this problem, we propose a high-resolution Direction of Arrival (DoA) estimation by using multiple small radar sensors distributed on the fascia of the automobile. To exploit the diversity gain due to different target observation angles by different radars, a block Focal Under determined System Solver based approach is proposed to incoherently fuse the data from multiple small MIMO sensors. This method significantly improves the DoA estimation compared to single sensor, decreases probability of false alarm and increases probability of multiple target detection. Its performance is demonstrated through both numerical simulations and experimental results.**

***Index Terms*—Compressive Sensing (CS), FOCUSS, Block sparsity, distributed radar, MIMO, automotive radar, OMP, BOMP, incoherent processing, ambiguity function, single snapshot, DoA estimation.**

I. Introduction

FMCW radars play an important role in the safety of autonomous driving as they are robust to lighting and weather conditions. They are mainly used to estimate the distance, the radial velocity and the angular location of objects relative to the car. With advances in signal processing techniques and improvement of hardware used in radar sensors, the estimation of distance (range) and velocity has been improved over the years. There are sufficient cases which needs to resolve the objects with same range and Doppler. Resolving such objects in the angular domain, called Direction of Arrival (DoA) estimation, is still a challenge. Traditional approach to deal with it, is usage of radar sensors with multiple transmit and receive antennas, i.e. Multiple Input Multiple Output (MIMO) systems in which a higher angular resolution is obtained by increasing the array size in the radar. This approach is costly and leads to bulky systems that are difficult to integrate in the design of the automobile. In this paper, we look for a way to fuse the data from multiple smaller radar units that are spread out on the fascia of a car. This approach benefits from spatial diversity gain as discussed in [1]. In automotive applications it is critical to provide real time estimation of the DoA of targets. We develop a single snapshot DoA estimation technique which fuse data from multiple radar units after range and Doppler processing in each system cycle.

However, combining data from multiple sensors can be challenging. When an extended target like a car is present in the near field of the radar, it can appear as a non-isotropic target to the system under consideration. The radar cross-section (RCS) observed by individual sensors can be different for such extended targets and the target will be perceived incoherently by the radar sensors [1]. Moreover, achieving full synchronization between the sensors is not easy as discussed in [2]. The conditions under which coherent fusion of data can be performed, the performance of the algorithm and the drawbacks of the same are discussed in [3]. In this paper we propose incoherent fusion of data from distributed sensors.

Sparsity based algorithms are advantageous as they do not require a prior knowledge of the number of targets and have good performance in estimating DoA using single snapshot [4]. The imaging scene in automotive radar application can be considered sparse, consisting of very few point targets with the same range and Doppler [5]. Hence, in this paper sparsity-driven algorithms are used to estimate the DoA from an under determined system of equations [6]. Some of the grid based algorithms are Basis Pursuit De-Noising (BPDN), Matching Pursuit (MP), Orthogonal Matching Pursuit (OMP) and Focal Under determined System Solver (FOCUSS), while there are also grid-less algorithms [7]. Estimating the DoA of targets in radar applications through sparsity based algorithms is explained in detail in [6]. Moreover, there have been some studies on DoA estimation using data from multiple sensors [8]–[13]. The resolution obtained by incoherent combining of data from multiple apertures is limited by the largest sub-aperture used in the distributed system [13]. The Block Orthogonal Matching Pursuit (BOMP) algorithm, that incoherently fuses the data from multiple apertures for DoA estimation, can be considered as the state-of-the-art and is proposed in [13]. The BOMP algorithm is an extension of OMP which is a greedy algorithm and thus does not always converge to the true solution. On the other hand, FOCUSS outperforms OMP in resolution capabilities [14]. In this paper the merits of FOCUSS are exploited in a new sparsity-driven algorithm, termed as Block FOCUSS, for high resolution DoA estimation through incoherent fusion of data.

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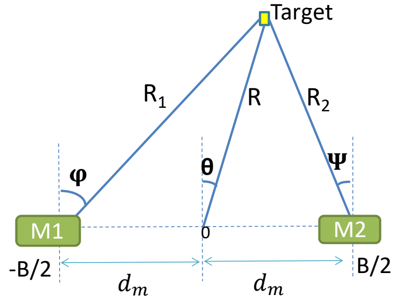

Fig. 1. System model

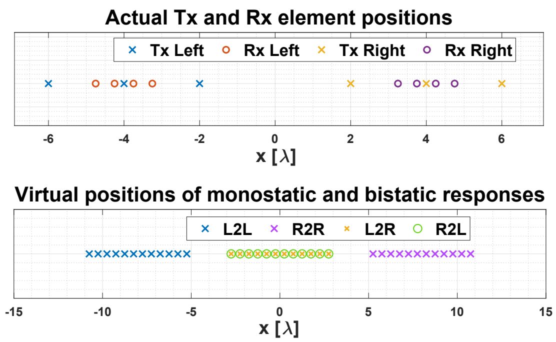

Fig. 2. Mono-static and bi-static response for a 3 × 4 MIMO sub-systems M1 and M2

Some common notations used in this paper are as follows. The notations x, $\mathbf{x}$ and $\mathbf{X}$, represent a scalar, a vector and a matrix respectively. $\mathbf{X}^H$ and $\mathbf{X}^T$ represent the Hermitian and the transpose of a matrix $\mathbf{X}$.

II. System and Signal Model

A distributed system, comprising of two sub-systems, is considered as shown in Fig. 1. The two sub-systems ($M1$ and $M2$) are separated by a distance $B(= 2d_m)$, called the baseline (B) and centered at the origin (O). The proposed system model can be easily extended with more sub-systems. Each sensor comprises of N_{Tx} transmitters and N_{Rx} receivers which can be operated in a MIMO configuration. The two sub-systems are coarsely synchronized on millisecond level to ensure the measurements are performed at the same time. This allows us to assume that the targets are in the same range-Doppler bin for a given field of view and that there is no displacement due to difference in measurement time. A target present at range R with DoA θ from the center of the system is depicted in Fig. 1. It has range R_1 with DoA φ from $M1$, and range R_2 with DoA ψ from $M2$. From the geometry of the system, for every range R and angle θ the corresponding range R_1, R_2 and angle φ, ψ from each sensor in the system can be calculated, as B is known. The target is said to be in the far-field if the distance of the target to the radar is greater than the Fraunhofer distance (D_F) given as $2D^2/\lambda$, where D is the virtual aperture of the sensor and λ is the wavelength. For individual sensors $M1$ or $M2$ the target can be assumed to be in the far-field, but for the distributed system the aperture is now equivalent to baseline B and thus, the far-field assumption is easily violated. Hence, for the distributed system the DoA as seen by $M1$ and $M2$ will be different when the target is in the near-field. Moreover, the RCS observed by the sub-systems can be different as well.

The signal model to perform DoA estimation from spatial samples obtained after the Range-Doppler processing is given by [6].

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{n}, \tag{1}$$

where $\mathbf{y} \in \mathbb{C}^{N\times 1}$ is the measurement vector containing samples from the N virtual antenna elements of the sensor, $\mathbf{x}$ is the source vector to be estimated, $\mathbf{A}$ is the steering matrix and $\mathbf{n}$ is the noise vector. In case of K targets, the source vector $\mathbf{x}$ contains K elements and the steering matrix $\mathbf{A}$ will consist of K steering vectors representing the DoA of the K targets. Sparsity based algorithms use a similar signal model for solving the DoA estimation problem, but approximate the model by assuming that $\mathbf{A}$ is a dictionary containing $N_s > K$ steering vectors and the source vector $\mathbf{x}$ is an N_s dimensional vector with K non-zero elements. The N_s elements of the dictionary represent candidate DoAs $\theta_1, \theta_2, \ldots, \theta_{N_s}$, and is also called the search grid. From the DoA estimation algorithm's perspective, the matrix $\mathbf{A}$ is called the sensing matrix and is given by :

$$\mathbf{A} = [\mathbf{a}(\theta_1),\ \mathbf{a}(\theta_2),\ \cdots,\ \mathbf{a}(\theta_{N_s})] \in \mathbb{C}^{N\times N_s} \tag{2}$$

The steering vectors in the sensing matrix $\mathbf{A}$ are the Kronecker product of transmitter and receiver steering vectors

$$\mathbf{a}(\theta) = \mathbf{a}_{Tx}(\theta) \otimes \mathbf{a}_{Rx}(\theta) \tag{3}$$

with

$$\begin{aligned} \mathbf{a}_{Tx}(\theta) &= \exp\left(j2\pi \mathbf{d_{Tx}} \sin\theta\right) \\ \mathbf{a}_{Rx}(\theta) &= \exp\left(j2\pi \mathbf{d_{Rx}} \sin\theta\right) \end{aligned} \tag{4}$$

where $\mathbf{d_{Tx}}$ and $\mathbf{d_{Rx}}$ denote the transmitter and receiver element positions (normalized to the wavelength λ) in an individual sensor, respectively. In (4) the Direction of Departure (DoD) and DoA are considered to be same, hence this equation represents the steering vectors for co-located receiver and transmitter elements and can be used for the mono-static responses in the system. For bi-static responses, as the transmitter and receiver positions are not co-located, the DoD and DoA are different. For the system shown in Fig. 1, there are four virtual apertures, two representing the mono-static responses and two representing the bi-static responses. As an example the four virtual responses for a system with baseline of 8λ are depicted in Fig. 2. The mono-static responses from $M1$ and $M2$ have DoA and DoD equal to φ and ψ, respectively. The steering vectors of the bi-static responses are given as $\mathbf{a}_{Tx}(\varphi) \otimes \mathbf{a}_{Rx}(\psi)$ when $M1$ is transmitting and $M2$ is receiving, and vice versa. The dictionary is defined in terms of θ and the corresponding values for φ and ψ are used to define the steering vectors for all the responses.

III. Incoherent processing

Data from multiple apertures can be fused incoherently to improve the DoA estimate. If the system is not fully synchronized then only the mono-static responses can be used. We assume that the signal to be recovered from multiple apertures is block sparse [15], i.e., the vector $\mathbf{x}$ that needs to be estimated has non-zero values at the same location in all the apertures. If we have L virtual apertures then the optimization problem can be written as

$$\min_{\mathbf{x}_1,..\mathbf{x}_L} \sum_{l=1}^{L} \|\mathbf{y}_l - \mathbf{A}_l\mathbf{x}_l\|_2^2 + \mu\|\mathbf{X}\|_{2,p} \tag{5}$$

$$\mathbf{X} = [\mathbf{x}_1,\ \mathbf{x}_2,\ \cdots,\ \mathbf{x}_L] \in \mathbb{C}^{N_s\times L} \tag{6}$$

$$||\mathbf{X}||_{2,p} = \sum_{n=1}^{N_s}(c_n)^p, \tag{7}$$

where,

$$c_n = \sqrt{\sum_{l=1}^{L}|x_{n,l}|^2} \tag{8}$$

$\|\mathbf{X}\|_{2,p}$ $(0 < p < 1)$ is calculated as shown in (7), where each column in $\mathbf{X}$ corresponds to the estimated vector $\mathbf{x}_l$ for aperture l ($\mathbf{x}_l \in \mathbb{C}^{N_s\times 1}$ for $1 \leq l \leq L$). An alternative method such as maximum of $|x_{n,l}|$ over all l's in calculation of c_n in (8) can also be considered.

In (5), $\mathbf{y}_l, \mathbf{x}_l$ and $\mathbf{A}_l$ represent measurement vector, source vector and sensing matrix, respectively for each aperture l $(l = 1,\ldots,L)$. Note that $\mathbf{A}_l$ is defined for each aperture with its corresponding DoA and DoD as shown in Fig. 1. A variant of FOCUSS algorithm, termed as Block FOCUSS, is proposed in this paper which can be used to solve the block sparse problem. In block sparse we assume that the non-zero values occur in the same position for each virtual aperture, $\mathbf{x}_l$ i.e., they have the same support vector. The non-zero values at the same position don't have to be identical and allow therefore different reflection coefficients from the same target perceived by the different apertures.

Algorithm 1 Block FOCUSS algorithm for multiple apertures (with noise)

Inputs: $\mathbf{y}_l$, $\mathbf{A}_l$ for $l = [1, 2, \ldots L]$
Outputs: $\hat{\mathbf{x}}$, δ
Initialize $k = 0$; $\mathbf{W}^{(0)} = \mathbf{I}$; $\delta_t = 10^{-8}$; $\delta = 1$; $\hat{\mathbf{x}}^{(0)} = \mathbf{y}$
    $\mu =$ noise variance
while $\delta > \delta_t$ **do**
    $k = k + 1$
    for $l = [1, 2, \ldots L]$ **do**
        $\mathbf{A}_l^{(k)} = \mathbf{A}_l\mathbf{W}^{(k-1)}$
        $\mathbf{q}_l^{(k)} = (\mathbf{A}_l^{(k)})^H \left(\mathbf{A}_l^{(k)}(\mathbf{A}_l^{(k)})^H + \mu\mathbf{I}\right)^{-1} \mathbf{y}_l$
        $\mathbf{x}_l^{(k)} = \mathbf{W}^{(k-1)}\mathbf{q}_l^{(k)}$
    end for
    $\mathbf{W}^{(k)} = \text{diag}\left((c_1^{(k)})^p, (c_2^{(k)})^p, \ldots, (c_{N_s}^{(k)})^p\right)$
    where $c_n^{(k)}$ is calculated as per Eq. (8)
    $\hat{\mathbf{x}}^{(k)} = \left[(c_1^{(k)})^p, (c_2^{(k)})^p, \ldots, (c_{N_s}^{(k)})^p\right]^T$
    $\delta = \frac{\|\hat{\mathbf{x}}^{(k)} - \hat{\mathbf{x}}^{(k-1)}\|_2}{\|\hat{\mathbf{x}}^{(k-1)}\|_2}$
end while

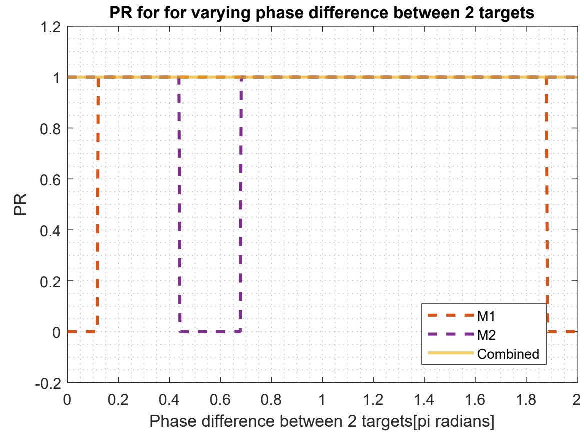

Fig. 3. Spatial diversity by combining the responses from two distributed radar sub-systems

In each iteration of Block FOCUSS the $\|\mathbf{X}\|_{2,p}$ norm of the estimated signal $\mathbf{x}_l$ from each aperture is fused into a single $\mathbf{x}$. The combined estimate represented as $\mathbf{x}$ is used to calculate the weighting matrix $\mathbf{W}$. The detailed steps of the Block FOCUSS are shown in Algorithm 1. In each iteration the weighting matrix $\mathbf{W}$ is used to choose the columns of $\mathbf{A}$ that best represent the sparse solution. In contrast to greedy algorithms, initial estimates are reconsidered through the iterations in order to improve the result. To further improve the performance of Block FOCUSS, pruning of the solutions in each iterations can be used [16].

IV. Results

A. Simulation results

A simulation is performed with two targets at a distance of 20 m from the system with varying angular separations. The system consists of two sensors separated by a baseline of 128λ, where each MIMO sensor has a virtual aperture of 6λ. We consider the Signal-to-Noise ratio (SNR) for both targets to be 20 dB. In total 500 trials of Monte-Carlo simulations were performed for each angular separation case, where a random initial phase is added to the targets. A comparison of Block FOCUSS is given along with the state-of-the-art algorithm BOMP. A detection window (DTW) of $6°$ is defined around the ground truth of the target position. If a detection is found in this window then it is declared as a target. If there is more than one detection then the closest to the ground truth is declared as the target. To quantitatively evaluate the performance of the algorithms the Root Mean Square Error (RMSE), probability of resolution (PR), probability of false alarms (PFA) and average false alarm (AvgFA) are used. The RMSE is determined by taking the square root of the mean of

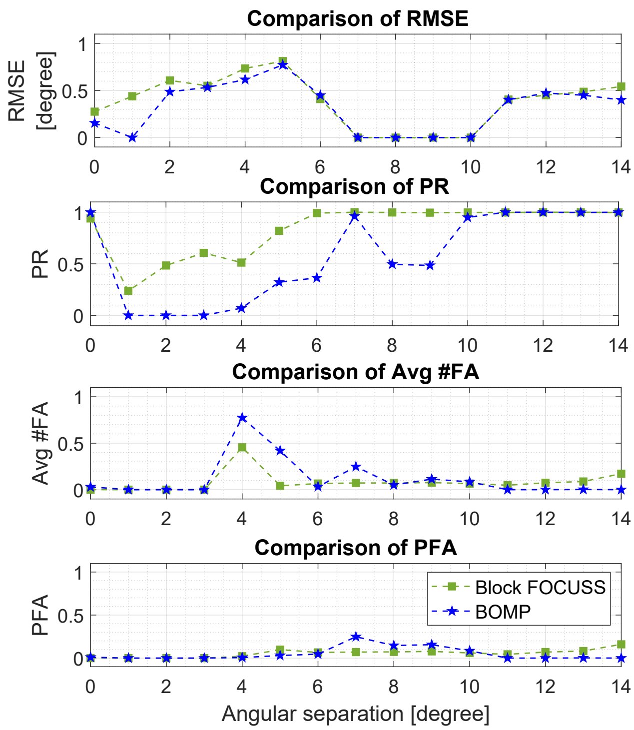

Fig. 4. Results from Monte Carlo simulations for a baseline separation of 128λ and SNR values of 20 dB for two targets at 20m

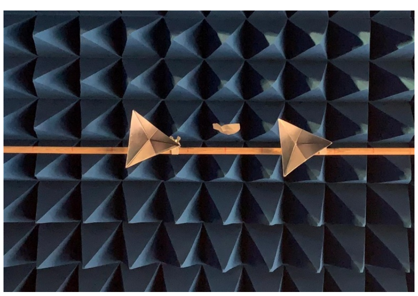

Fig. 5. Two trihedral reflectors used as targets separated in the x-axis

the square of error between the ground truth of the target and the detected target by the algorithm. PR is the number of times all the targets are detected in the DTW in a single Monte Carlo simulation. PFA is defined as the number of trials which detect more than two targets in the entire Field of View (FOV). The AvgFA is defined as the average number of detections found in the entire FOV minus the number of detected targets.

Distributed systems enable the radar to view a potential target from different angles such that each transmitter–receiver pair can experience a different RCS. This provides spatial diversity for the radar and enables better detection performance. The phase difference between the targets consists of two components, the phase difference due to different RCS of the targets and the phase difference that arises due to path length difference between the sensors and the targets. A simulation is performed in software to create varying phase difference between the targets among the two sensors. The

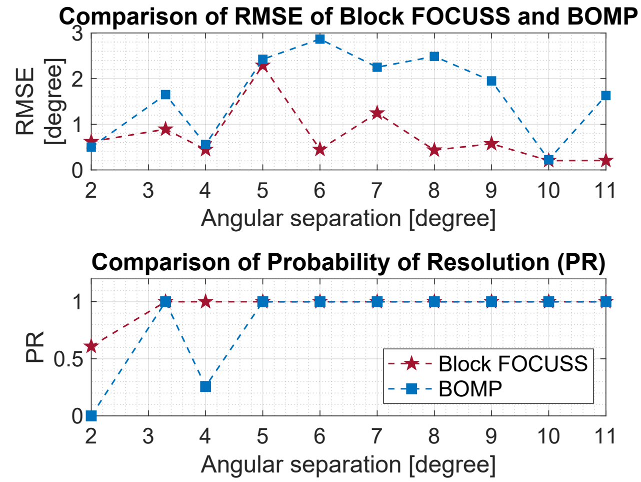

Fig. 6. RMSE and PR of two targets after DoA estimation using Block FOCUSS and BOMP algorithms

results of the simulation is illustrated in Fig. 3, where the x-axis represents the phase difference between the two targets as seen by the radar and the y-axis represents the PR. It is shown that sensors $M1$ and $M2$ when operated as standalone systems fail to resolve the two targets for a certain phase difference between the targets, whereas by incoherently combining the responses of the two sensors the system can always resolve the targets.

Fig. 4 shows the results of the algorithms for two targets with varying angular separation in steps of one degree applied in a system with a baseline of 128λ. The SNR after the Range-Doppler processing is 20 dB and the targets are at a range of 20 m from the radar system. It is shown that Block FOCUSS has a resolving capability of $5°$ with a PR greater than 80 percent, whereas BOMP has a resolving capability of $10°$ for the same configurations. Block FOCUSS outperforms BOMP with double resolving capability and lower PFA.

B. Experimental results

An experiment was conducted in an anechoic chamber in TU Delft using two radar modules based on NXP's TEF810X radar transceiver IC [17]. The radar modules were operating at 78.8 GHz with a bandwidth of 1 GHz, and in the experiment separated by 0.4 m (about 104λ). Only the mono-static responses are used as the modules are not synchronized. Two trihedral reflectors with an RCS of 11.8 dB_{sm} are used as targets, placed at a distance of about 4.5 m from the sensors, which are separated in the x-axis. The two targets are separated along the x-axis to have angular separations in steps of $1°$ as shown in Fig. 5.

The outcome for experimental data processing is shown in Fig. 6. One can see that Block FOCUSS algorithm is able to resolve targets separated by $3°$ and more with a PR greater than 80 percent, whereas BOMP fails to do so. The RMSE for most of the cases is also acceptable. The spatial diversity gain obtained by the distributed system compared to single

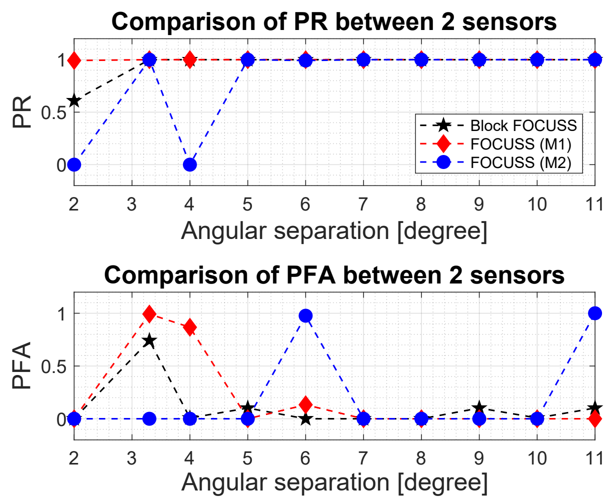

Fig. 7. Comparison of PR and FA for single sensor vs distributed system

system is shown in Fig. 7. The Block FOCUSS achieves better resolution compared to the single sensors $M1$ and $M2$ in terms of both PR and PFA, providing a spatial diversity gain.

V. Conclusion

A novel sparsity based algorithm called Block FOCUSS, which is an extension of FOCUSS, is proposed for high resolution DoA estimation through incoherent processing of distributed radar sensors. The proposed method is able to account for non-isotropic behaviour of targets which is experienced by sensors in a distributed system with a different reflection coefficient when they observe a target from a different angle. An angular resolution of 5° is achieved for two targets at a range of 20 m and an SNR of 20 dB, with each MIMO sensor having a virtual aperture of 6λ. The Block FOCUSS algorithm outperforms the state-of-the-art algorithm BOMP by two times in terms of angular resolution. However, it is to be noted that BOMP is a greedy algorithm and thus computationally more efficient than Block FOCUSS. Block FOCUSS algorithm is also experimentally verified through hardware evaluation achieving a 3° resolution in the near field. In-depth study on scalability of the approach to a large number of scatterers is a subject of future work.

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References

[1] A. M. Haimovich, R. S. Blum, and L. J. Cimini, "MIMO radar with widely separated antennas," *IEEE Signal Processing Magazine*, vol. 25, no. 1, pp. 116–129, 2008.

[2] M. Gottinger, M. Hoffmann, M. Christmann, M. Schutz, F. Kirsch, P. Gulden, and M. Vossiek, "Coherent Automotive Radar Networks: The Next Generation of Radar-Based Imaging and Mapping," *IEEE Journal of Microwaves*, vol. 1, no. 1, pp. 149–163, 1 2021.

[3] A. Ravish Suvarna, "Fusion of radar data from multiple MIMO systems to achieve higher angular resolution," Delft University of Technology, Tech. Rep., 2021. [Online]. Available: http://resolver.tudelft.nl/uuid:5427d75a-fca7-4214-a075-9a6bdc131342

[4] S. Fortunati, R. Grasso, F. Gini, M. S. Greco, and K. LePage, "Single-snapshot DOA estimation by using compressed sensing," *Eurasip Journal on Advances in Signal Processing*, vol. 2014, no. 1, 2014.

[5] M. Andres, P. Feil, W. Menzel, H.-L. Bloecher, and J. Dickmann, "Analysis of automobile scattering center locations by sar measurements," in *2011 IEEE RadarCon (RADAR)*, 2011, pp. 109–112.

[6] J. H. Ender, "On compressive sensing applied to radar," *Signal Processing*, vol. 90, no. 5, pp. 1402–1414, 5 2010.

[7] Z. Yang, J. Li, P. Stoica, and L. Xie, *Sparse methods for direction-of-arrival estimation*. Elsevier, 12 2017.

[8] M. Weiß, "Passive wireless local area network radar network using compressive sensing technique," *IET Radar, Sonar and Navigation*, vol. 9, no. 1, pp. 84–91, 1 2015.

[9] M. Weiß, "Single frequency surveillance radar network using an adapted ℓ minimization approach for extended targets," in *2016 4th International Workshop on Compressed Sensing Theory and its Applications to Radar, Sonar and Remote Sensing, CoSeRa 2016*. Institute of Electrical and Electronics Engineers Inc., 11 2016, pp. 153–157.

[10] S. Gogineni and A. Nehorai, "Target estimation using compressive sensing for distributed MIMO radar," in *Conference Record - Asilomar Conference on Signals, Systems and Computers*, 2010, pp. 793–797.

[11] C. R. Berger and J. M. F. Moura, "Noncoherent Compressive Sensing with Application to Distributed Radar," Tech. Rep.

[12] D. Liu, U. S. Kamilov, and P. T. Boufounos, "Sparsity-driven distributed array imaging," in *2015 IEEE 6th International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP)*, 2015, pp. 441–444.

[13] D. Mateos-Núñez, R. Simoni, M. A. González-Huici, and A. Correas-Serrano, "Design of mutually incoherent arrays for DoA estimation via group-sparse reconstruction," in *2019 IEEE Radar Conference (RadarConf)*, 2019, pp. 1–6.

[14] D. Mateos-Nunez, M. A. Gonzalez-Huici, R. Simoni, F. B. Khalid, M. Eschbaumer, and A. Roger, "Sparse array design for automotive MIMO radar," in *EuRAD 2019 - 2019 16th European Radar Conference*, 2019.

[15] J. H. G. Ender, "A compressive sensing approach to the fusion of pcl sensors," in *21st European Signal Processing Conference (EUSIPCO 2013)*, 2013, pp. 1–5.

[16] I. F. Gorodnitsky and B. D. Rao, "Sparse Signal Reconstruction from Limited Data Using FOCUSS: A Re-weighted Minimum Norm Algorithm," Tech. Rep. 3, 1997.

[17] NXP Semiconductors. (2019, May) TEF810X product data sheet. [Online]. Available: https://www.nxp.com/docs/en/data-sheet/TEF810XDS.pdf