**QUEEN'S
UNIVERSITY
BELFAST**

Frequency-Diverse Computational Automotive Radar Technique for Debris Detection

Yurduseven, O., Fromenteze, T., Decroze, C., & Fusco, V. (2020). Frequency-Diverse Computational Automotive Radar Technique for Debris Detection. *IEEE Sensors Journal*.
<https://doi.org/10.1109/JSEN.2020.3004065>

Published in:
IEEE Sensors Journal

Document Version:
Peer reviewed version

Queen's University Belfast - Research Portal:
[Link to publication record in Queen's University Belfast Research Portal](#)

Publisher rights
© 2020 IEEE.

This work is made available online in accordance with the publisher's policies. Please refer to any applicable terms of use of the publisher.

General rights

Copyright for the publications made accessible via the Queen's University Belfast Research Portal is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy

The Research Portal is Queen's institutional repository that provides access to Queen's research output. Every effort has been made to ensure that content in the Research Portal does not infringe any person's rights, or applicable UK laws. If you discover content in the Research Portal that you believe breaches copyright or violates any law, please contact openaccess@qub.ac.uk.

Frequency-Diverse Computational Automotive Radar Technique for Debris Detection

Okan Yurduseven, *Senior Member, IEEE*, Thomas Fromenteze, Cyril Decroze, and Vincent Fusco, *Fellow, IEEE*

Abstract—Frequency-diversity is a computational imaging technique that can offer all-electronic imaging systems by leveraging spatio-temporally incoherent radiation patterns as an enabling technology. This approach exhibits a significant contrast to conventional imaging modalities, such as synthetic aperture radars (SAR) and phased arrays in that the raster scanning requirement of a scene to be imaged (mechanical or electronic) can be broken and replaced by a quasi-random interrogation of the scene. This aspect of frequency-diverse computational imaging systems significantly simplifies the physical hardware requirements of conventional radars. Despite this advantage, the application of the frequency-diversity technique has been mostly limited to static imaging scenarios, where the position of the scene to be imaged remains fixed over the data acquisition cycle. This limitation hinders the frequency-diverse computational radars from being deployed for applications where the scene dynamics may vary over the data acquisition cycle, such as in automotive radars. In this paper, we demonstrate that by modifying the sensing matrix to account for the movement of the radar platform, frequency-diverse computational imaging radars can be successfully used in debris detection on roads. We show that operating within the frequency band of 77-81 GHz, the presented dynamic frequency-diverse radar technique can produce high fidelity point spread function (PSF) patterns eliminating the distortions caused by the motion of the radar. We also prove that the PSF patterns of the radar are in excellent agreement with theoretical diffraction limited resolution limits.

Index Terms—Computational imaging, frequency-diversity, debris detection, millimeter-wave, radar, Doppler.

I. Introduction

COMPUTATIONAL imaging has recently received significant traction as a new means of enabling millimeter-wave radar technology [1-11]. A distinct type of computational imaging technique, known as frequency-diversity, has been studied in several applications, such as millimeter-wave radars for security-screening [12-18] and ultrasound transducers for nondestructive testing [19-21] to name a few. The frequency-diverse computational radar technique relies on frequency controlled quasi-random modes to probe the imaged scene and encode the backscattered measurements. An estimate of the scene information can then be reconstructed from these encoded measurements using various computational techniques. In comparison to conventional imaging modalities, such as synthetic aperture radars (SAR) [22-26] and phased arrays [27-30], computational frequency-diverse millimeter-wave radars bring several advantages. First, frequency-diverse radar systems exhibit all-electronic operation. This suggests

that sampling of the scene is achieved without the need for any moving apparatus. Second, frequency-diverse radars remove the requirement of raster scanning the imaged scene. Instead, they use spatio-temporally varying quasi-random radiation patterns to encode and compress the backscattered radar measurements into a substantially reduced number of channels. This advantage of the frequency-diverse radars significantly reduces the hardware constraints. Third, despite offering all-electronic operation, frequency-diverse radars do not rely on complex phase shifting circuits to achieve beam synthesis. This is a significant advantage of frequency-diverse radars over their phased array counterparts. These advantages on the system hardware layer come at the cost of a more complicated signal processing layer for the frequency-diverse computational imaging. However, with the increased computing power of today's computing systems, as will be shown later in this article, this challenge can be overcome.

In the context of frequency-diverse imaging, research has been mostly limited to applications where the scene position relative to the radar remains static. In other words, as the radar performs a frequency sweep, there is no variation in the position of the imaged object. Whereas such an assumption can hold for certain applications, such as security-screening [12], where the imaged object operates in a cooperative mode and remains static while the measurements are taken, in many other applications, this approach is not feasible. One particular example to this problem can be thought in the context of

Manuscript received April 23, 2020; accepted June 18, 2020. This work was partially supported by the "PHC Alliance" programme, funded by the UK Department for Business, Energy & Industrial Strategy, the French Ministry for Europe and Foreign Affairs, and the French Ministry of Higher Education, Research and Innovation.

O. Yurduseven and V. Fusco are with the Centre for Wireless Innovation, School of Electronics, Electrical Engineering and Computer Science, Queen's University Belfast, Belfast BT3 9DT, Northern Ireland, United Kingdom (e-mail: okan.yurduseven@qub.ac.uk).

T. Fromenteze and C. Decroze are with the University of Limoges, XLIM Research Institute, UMR 7252, F-87000 Limoges, France.

automotive radars. For example, for the frequency-diverse imaging technique shown in [12], it is indicated that the system can perform 70 frequency sweeps per second, resulting in a sweep time, t_s , on the order of ms. Considering the same system for a vehicle moving at a constant speed v , the vehicle moves by a distance $v \times t_s$ by the end of the frequency sweep with respect to its original position at the beginning of the sweep $t=0$. In this application, because the radar platform is mounted on a moving vehicle, it is vital that the radar system can operate in real-time and compensate for the dynamic nature of the imaging problem at hand. In this paper, we demonstrate the first proof-of-concept study of the frequency-diverse computational imaging technique applied to dynamically varying scenes. Different from the quasi-static approach where multi-looks of a single object can be taken in a static manner and stitched together afterwards [12, 31], the presented study demonstrates, the application of a millimeter-wave computational, frequency-diverse radar technique to dynamically varying scenes while the data is acquired. The novelty of the presented work can be highlighted under three aspects: First, this is the first time that the mathematical framework behind the frequency-diverse computational imaging technique is redeveloped to handle dynamically varying scenes. Second, this is the first time that the application of the frequency-diverse computational imaging technique is studied and demonstrated for an automotive radar. Third, and finally, to the best of our knowledge, this is the first time that the application of a compressive system that can reconstruct 3D images using a single antenna (with a single channel) is presented for automotive radar applications. Therefore, this work addresses a major limitation of the frequency-diversity technique, which has historically been limited to static and quasi-static scenes. As a particular application example, we present this technique in the context of automotive radars operating within the frequency-band of 77-81 GHz. The outline of this paper is as follows: In Section II, we explain the frequency-diverse computational imaging technique and its application to static and dynamic scenes. We show that a compensation technique needs to be applied to the sensing matrix to successfully recover the scene information when the scene dynamics change during data acquisition. In Section III, we present an example imaging scenario involving a frequency-diverse radar integrated with an automotive platform moving at a speed of 30 miles per hour (mph), or 48 kilometers per hour (km/h), towards the imaged scene. We present the point-spread-function (PSF) patterns of the radar with and without the modified sensing matrix and prove that without compensation, the reconstructed images are heavily distorted. Using the developed technique, we later study a debris detection scenario. We also present a systematic study of different imaging parameters, such as positioning errors of the vehicle, system noise, positioning and size of the debris object, and their effect on the reconstructed images. Finally, in Section IV, we provide our concluding remarks and further applications of the proposed technique.

II. FREQUENCY-DIVERSE COMPUTATIONAL IMAGING

Frequency-diversity is a computational imaging technique that relies on encoding the scene information onto a set of spatially varying radiation patterns controlled by a simple frequency sweep. A computational radar leveraging this principle can be synthesized using frequency-diverse antennas [3, 12]. Using the concept of frequency-diversity, an operating frequency-band is sampled at certain intervals governed by the Q-factor of the antennas to illuminate the scene with quasi-random field patterns and collect the backscattered signals. Mathematically, using the first Born approximation, the imaging equation can be given as follows:

$$\mathbf{g}_{M \times 1} = \mathbf{H}_{M \times N} \mathbf{f}_{N \times 1} + \mathbf{n}_{M \times 1} \quad (1)$$

Eq. (1) constitutes a forward-model in which $\mathbf{g}$ is the measured signal collected from the imaged scene, $\mathbf{H}$ is the sensing matrix, $\mathbf{f}$ is the scene susceptibility distribution and $\mathbf{n}$ is the measurement noise. It should be noted that, in this paper, we consider scalar fields and the bold font in (1) is to denote the vector-matrix notation.

For a frequency-diverse radar producing M measurement modes to image a scene consisting of N voxels, the size of the sensing matrix is $M \times N$. This suggests that, in the most general case, the sensing matrix is a fat matrix and, hence, does not have an exact inverse. To solve the inverse problem and retrieve an estimate of the scene information, $\mathbf{f}_{\text{est}}$, several approaches can be used, such as single-shot matched-filtering or iterative algorithms based on least-square techniques [32]. In this work, we make use of the matched-filter approach, which consists of an adjoint operation on the sensing matrix applied to the backscattered measurements as follows:

$$\mathbf{f}_{\text{est}} = \mathbf{H}^\dagger \mathbf{g} \quad (2)$$

Eq. (2) suggests that retrieving an estimate of the scene information can be achieved by doing a phase compensation of the sensing matrix applied on the measured radar data.

A significant challenge in the data acquisition step is the fact that the scene information, or the objective function, for the inverse problem defined in (1) needs not be changed as the data acquisition cycle is in progress. To put this statement into context, let us consider the data acquisition cycle for a frequency-diverse computational radar. From our previous work [1, 12], we consider a linearly-swept stepped frequency continuous wave (SFCW) as the waveform of choice for the presented work. Using the SFCW technique, Fig. 1 depicts a complete frequency sweep cycle.

Fig. 1 shows that given a frequency band of operation (bandwidth), the imaging bandwidth is sampled at K frequencies. At each frequency interval (from f_1 to f_K), the radar transmits and receives data, with the width of this interval is known as the dwell time (t_d). This process is repeated for K frequency points in a single chirp, resulting in a total sweep time, $t_s = K \times t_d$. For an imaging scenario where the scene remains static with respect to the radar platform, this approach does not pose a challenge from a data acquisition perspective. However, for an application where the scene

changes rapidly, variations in the objective function (scene information) can easily fall within the single SFCW cycle. In order to address this challenge, the sensing matrix of the computational radar must be compensated.

Fig. 1. Depiction of a single chirp for a SFCW radar.

For the imaging problem at hand, we consider an automotive radar application for close proximity debris detection. The radar consists of a single frequency-diverse antenna, transmit and receive, similar to the frequency-diverse antenna presented in [33]. The operating frequency-band for the radar is selected to be 77 – 81 GHz, which is known as the automotive short range radar (SRR) band [34]. The Q-factor of the antenna is selected to be $Q=330$ and the 77-81 GHz band is sampled at 101 frequency points. From our previous work on frequency-diverse radars [1, 12], we assume that the total sweep time for a single SFCW chirp is $t_s=10$ ms, suggesting that the dwell time for each data acquisition point across the 77-81 GHz band is $t_d=10 \text{ ms} / 101 = 99 \mu\text{s}$. Whereas this sweep time can seem to be excessive for automotive radars, our purpose in this work is to show that the proposed compensation algorithm can work with even such large sweep times, and hence displacements. It should also be mentioned that the time domain impulse response width of a frequency-diverse antenna is directly proportional to the Q-factor [1, 3]. With a Q-factor 330, the time domain impulse response of the frequency diverse antenna is on the order of 20 ns [3], significantly smaller than the assumed dwell time, $t_d=99 \mu\text{s}$. A detailed discussion on the design of frequency-diverse computational antennas is given in [35]. For a vehicle traveling at a speed of 30 mph, the maximum Doppler frequency can be calculated to be 3.6 kHz at 80 GHz, resulting in a coherence time of 9.28 ms, which is substantially larger than the dwell time $t_d=99 \mu\text{s}$ at each frequency sampling point. Therefore, in this proof-of-concept study, we assume that the caused Doppler shift is negligible across the dwell time at each frequency sampling point t_d .

Assuming that the vehicle travels at a constant speed of $v=30$ mph (speed limit in the UK for urban areas), it is evident that at each new measurement forming the rows of the sensing matrix, the car moves by 1.3 mm, corresponding to 0.35λ , where λ denotes the wavelength at 80 GHz. This suggests that at each frequency sampling point, $f_{1 \rightarrow M}$, the radar platform advances towards the imaged scene by a distance of 0.35λ . In other words, by the end of a single chirp, the car travels by a total distance of 0.1341 m, which is 35.7λ at 80 GHz. With no

compensation applied in the sensing matrix, this creates a substantial discrepancy in the forward-model of (1), effectively destroying the reconstructed images as will be shown in the next section. To illustrate the difference between the static and dynamic cases, in Fig. 2, we compare the sensing matrix in the range plane (xy -plane) for three discrete frequencies within the SFCW sweep (f_1, f_2, f_k) and we choose an arbitrary pixel as the imaged object. As depicted in Fig. 2(a), for the static case, the positions of the vehicle and the imaged object remain fixed during the frequency sweep. In contrast, as shown in Fig. 2(b), for the dynamic case, this position information changes as the frequency is swept from f_1 to f_k . It should be noted that in Fig. 2(b), for the sake of clarity, we depict the dynamic case by moving the object with respect to a stationary vehicle. This is reciprocal to moving the vehicle with respect to a stationary object.

Fig. 2. Depiction of an example frequency-diverse sensing matrix in the xy -plane (a) static case (b) dynamic case. The coordinate system for the imaging problem is shown as inset.

To compensate for the effect of the movement on the frequency-diverse radar, we can leverage several techniques. The first technique could be thought of a hardware-based solution. In this approach, we can leverage several frequency-diverse antennas placed at different depths and sequentially activate them as the vehicle moves to reduce the imaging problem at hand to a static problem. However, such a solution would increase the hardware complexity of the radar system. Alternatively, in this paper, we demonstrate that by appropriately modifying each row of the sensing matrix by taking into account the new position of the radar as the frequency is swept, we can eliminate this distortion. This modification of the sensing matrix can be achieved by

multiplying each row of the sensing matrix by the corresponding Green's function to propagate the panel fields to the correct position that matches with the physical position of the radar with respect to the scene as the vehicle moves. This simple modification is equivalent to updating the location coordinates of the antenna in the calculation of the Green's function when the transmit and receive antenna fields are propagated to the imaged scene to build the sensing matrix, $\mathbf{H}$. The sensing matrix is proportional to the radiated fields by the frequency-diverse antenna as follows [11]:

$$\mathbf{H} \propto \mathbf{E}_{Tx} \mathbf{E}_{Rx} \quad (3)$$

In (3), $\mathbf{E}_{Tx}$ and $\mathbf{E}_{Rx}$ are the radiated fields by the frequency-diverse antenna propagated to the imaged scene:

$$E_{Tx}(\mathbf{r}', f(t)) = \int_{\mathbf{r}} J_{Tx}(\mathbf{r}(t)) \frac{e^{-j\frac{2\pi}{c}f(t)|\mathbf{r}(t)-\mathbf{r}'|}}{|\mathbf{r}(t)-\mathbf{r}'|} \partial^2 \mathbf{r}(t) \quad (4)$$

$$E_{Rx}(\mathbf{r}', f(t)) = \int_{\mathbf{r}} J_{Rx}(\mathbf{r}(t)) \frac{e^{-j\frac{2\pi}{c}f(t)|\mathbf{r}(t)-\mathbf{r}'|}}{|\mathbf{r}(t)-\mathbf{r}'|} \partial^2 \mathbf{r}(t) \quad (5)$$

In (4) and (5), $J(\mathbf{r})$ denotes the surface current distribution of the frequency-diverse antenna while $\mathbf{r}$ and $\mathbf{r}'$ denote the radar and scene coordinates, respectively. The frequency-diverse radar that we study in this paper consists of a single antenna sharing the same aperture to transmit and receive, and hence $J_{Tx}=J_{Rx}$ and $E_{Tx}=E_{Rx}$. Because the radar location with respect to the scene changes over time, t , the antenna coordinates are time dependent, $\mathbf{r}(t)$, and linking the antenna location with the measurement time we have:

$$\mathbf{r}(t) = \mathbf{r}_0 + \int_0^t \mathbf{v}(t) \partial t \quad (6)$$

In (6), $\mathbf{r}_0$ denotes the initial position of the frequency-diverse radar before the sweep is initiated ($t=0$). Alternatively, for the sake of simplicity, we can also consider a reciprocal situation with the coordinate system defined with respect to the vehicle, considering that the target is moving toward the vehicle instead. In this case, (6) can be represented in terms of the scene coordinates as follows:

$$\mathbf{r}'(t) = \mathbf{r}'_0 + \int_0^t \mathbf{v}'(t) \partial t \quad (7)$$

In (7), $\mathbf{r}'_0$ is the initial scene position at the time the frequency sweep is initiated ($t=0$) and $\mathbf{v}'$ is the speed at which the scene is moving towards the radar. In this case, the transmit and receive fields in the scene domain can be represented as:

$$E_{Tx}(\mathbf{r}'(t), f(t)) = \int_{\mathbf{r}} J_{Tx}(\mathbf{r}) \frac{e^{-j\frac{2\pi}{c}f(t)|\mathbf{r}-\mathbf{r}'(t)|}}{|\mathbf{r}-\mathbf{r}'(t)|} \partial^2 \mathbf{r} \quad (8)$$

$$E_{Rx}(\mathbf{r}'(t), f(t)) = \int_{\mathbf{r}} J_{Rx}(\mathbf{r}) \frac{e^{-j\frac{2\pi}{c}f(t)|\mathbf{r}-\mathbf{r}'(t)|}}{|\mathbf{r}-\mathbf{r}'(t)|} \partial^2 \mathbf{r} \quad (9)$$

Although in this paper we focus on the on the movement along the range direction (x-axis), $v = v_x = 30\text{mph}$, for the sake of completeness, the coordinates projected along the principal axes of the Cartesian coordinate system can be given as follows:

$$\dot{x}(t) = \dot{x}_0 - v_x t \quad (10)$$

$$\dot{y}(t) = \dot{y}_0 + v_y t \quad (11)$$

$$\dot{z}(t) = \dot{z}_0 + v_z t \quad (12)$$

In (10-12), $\mathbf{v} = \{v_x, v_y, v_z\}$ and the negative sign on the car speed along the x-axis accounts for the definition of the reciprocal coordinates (target is moving towards the vehicle). The linear approximation in (10-12) is justified given the sweep time considered, $t_s=10$ ms. Following the definition of SFCW parameters in Fig. 1, using frequency step indices as $q \in \{1, \dots, K\}$ corresponding to frequencies $\{f_1, \dots, f_k\}$:

$$t_q = (q + \frac{1}{2})t_d \quad (13)$$

$$\dot{x}_q(t) = \dot{x}_0 - v_x t_q \quad (14)$$

$$\dot{y}_q(t) = \dot{y}_0 + v_y t_q \quad (15)$$

$$\dot{z}_q(t) = \dot{z}_0 + v_z t_q \quad (16)$$

Using the updated coordinates in (14-16), we can interpolate the sensing matrix on these new locations for each index q in the entire sweep time. In the case of a nearest neighbor approach, we find the closest samples to our initial grid sampled by δ_x , δ_y and δ_z . A spatial offset of integer number of samples is defined for each dimension, denoted m_x , m_y and m_z .

$$m_x = \lceil -v_x t_q / \delta_x \rceil \quad (17)$$

$$m_y = \lceil v_y t_q / \delta_y \rceil \quad (18)$$

$$m_z = \lceil v_z t_q / \delta_z \rceil \quad (19)$$

Finally, the updated fields can be given as follows:

$$E_{Tx}(x', y', z', f(q)) \rightarrow E_{Tx}(x' + m_x \delta_x, y' + m_y \delta_y, z' + m_z \delta_z, f(q)) \quad (20)$$

$$E_{Rx}(x', y', z', f(q)) \rightarrow E_{Rx}(x' + m_x \delta_x, y' + m_y \delta_y, z' + m_z \delta_z, f(q)) \quad (21)$$

As will be shown in the next section, updating the sensing matrix to account for the movement during the frequency sweep is sufficient to successfully recover the scene information using a computational frequency-diverse radar for dynamic scenes.

III. RESULTS AND DISCUSSION

A. Validation of the Technique and Resolution Analysis

To validate the proposed technique, we first characterize the PSF patterns of the frequency diverse radar on the move. The size of the frequency-diverse aperture is assumed to be 30 cm x 30 cm, imaging a point scatterer placed at a distance of $d=1$ m along the x-axis. The frequency-diverse antenna is modelled as an array of cavity-backed metamaterial elements radiating across the 77-81 GHz operating frequency band. The radiation mechanism for each metamaterial element can be derived in the form of a magnetic dipole and the antenna radiated fields propagated to the imaged scene are then calculated using dyadic Green's functions at each frequency to form the sensing matrix $\mathbf{H}$ [35]. For this PSF analysis, we study three cases. Case 1 represents a static scenario where the position of the scene with respect to the frequency diverse radar is fixed (no movement is involved). For case 2, we study a scenario where the radar moves at $v=30$ mph, but for the adjoint operation of (2), we make use of the static sensing matrix (no compensation for the radar movement is applied). Finally, for case 3, we study a scenario where the radar moves at a speed of $v=30$ mph and the sensing matrix is compensated for this movement.

For these studies, using standard radar resolution equations below [32], the diffraction limited resolution limit of the frequency diverse aperture is calculated as $\delta_{cr}=1.23$ cm in cross-range (yz -plane) and $\delta_r=3.75$ cm in range (x -axis), respectively.

$$\delta_{cr} = \frac{\lambda d}{D} \quad (22)$$

$$\delta_r = \frac{c}{2BW} \quad (23)$$

In (22) and (23), λ is the wavelength, d is the imaging distance, D is the frequency-diverse aperture size, and BW is the frequency bandwidth of operation. The size of the imaged scene is 10 cm x 10 cm x 10 cm, and the scene is discretised into cubic voxels of $\delta_x=\delta_y=\delta_z=1$ cm. Hence the total number of voxels can be calculated as $N=1000$. Discretization of the scene is done below the resolution limit to interpolate and smooth the reconstructed images for plotting. Hence, for the imaging problem at hand, the size of the sensing matrix is $M=101 \times N=1000$, corresponding to 0.8 Mb with single

precision. For the considered problem in this paper, solving the inverse problem of (2) can be achieved in real-time, especially by using parallel-processing solutions, such as field programmable gate arrays (FPGAs) and general purpose graphical processing units (GPUs) [37, 38]. In this work, we make use of a NVIDIA GeForce GTX Titan X GPU and solving (2) for $\mathbf{f}_{est}$ using a GPU acceleration takes around 0.015 s. The reconstructed PSF pattern of the frequency-diverse radar for case 1 (static) is shown in Fig. 3.

Fig. 3. Reconstructed PSF pattern for the static scenario (case 1) (a) 3D view (b) range (top) view. Colorbar is in dB scale.

As shown in Fig. 3, the obtained PSF pattern does not exhibit any distortions. This is expected, as the scene information is static. Analysing the full-width-half-maximum (FWHM) of the reconstructed PSF pattern, the obtained resolution limit is 1.4 cm in cross-range and 4.25 cm in range. These values are in good agreement with the theoretical limit calculated earlier, 1.23 cm in cross-range and 3.75 cm in range. From the range plot of the reconstructed PSF pattern shown in Fig. 3(b), it is evident that the reconstructed point scatterer is located at the correct distance, $d=1$ m.

The reconstructed PSF pattern for case 2 (dynamic, without movement compensation) is shown in Fig. 4.

Fig. 4. Reconstructed PSF pattern for the dynamic case without movement compensation in the sensing matrix (case 2) (a) 3D view (b) range (top) view. Colorbar is in dB scale.

Analysing Fig. 4, it is evident that the reconstructed image is heavily distorted by the mismatch introduced between $\mathbf{g}$ and $\mathbf{H}$ due to the movement of the radar platform towards the imaged scene. Because, for this scenario, the sensing matrix is not compensated for the movement of the radar, the reconstructed PSF pattern in Fig. 4 does not contain any useful information.

Finally, the reconstructed PSF pattern for case 3 (dynamic, with movement compensation) is shown in Fig. 5.

Fig. 5. Reconstructed PSF pattern for the dynamic case with movement compensation applied to the sensing matrix (case 3) (a) 3D view (b) range (top) view. Colorbar is in dB scale.

Analysing Fig. 5, it can be seen that the reconstructed PSF pattern is free from the distortions present in Fig. 4 caused by the motion of the radar during the SFCW acquisition cycle. The range plot along the x-axis shown in Fig. 5(b) clearly shows the correct distance for the imaged point scatter at $d=1$ m. Another important feature observed in this reconstruction is that the resolution is slightly improved due to the reduced distance of the frequency-diverse radar as it moves closer to the imaged object during the frequency sweep. For case 3, the cross-range and range resolution limits were calculated to be 1.3 cm and 4.1 cm, respectively.

B. Application as an Automotive Radar and Debris Detection

Following the analysis of the PSF patterns, we study a potential application of the presented frequency-diverse automotive radar for the detection of possible debris on roads. For this study, a fully reflective debris considered to be metal is placed at a distance of $d=2$ m away from the frequency-diverse antenna. The size of the debris is 9.5 cm (y-axis) x 3.5 cm (z-axis). Due to the limited integration space available on vehicles for radar antennas, we make use of a single frequency-diverse antenna with a size of 10 cm x 10 cm. A depiction of the debris detection scenario is given in Fig. 6(a) whereas the frequency-diverse antenna as the enabling medium radiating spatio-temporally varying quasi-random bases is shown in Figs. 6(b)-6(d).

Fig. 6. Depiction of the studied close-range debris detection scenario. (a) The vehicle with the frequency-diverse antenna moves towards the object at $v=30$ mph speed (b) frequency-diverse antenna: front-view with the aperture radiated field at 77 GHz (left) and back-view with the single compressed channel (right) (c) frequency-diverse antenna: front-view with the aperture radiated field at 79 GHz (left) and back-view with the single compressed channel (right) (d) frequency-diverse antenna: front-view with the aperture radiated field at 81 GHz (left) and back-view with the single compressed channel (right). Dimensions: $D=10$ cm and $h=0.5$ cm.

Similar to the PSF analyses carried out, it is assumed that the car moves at a constant speed of $v=30$ mph in the direction of the debris. Processing the backscattered measurements using the modified sensing matrix, we reconstruct the image shown in Fig. 7. For this study, we consider a noiseless scenario and investigate the effect of measurement noise later in Section III.C.

Fig. 7. Reconstructed images of the debris. For reconstruction, the sensing matrix is modified to take into account the movement of the radar platform (a) 3D view (b) range (top) view. Colorbar is in dB scale.

Analysing the reconstructed images in Fig. 7, the presence of the imaged debris is evident. The range plot shown in Fig. 7(b) correctly predicts the initial distance of the debris from the radar, $d=2$ m.

In order to put the presented frequency-diverse technique into context, in Table I, we provide a comparison between different types of automotive radar sensor modalities studied in the literature and the presented work in this paper. Analysing Table I, it is evident that most sensor topologies studied in the literature are various forms of array antenna architectures. Majority of these works rely on a linear array architecture [39-44, 47, 48], synthesizing a fixed, broadside radiation pattern. Using a planar array topology [45, 46], beam scanning in 3D space can be achieved within a certain frequency band of operation. However, this is accomplished at the expense of increased hardware complexity, requiring a substantially increased number of antennas (and channels) in comparison to the presented computational imaging concept in this paper, which can capture and reconstruct 3D images using a single antenna with a single channel. This advantage of the proposed technique can substantially simplify the hardware requirements for automotive radar applications.

Table I. Comparison of existing sensor techniques for automotive radar to the presented frequency-diverse technique.

Work	Frequency Band (GHz)	Sensor Type	All-Electronic 3D Imaging
[39]	76-79	Patch Array	No. Linear array with fixed broadside radiation.
[40]	76-77	Patch Array	No. Linear array with fixed broadside radiation.
[41]	77	Patch Array	No. Linear array with fixed broadside radiation.
[42]	76.2 – 77.8	Slot Array	No. Linear array with fixed broadside radiation.
[43]	77 – 81	Grid Array	No. Linear array with fixed broadside radiation.
[44]	77 – 81	Comb Line Array	No. Linear array with fixed broadside radiation.
[45]	77	Orthogonal Linear Array	Possible. Uses 4 transmit and 4 receive channels to produce multiple fixed beams to cover both azimuth and elevation.
[46]	76 – 81	Rectangular carved horn array	Possible. Uses an array of 64 (8x8) carved horn antennas.
[47]	77 – 81	Grid Antenna Array	No. Linear array with fixed broadside radiation.
[48]	75 – 82	Slotted Waveguide Array	No. Linear array with fixed broadside radiation.
This Work	77-81 GHz	Frequency-diverse aperture	Yes. Backscattered signal is compressed into a single channel using a single sensor. 3D images from compressed data are reconstructed.

C. Uncertainty Analysis for the Forward-Model

For the studied imaging problem, two types of uncertainties can be present in the forward-model of (1). First is the measurement noise, which can be present in any radar system. In this work, we can analyse the effect of noise uncertainty by adding a distortion to the measured signal, $\mathbf{g}$, as a function of different signal-to-noise (SNR) levels. To this end, we use the measured signal, $\mathbf{g}$, for the original reconstruction in Fig. 7 (noiseless) and add to it a Gaussian white noise modelled distortion at SNR rates of 0 dB, 5 dB, 10 dB and 20 dB, respectively. The reconstructed images as a function of noise uncertainty are shown in Fig. 8.

Fig. 8. The effect of noise uncertainty in image reconstruction for debris detection as a function of SNR (a) SNR=0 dB (b) SNR=5 dB (c) SNR=10 dB (d) SNR=20 dB. Colorbar is in dB scale.

Analysing Fig. 8, it is evident that the presented technique is robust to measurement noise. Whereas we observe a slight distortion in the reconstructed image below 5 dB SNR level, increasing the SNR above this level, the fidelity of the reconstructed image remains almost the same.

The second uncertainty can be observed in the presence of non-precise calculation of the position of the vehicle with respect to the imaged object as the vehicle moves. We emphasize that the goal of this paper is to show that the frequency-diverse computational imaging technique, which has been historically limited to static scenes, can be adopted to dynamically varying scenes in the context of automotive radars. Hence, the analysis of inaccurate calibration of vehicle's trajectory is not the main scope of this paper, nevertheless, we present a systematic study to demonstrate the effect of positioning uncertainty on the reconstructed images. To this end, in Fig. 9, we study four scenarios. Scenario 1: Ideal case – the vehicle moves at a speed of $v=30$ mph for the forward-model and for the adjoint operation this speed is registered correctly ($v=30$ mph). Scenario 2: The vehicle moves at a speed of $v=30$ mph for the forward-model but for the adjoint operation, the vehicle speed is registered as $v=30.5$ mph in error. Scenario 3: The vehicle moves at a speed of $v=30$ mph for the forward-model but the adjoint operation, the vehicle speed is registered as $v=32.5$ mph in error. Scenario 4: The vehicle moves at a speed of $v=30$ mph for the forward-model but for the adjoint operation, the vehicle speed is registered as $v=35$ mph in error. The reconstructed images for these scenarios are shown in Fig. 9. For this analysis the SNR level was chosen to be 20 dB.

Fig. 9. Effect of position uncertainty in image reconstruction (a) Scenario 1: original case – no positioning error is present (b) Scenario 2: $\Delta d=0.1$ mm positioning error for each frequency step (c) Scenario 3: $\Delta d=0.2$ mm positioning error for each frequency step (d) Scenario 4: $\Delta d=0.3$ mm positioning error for each frequency step. Colorbar is in dB scale.

Analysing Fig. 9, it is evident that positioning uncertainties, when not correctly calculated, can substantially affect the reconstructed images. For the studied scenario 2 shown in Fig. 9(b), the vehicle moves at the intended speed of $v=30$ mph for the forward-model, suggesting that at each frequency sampling point interval, the vehicle moves by 1.3 mm. For the adjoint operation, however, miscalculating this speed as $v=30.5$ mph, the vehicle moves by 1.4 mm at each frequency sampling point interval. As a result, by the end of the frequency sweep of 101 frequency points, we have a total positioning error of 1 cm, or 2.67λ at 80 GHz, degrading the reconstructed image as can be seen in Fig. 9(b). Increasing the positioning error, we can see that the reconstructed images in Figs. 9(c) and 9(d) are heavily distorted. For the studied scenario 3 shown in Fig. 9(c), the vehicle moves at a speed of $v=30$ mph for the forward-model and is assumed to move at $v=32.5$ mph for the adjoint operation in error, resulting in a total positioning error of 2 cm, or 5.3λ at 80 GHz. Finally, for the studied scenario 4 in Fig. 9(d), the vehicle moves at a speed of $v=30$ mph for the forward-model and is assumed to move at $v=35$ mph for the adjoint operation in error, resulting in a total positioning error of 3 cm, 8λ at 80 GHz.

D. Systematic Analysis of the Debris Position and Size for the Debris Detection Scenario

Finally, to further understand the imaging characteristics of the proposed technique as an automotive radar application, we study the size and position of the imaged debris, and investigate the reconstructed images as a function of these parameters. First, in Fig. 10, we vary the position of the object from $d=2$ m to $d=5$ m. For each studied scenario, we use the original imaging parameters, i.e. the vehicle moves at a

constant speed of $v=30$ mph and the sensing matrix is compensated with respect to the movement of the frequency-diverse antenna as detailed in Section II. The selected SNR level is 20 dB. The reconstructed images of the debris as a function of varying position are shown in Fig. 10.

Fig. 10. Reconstructed images of the debris as a function of varying distance (a) $d=2$ m (b) $d=3$ m (c) $d=4$ m (d) $d=5$ m. Colorbar is in dB scale.

As shown in Fig. 10, as the debris is positioned further away, the cross-range profile of the reconstructed image widens and becomes less informative due to the worsening cross-range resolution. This is expected, because, from (22), the cross-range resolution of the radar is directly impacted by the imaging distance. For each case in Fig. 10, we can clearly identify the position of the debris in range. As can be seen from (23), for the presented scenario, the range-resolution is governed by the imaging bandwidth, which remains constant at 4 GHz (77-81 GHz).

Next, we study the same imaging scenario, but as a function of varying debris size. For this study, the debris size is varied from half of the original size, 4.75 cm x 1.75 cm to 1.5 times the original size, 14.25 cm x 5.2 cm. The reconstructed images are shown in Fig. 11. As can be seen in Fig. 11, the outline of the reconstructions is sensitive to the size of the debris and increasing in size as the debris size is increased. An important point can be seen in Fig. 11(c), where the physical size of the debris exceeds the size of the frequency diverse antenna in the y-axis, limiting the reconstruction fidelity. This is expected and can be overcome by using a larger aperture.

Fig. 11. Reconstructed images of the debris for varying size (a) half of the original size ($W=4.75$ cm, $L=1.75$ cm) (b) original size ($W=9.5$ cm, $L=3.5$ cm) (c) 1.5 times the original size ($W=14.25$ cm, $L=5.2$ cm). The size of the frequency-diverse antenna is $D=10$ cm. The debris is shown in purple color and the antenna is in orange color. Colorbar is in dB scale.

IV. CONCLUSIONS

We have presented a proof-of-concept study for a computational frequency-diverse automotive radar scheme for detection of debris at W-band frequencies. It has been presented that for the imaging problem at hand, the scene characteristics change during the SFCW data acquisition cycle and hence the sensing matrix of the computational radar needs to be compensated for this variation to achieve imaging. We have successfully demonstrated this compensation technique in the context of a computational frequency-diverse automotive radar for debris detection and validated that the proposed radar technique can reconstruct images free of movement related artifacts. We have further studied the imaging characteristics of the frequency-diverse radar by analyzing the PSF patterns and shown that the proposed movement compensation applied to the sensing matrix is vital

to retrieve high fidelity PSF patterns from the radar. Although shown for W-band, the proposed technique can be scaled to other frequencies and find applications in biomedical imaging, non-destructive evaluation and spectroscopy where the objective function has dynamic characteristics and may vary during the data acquisition cycle.

REFERENCES

- [1] T. Fromenteze, O. Yurduseven, M. F. Imani, J. Gollub, C. Decroze, D. Carsenat, and D. R. Smith, "Computational imaging using a mode-mixing cavity at microwave frequencies", *Applied Physics Letters*, vol. 106, no. 19, pp. 194104, 2015.
- [2] T. Zvolensky, J. N. Gollub, D. L. Marks and D. R. Smith, "Design and Analysis of a W-Band Metasurface-Based Computational Imaging System," *IEEE Access*, vol. 5, pp. 9911-9918, 2017.
- [3] O. Yurduseven, J. N. Gollub, D. L. Marks, and D. R. Smith, "Frequency-diverse microwave imaging using planar Mills-Cross cavity apertures", *Optics Express*, vol. 24, no. 8, pp.8907-8925, 2016.
- [4] C. M. Watts, D. Shrekenhamer, J. Montoya, G. Lipworth, J. Hunt, T. Sleasman, S. Krishna, D. R. Smith, D.R. and W. J. Padilla, "Terahertz compressive imaging with metamaterial spatial light modulators", *Nature Photonics*, vol. 8, no. 8, pp. 605, 2014.
- [5] S. Venkatesh, N. Viswanathan, and D. Schurig, "W-band sparse synthetic aperture for computational imaging", *Optics Express*, vol. 24, no. 8, pp.8317-8331, 2016.
- [6] D. J. Brady, *Optical imaging and spectroscopy*. John Wiley & Sons, 2009.
- [7] A. Molaei, J. Heredia-Juesas, G. Ghazi, J. Vlahakis and J. A. Martinez-Lorenzo, "Digitized Metamaterial Absorber-Based Compressive Reflector Antenna for High Sensing Capacity Imaging," *IEEE Access*, vol. 7, pp. 1160-1173, 2019.
- [8] G. Barbastathis, A. Ozcan, and G. Situ, "On the use of deep learning for computational imaging", *Optica*, vol. 6, no. 8, pp.921-943, 2019.
- [9] T. Fromenteze, E. L. Kpré, D. Carsenat, C. Decroze and T. Sakamoto, "Single-Shot Compressive Multiple-Inputs Multiple-Outputs Radar Imaging Using a Two-Port Passive Device," *IEEE Access*, vol. 4, pp. 1050-1060, 2016.
- [10] J. Hunt, T. Driscoll, A. Mrozack, G. Lipworth, M. Reynolds, D. Brady, and D. R. Smith, "Metamaterial apertures for computational imaging", *Science*, vol. 339, no. 6117, pp. 310-313, 2013.
- [11] J. Hunt, *et al*, "Metamaterial microwave holographic imaging system", *JOSA A*, vol. 31, no. 10, pp. 2109-2119, 2014.
- [12] J. N. Gollub, *et al.*, "Large metasurface aperture for millimeter wave computational imaging at the human-scale," *Scientific Reports*, vol. 7, pp. 42650, 2017.
- [13] M. Liang, Y. Li, H. Meng, M. A. Neifeld and H. Xin, "Reconfigurable Array Design to Realize Principal Component Analysis (PCA)-Based Microwave Compressive Sensing Imaging System," *IEEE Antennas and Wireless Propagation Letters*, vol. 14, pp. 1039-1042, 2015.
- [14] D. L. Marks, O. Yurduseven, and D. R. Smith, "Cavity-backed metasurface antennas and their application to frequency diversity imaging," *Journal of the Optical Society of America A* vol. 34, no. 4, 472-480, 2017.
- [15] A. Pedross-Engel *et al.*, "Orthogonal Coded Active Illumination for Millimeter Wave, Massive-MIMO Computational Imaging With Metasurface Antennas," *IEEE Transactions on Computational Imaging*, vol. 4, no. 2, pp. 184-193, June 2018.
- [16] B. Gonzalez-Valdes, Y. Alvarez, S. Mantzavinos, C. M. Rappaport, F. Las-Heras and J. A. Martinez-Lorenzo, "Improving Security Screening: A Comparison of Multistatic Radar Configurations for Human Body Imaging," *IEEE Antennas and Propagation Magazine*, vol. 58, no. 4, pp. 35-47, Aug. 2016.
- [17] Y. Rodríguez-Vaqueiro, Y. Álvarez López, B. González-Valdes, J. Á. Martínez, F. Las-Heras and C. M. Rappaport, "On the Use of Compressed Sensing Techniques for Improving Multistatic Millimeter-Wave Portal-Based Personnel Screening," *IEEE Transactions on Antennas and Propagation*, vol. 62, no. 1, pp. 494-499, Jan. 2014.
- [18] E. Kpré, C. Decroze, M. Mouhamadou and T. Fromenteze, "Computational Imaging for Compressive Synthetic Aperture Interferometric Radiometer," *IEEE Transactions on Antennas and Propagation*, vol. 66, no. 10, pp. 5546-5557, Oct. 2018.

- [19] A. Ghanbarzadeh-Dagheyan, C. Liu, A. Molaei, J. Heredia, and J. Martinez Lorenzo, "Holey-cavity-based compressive sensing for ultrasound imaging", *Sensors*, vol. 18, no. 6, pp. 1674, 2018.
- [20] S. George, R. Cheng and Z. Ignjatovic, "A novel ultrasound imaging technique for portable and high speed imaging," *2015 IEEE 13th International New Circuits and Systems Conference (NEWCAS)*, Grenoble, pp. 1-4, 2015
- [21] P. Kruizinga, *et al*, "Compressive 3D ultrasound imaging using a single sensor", *Science Advances*, vol. 3, no. 12, pp. e1701423, 2017.
- [22] D. M. Sheen, D. L. McMakin, and T. E. Hall, "Three-dimensional millimeter-wave imaging for concealed weapon detection," *IEEE Trans. Microw. Theory Tech.*, vol. 49, no. 9, pp. 1581-1592, 2001.
- [23] J. A. Martinez-Lorenzo, F. Quivira, and C. M. Rappaport, "SAR imaging of suicide bombers wearing concealed explosive threats," *Prog. Electromagnetics Res.*, vol. 125, pp. 255-272, 2012.
- [24] X. Zhuze, and A. G. Yarovsky, "A Sparse Aperture MIMO-SAR-Based UWB Imaging System for Concealed Weapon Detection," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 49, no. 1, pp. 509-518, 2011.
- [25] O. Yurduseven, "Indirect microwave holographic imaging of concealed ordnance for airport security imaging systems," *Progress in Electromagnetics Research*, vol. 146, pp. 7-13, 2014.
- [26] D. Smith, O. Yurduseven, B. Livingstone and V. Schejbal, "Microwave imaging using indirect holographic techniques," *IEEE Antennas and Propagation Magazine*, vol. 56, no. 1, pp. 104-117, Feb. 2014.
- [27] R. C. Hansen, *Phased array antennas*. John Wiley & Sons, 2009.
- [28] B. H. Ku, *et al*, "A 77-81-GHz 16-element phased-array receiver with $\pm 50^\circ$ beam scanning for advanced automotive radars," *IEEE Trans. Microw. Theory Tech.*, vol. 62, no. 11, pp. 2823-2832, 2014.
- [29] A. J. Fenn, D. H. Temme, W. P. Delaney, *et al*, "The development of phased array radar technology," *Lincoln Laboratory Journal*, vol. 12, no. 2, pp. 321-340, 2000.
- [30] Y. Chen, Q. Zhang, Y. Luo and K. Li, "Multi-Target Radar Imaging Based on Phased-MIMO Technique—Part I: Imaging Algorithm," *IEEE Sensors Journal*, vol. 17, no. 19, pp. 6185-6197, 2017.
- [31] J. Laviada, A. Arboleya-Arboleya, Y. Álvarez, B. González-Valdés, and F. Las-Heras, "Multiview three-dimensional reconstruction by millimetre-wave portable camera", *Scientific Reports*, vol. 7, no. 1, pp. 1-11, 2017.
- [32] O. Yurduseven, M. F. Imani, H. Odabasi, J. Gollub, G. Lipworth, A. Rose, and D. R. Smith, "Resolution of the Frequency Diverse Metamaterial Aperture Imager," *Progress in Electromagnetics Research*, vol. 150, pp. 97-107, 2015.
- [33] T. Fromenteze, O. Yurduseven, M. Boyarsky, J. Gollub, D. L. Marks, and D. R. Smith, "Computational polarimetric microwave imaging," *Optics Express*, vol. 25, no. 22, pp. 27488-27505, 2017.
- [34] K. M. Stroh, H. -. Bloecher, R. Schneider and J. Wenger, "Development of future short range radar technology," *European Radar Conference, 2005. EURAD 2005.*, Paris, pp. 165-168, 2005.
- [35] O. Yurduseven, V. R. Gowda, J. N. Gollub and D. R. Smith, "Multistatic microwave imaging with arrays of planar cavities," *IET Microwaves, Antennas & Propagation*, vol. 10, no. 11, pp. 1174-1181, 20 8 2016.
- [36] G. Lipworth, A. Mrozack, J. Hunt, D. L. Marks, T. Driscoll, D. Brady, and D. R. Smith, "Metamaterial apertures for coherent computational imaging on the physical layer", *JOSA A*, vol. 30, no. 8, pp.1603-1612, 2013.
- [37] D. L. Marks, O. Yurduseven, and D. R. Smith, "Near-field multistatic radar reconstruction with stretched phase Fourier accelerated multistatic imaging (SP-FAMI)," *IET Radar, Sonar & Navigation*, vol. 11, no. 11, pp. 1718-1729, 2017.
- [38] D. L. Marks, O. Yurduseven, and D. R. Smith, "Fourier accelerated multistatic imaging: A fast reconstruction algorithm for multiple-input-multiple-output (MIMO) radar imaging," *IEEE Access*, vol. 5, pp. 1796-1809, 2017.
- [39] S. Yoo, Y. Milyakh, H. Kim, C. Hong and H. Choo, "Patch Array Antenna Using a Dual Coupled Feeding Structure for 79 GHz Automotive Radar Applications," *IEEE Antennas and Wireless Propagation Letters*, vol. 19, no. 4, pp. 676-679, April 2020
- [40] J. Xu, W. Hong, H. Zhang, G. Wang, Y. Yu and Z. H. Jiang, "An Array Antenna for Both Long- and Medium-Range 77 GHz Automotive Radar Applications," *IEEE Transactions on Antennas and Propagation*, vol. 65, no. 12, pp. 7207-7216, Dec. 2017.
- [41] J. Xu, W. Hong, H. Zhang and Y. Yu, "Design and measurement of array antennas for 77GHz automotive radar application," *2017 10th UK-Europe-China Workshop on Millimetre Waves and Terahertz Technologies (UCMMT)*, Liverpool, 2017, pp. 1-4.
- [42] Y. Yu, W. Hong, H. Zhang, J. Xu and Z. H. Jiang, "Optimization and Implementation of SIW Slot Array for Both Medium- and Long-Range 77 GHz Automotive Radar Application," *IEEE Transactions on Antennas and Propagation*, vol. 66, no. 7, pp. 3769-3774, July 2018.
- [43] E. Arneri, F. Greco, L. Boccia and G. Amendola, "A Reduced Size Planar Grid Array Antenna for Automotive Radar Sensors," *IEEE Antennas and Wireless Propagation Letters*, vol. 17, no. 12, pp. 2389-2393, Dec. 2018.
- [44] M. Mosalanejad, I. Ocket, C. Soens and G. A. E. Vandenbosch, "Wideband Compact Comb-Line Antenna Array for 79 GHz Automotive Radar Applications," *IEEE Antennas and Wireless Propagation Letters*, vol. 17, no. 9, pp. 1580-1583, Sept. 2018.
- [45] S. Wang, H. Chen, V. M. Patel and A. Petropulu, "Two-Dimensional Beamforming Automotive Radar with Orthogonal Linear Arrays," *2019 IEEE Radar Conference (RadarConf)*, Boston, MA, USA, 2019, pp. 1-6.
- [46] Ling, C., MaxLinear Inc, 2019. Phased Array Automotive Radar. U.S. Patent Application 16/372,600.
- [47] M. Mosalanejad, I. Ocket, C. Soens and G. A. E. Vandenbosch, "Multilayer Compact Grid Antenna Array for 79 GHz Automotive Radar Applications," in *IEEE Antennas and Wireless Propagation Letters*, vol. 17, no. 9, pp. 1677-1681, Sept. 2018.
- [48] K. Lomakin *et al.*, "3D Printed Slotted Waveguide Array Antenna for Automotive Radar Applications in W-Band," *2018 15th European Radar Conference (EuRAD)*, Madrid, 2018, pp. 389-392.

Okan Yurduseven (S'09-M'11-SM-16) received the B.Sc. and M.Sc. degrees in electrical engineering from Yildiz Technical University, Istanbul, Turkey, in 2009 and 2011, respectively, and the Ph.D. degree in electrical engineering from Northumbria University, Newcastle upon Tyne, United Kingdom in 2014.

He is currently a Senior Lecturer (Associate Professor) at the School of Electronics, Electrical Engineering and Computer Science, Queen's University Belfast, UK. He is also an Adjunct Assistant Professor at Duke University, USA. Between 2018-2019, he was a NASA Postdoctoral Fellow at the Jet Propulsion Laboratory, California Institute of Technology, USA. From 2014 to 2018, he was a Postdoctoral Research Associate within the Department of Electrical and Computer Engineering at Duke University, USA.

His research interests include microwave and millimeter-wave imaging, multiple-input-multiple-output (MIMO) radar, wireless power transfer, antennas and propagation, antenna measurement techniques, and metamaterials. He has authored more than 100 peer-reviewed technical journal and conference articles. He has served as a Technical Program Committee Member and a Guest Editor of several conferences and journals in these fields.

In 2017, Dr Yurduseven received an Outstanding Postdoctoral Award from Duke University. He was the recipient of the NASA Postdoctoral Program Fellowship administrated by Universities Space Research Association (USRA) in 2018. In 2019, in collaboration with the University of Limoges, France, he received the Alliance Hubert Curien Award funded by the British Council. In 2020, he was bestowed the Leverhulme Trust Research Leadership Award. He is a member of the European Association on Antennas and Propagation (EurAAP).

Vincent F. Fusco (S'82-M'82-SM'96-F'04) received the bachelor's degree (Hons.) in electrical and electronic engineering, the Ph.D. degree in microwave electronics, and the D.Sc. degree from Queen's University Belfast (QUB), Belfast, U.K., in 1979, 1982, and 2000, respectively. He is currently the Director of Research with the ECIT Research Institute, QUB. His fundamental work on active antenna

front-end techniques has provided generic advances in low-cost phased and self-tracking antenna array architectures. He has authored or co-authored more than 500 papers and 2 books. He holds a number of antenna-related patents. Dr. Fusco is a fellow of the Institution of Engineering and Technology (IET) and the Royal Academy of Engineering. He was a recipient of the IET Senior Achievement Award and the Mountbatten Medal for seminal contributions in the field of microwave electronics and its impact on U.K. industry, in 2012.

Thomas Fromenteze received the Ph.D. degree from the University of Limoges, Limoges, France, in 2015. From 2015 to 2016, he was a Post-Doctoral Researcher with Duke University, Durham, NC, USA. He is currently a Maître de Conférences (Assistant Professor) with the Xlim Research Institute, University of Limoges, Limoges, France. He is also an Adjunct Assistant Professor with the Center for Metamaterials and Integrated Plasmonics, Duke University. His research interests

include ultra-wideband microwave and millimetre-wave imaging, wave propagation in complex media, computational/compressive imaging, and the various associated inverse problems.

Dr. Fromenteze received the 11th EuRAD Young Engineer Prize during the European Microwave Week 2015.

Cyril Decroze received the Ph.D. degree in telecommunications engineering from the University of Limoges, Limoges, France, in 2002. He is currently an Associate Professor in the XLIM research institute, and obtained the accreditation to direct research (HDR) in December 2013. Since 2016, he has been head of the Antennas & Signal team at XLIM. His field of research concerns multiple

antennas systems, and associated processing for communications and radar imaging. From 2015 to 2019 he was the coordinator of the PIXEL Project on millimeter waves interferometric imaging systems, and funded by the French National Research Agency. He has been involved in more than 25 research projects at the national and European levels, and has co-supervised 15 PHD theses. He has coauthored more than 80 peer-reviewed journal articles and conference papers.