# Wireless Sensing Using Dynamic Metasurface Antennas: Challenges and Opportunities

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## Abstract

Using wireless communication infrastructure to recognize human behaviors has achieved great success over the last decade. This article presents the opportunities and challenges posed by a novel class of antennas referred to as DMA for wireless sensing. In contrast to conventional solutions that rely on either frequency diversity or spatial diversity for sensing, the proposed system exploits the antenna pattern diversity and software programmability of the DMA to achieve high-performance wireless sensing. We present a general framework for DMA-based wireless sensing, and demonstrate the feasibility and benefits of the DMA in sensing using custom hardware. We identify several research challenges and future directions to fully realize this new concept.

## Introduction

In the Internet of Things (IoT) era, the pervasiveness of mobile devices has facilitated the use of wireless communication signals (RF signals) to sense dynamics in the environment [1]. For example, in the smart home scenario, RF-sensing applications have been designed to discern coarse-grained daily human activity [2, 3], as well as fine-grained vital sign monitoring [4] and elderly fall detection [5]. To achieve high sensing accuracy, the fundamental issue is to obtain a high-dimensional measurement of the wireless channel that captures sufficient details of the sensing subject. In existing solutions, such high-dimensional measurements are obtained by having enough spatial or frequency diversity (e.g., leveraging multiple IoT devices or using a wide sensing signal band).

For instance, in WiFi-based human activity sensing and elderly fall detection systems, multiple WiFi-enabled IoT devices are leveraged to capture human motion [2, 4, 6]. The devices are placed at independent locations, where the local wireless channels are affected by the same human movement differently. Thus, one can aggregate the channel measurements provided by different IoT devices to obtain a high-dimensional sensing signal. Moreover, 802.11n/ac WiFi radios leverage orthogonal frequency-division multiplexing (OFDM) for data transmission. On a 20 MHz frequency band, the channel consists of 64 subcarriers. Thus, with a pair of WiFi-enabled IoT devices, a WiFi-based sensing system can obtain 64-dimensional input for recognition [4]. Each signal dimension corresponds to the channel state information of a specific subcarrier.

An alternative to WiFi-based solutions is the radar-based system. Earlier works have demonstrated the use of micro-Doppler signatures for elderly fall detection [7] in the smart home. More recently, frequency modulated carrier wave (FMCW) radar is used for the same purpose [3, 5]. Similar to their WiFi-based peers, radar-based methods rely on spatial diversity (a total bandwidth of 1.69 GHz [3, 5]) to minimize the multipath effect and exploit the frequency diversity to achieve good sensing resolution. We encourage the reader to refer to a detailed survey [1] for a comprehensive review of the state of the art.

In practice, however, reliance on either frequency diversity or spatial diversity can be difficult and costly. For radar-based systems, their wide frequency band requirement makes radio frequency components (e.g., amplifiers and oscillators) more complex and expensive than those of a narrowband device. Moreover, increasing the number of antennas not only makes the system cumbersome, but also increases the complexity in digital processing. In contrast, WiFi-based solutions are more pervasive and widely deployed. However, they are known to degrade in performance due to the multi-path issues at the 2.4 GHz and 5 GHz bands [2, 4].

In contrast to existing efforts, we ask the question: *how can fine-grained wireless sensing with a single antenna pair that works at a single carrier be achieved?* Our solution is a radically different approach that exploits *antenna pattern diversity* to ensure high sensing performance. The key enabler is the dynamic metasurface antenna (DMA), a novel class of antennas that can effectively and rapidly change their radiation pattern in a software-programmable manner [8, 9]. By fusing the channel profiles measured from various radiation patterns, we can still obtain a high-dimensional channel measurement for sensing without the need for a wide frequency band or multiple sensing devices. In this article, we present the opportunities and challenges posed by DMA-based wireless sensing. In the following section we introduce the basic concepts of the DMA, followed by our design and implementation of a two-dimensional custom DMA. Then we present a general framework for a DMA-based wireless sensing system. Specifically, we introduce

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the learning-assisted transmitter and the end-to-end sensing pipeline that take advantage of the unique features of the DMA, such as antenna pattern diversity and programmability, to achieve high sensing accuracy. Following that, we demonstrate the benefits of the DMA in a non-line-of-sight fine-grained sensing task using our custom hardware. We then discuss challenges and future directions, and conclude in the final section.

## Dynamic Metasurface Antenna

### Background of the DMA

The DMA is a novel class of antennas that offers controllable radiation pattern diversity from a simplified hardware platform [9]. The key enablers are the metamaterial elements. Metamaterials were initially proposed as artificial media that were engineered to allow the manipulation of electromagnetic waves in a deliberate and controlled manner [10]. This notion was later adapted to planar counterparts, *metasurfaces*. In brief, a DMA is an antenna with a single-port waveguide exciting a set of sub-wavelength-sized metamaterial elements integrated into its top layer. Each of the embedded metamaterial elements radiates a portion of the energy from the waveguide into free space, and therefore, the overall radiation pattern of the DMA is the superposition of the radiations from all the excited elements. The electromagnetic response of each metamaterial element can be altered to control the amplitude and the phase of the radiated signal. The operation of each element is programmable using simple external electronic controls. Thus, by varying the electromagnetic features of the metamaterial elements and switching different sets of elements to radiate, the DMA provides dynamic radiation pattern diversity in a software-programmable way. In recent years, DMAs have been proposed as an attractive tool for computational microwave imaging systems [8, 9], as they considerably simplify the hardware complexity of conventional systems. In wireless communication, the DMA has been used to provide software control of the wireless environment [11].

### DMA Design and Implementation

The hardware design and implementation of our DMA prototype are given in Fig. 1. The device has a form-factor of $11 \times 11 \times 5.5\text{cm}^3$. As shown in Fig. 1a, the front-end of the device is embedded with 150 randomly placed irises (slots) to radiate the waves. The back-end is incorporated with a tunable-impedance plate (i.e., the dynamic metasurface highlighted in the dotted rectangle). The plate is made from the 1.5-mm-thick Rogers 4003C substrate with a dimension of $8 \times 8$ cm$^2$. As shown in Fig. 1c, the dynamic metasurface is a $4 \times 4$ matrix of binary tunable-impedance "pixels." Each of the pixels is again a $4 \times 4$ metamaterial elements array, which contains a varactor diode to ensure continuous capacitive tuning. Figure 1d shows the details for one of the pixels. The metamaterial element is an octagon inscribed in a 2-mm-diameter circle and has a via of 0.5 mm diameter connecting to the ground plane. As shown in Fig. 1b, each of the 16 tunable pixels is controlled externally by the DC voltage provided by an Arduino micro-controller. The tuning states

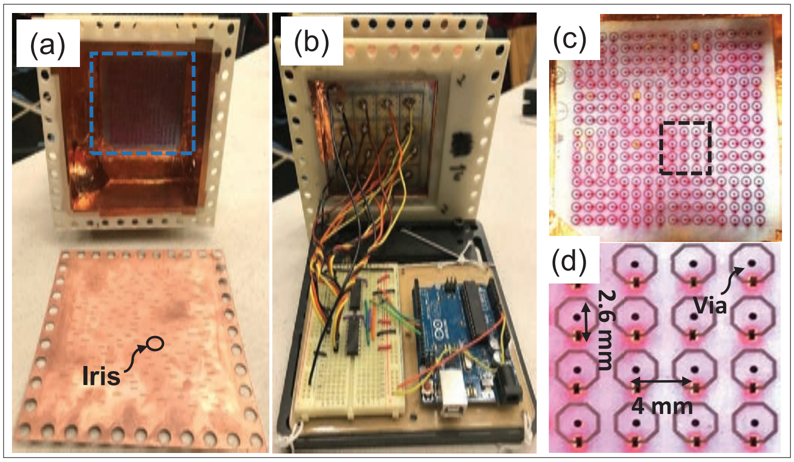


**Figure 1.** DMA design: a) front view: the front-end is separated from the device; b) back view: the tunable-impedance "pixels" are controlled by an Arduino; c) the $4 \times 4$ tunable-impedance pixels' matrix; d) close-up of a metamaterial elements array that corresponds to a tunable pixel.

of the pixels determine the impedance state of the back-end metasurface. Thus, by binary tuning the DC voltage (i.e., 0 V or 5 V) applied to the pixels, the DMA allows $2^{16}$ = 65,536 distinct surface impedance states.

Overall, we can consider the DMA as an electrically large disordered cavity with partially controllable boundary conditions. The impedance state of the back-end metasurface determines the boundary conditions of the cavity and decides the overall radiation pattern that will leak out from the front-end. In other words, by simply tuning the on/off states of the 16 tunable-impedance pixels, we can program the electromagnetic feature of the back-end metasurface and create diverse antenna patterns in a software-programmable way. Moreover, as our device can change the tuning state at megahertz rate, when different DMA antenna patterns are used for sensing, the changes in the monitoring motion are almost negligible within the time duration of a few hundred pattern switches.

## DMA-Based Wireless Sensing

In this section we present a general sensing framework that takes advantage of the unique features of the DMA to enable high-performance wireless sensing in the smart home scenario. Figure 2 shows the general design of the end-to-end system. The transmitter uses a DMA as the antenna, while the receiver is equipped with a simple monopole antenna. Overall, the system can be separated into two parts: the *learning-assisted transmitter* where the DMA is programmed with different antenna patterns to send the wireless signal, and the *sensing pipeline* where variations in the wireless signal are captured by the receiver to sense the motion of interest (e.g., human activity and elderly falling).

**Learning-Assisted DMA:** Extensive programmability is a unique advantage of the DMA, as with the DMA we have access to a large number of antenna patterns that we can select to sense the context of interest. However, in the sensing system, we need an intelligent mechanism to decide the set of antenna patterns that is needed for different tasks and configure the DMA accord-

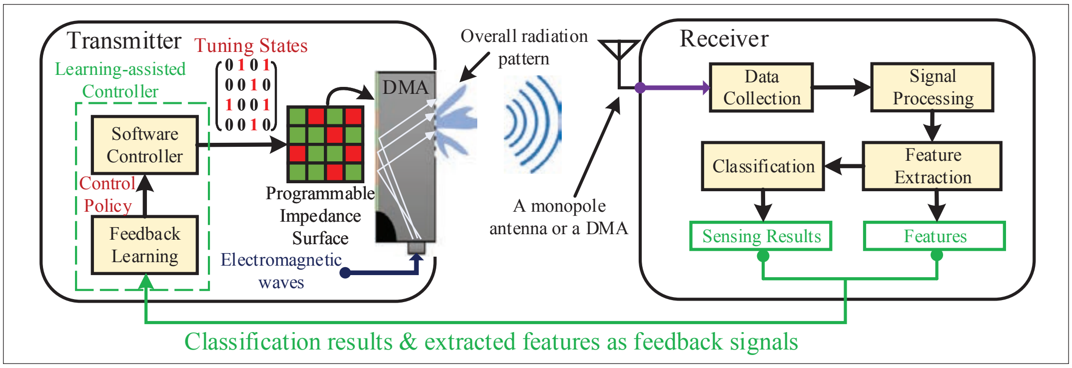


Figure 2. The end-to-end design of the DMA-based wireless sensing system.

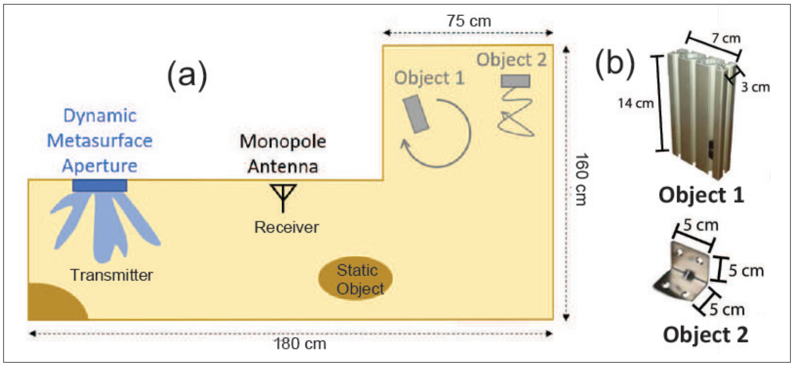


Figure 3. a) 2D layout of the experimental environment; b) illustration of the two objects.

ingly to generate those patterns. One can imagine, for example, having a simple setup process, where, during the installation of the system, the users are asked to perform activities in different locations of the smart home, and different sets of DMA patterns are then selected by the intelligent controller to maximize the activity recognition accuracy for different locations. Moreover, the configuration can also be adapted at runtime: we can activate different sets of DMA patterns for different sensing tasks (e.g., respiration monitoring, gesture recognition, and elderly fall detection), or activate additional patterns as needed to augment the accuracy of a previously selected DMA configuration. For instance, we may need fewer patterns for binary fall detection, but we may require additional patterns for a fine-grained respiration monitoring task. The ability to select the right set of patterns, and to do so adaptively at runtime, makes the DMA more versatile than existing wireless sensing solutions.

We introduce a *learning-assisted controller* to manage the DMA at runtime. As shown in Fig. 2, the learning-assisted controller includes a *feedback learning unit* and a *software controller*. The feedback learning unit takes the information (i.e., the activity recognition results and the extracted features) provided by the receiver as the input, and outputs an optimized control policy. The control policy selects a subset of antenna patterns from the 65,536 options. Based on the control policy, the software controller configures the tuning states of the 16 pixels to generate corresponding antenna patterns. Finally, the generated patterns are used to transmit the wireless signal.

**Sensing Pipeline:** As shown in Fig. 2, the pipeline includes several modules: data collection, signal processing, feature extraction, and classification. The *data collection* module collects the raw channel measurements from the receiving antenna. The challenge is to align the measured signal with the corresponding DMA pattern configuration. In our current implementation, we leverage a central controller to synchronize the measurements with the transmissions of different DMA patterns. After data collection, the *signal processing* module is used to prepare the raw wireless signal for feature extraction and classification. Techniques such as the Butterworth filter and the discrete wavelet transform (DWT) can be applied to clean the raw signal. Then we segment the signals into classification windows before feeding to the feature extraction and the *classification* models. One can use conventional machine learning, such as support vector machines (SVMs), or more advanced deep learning techniques [6] for recognition. Finally, both the sensing results and the extracted features are sent back to the DMA as the feedback to optimize its pattern configuration.

## Case Study

### Experimental Setup

As shown in Fig. 3a, we consider the smart home scenario and perform the experiment in a disordered L-shaped environment. The DMA is used as the transmitter, while a monopole antenna is used as the receiver. The DMA is configured to operate at $f$ = 19.4 GHz to ensure high sensitivity to small motions. To mimic the reflectivity characteristics of human body in the K-band, we deliberately work with two metallic objects. We place them at the corner of the environment to generate motions. The L shape of the environment ensures that the moving objects are clearly out of the line of sight of the probing antenna pair. Such settings mimic the practical sensing scenario where the DMA is used to detect an elderly person falling or an intrusion event that happens in the corner of the room. As shown in Fig. 3b, Object 1 is an aluminium block (with a form-factor of 14 cm × 7 cm × 3 cm) mounted on a rotating stage. It rotates in a circle with a radius of 5 cm. Object 2 is an aluminium corner (with a form-factor of 5 cm × 5 cm × 5 cm) mounted to a rail. The dimensions of both objects are only a few wavelengths of the probing signal, and are small compared to the size of the environment enclosure.

We control Object 1 to rotate at four different angular speeds $\Delta\theta$ to mimic different human motions. We deliberately introduce two types of interference to the motion of Object 1. As shown in Fig. 4, the first type of interference is introduced by adding noise to $\Delta\theta_1$, such that Object 1 is not rotating at a constant speed. This simulates the practical case where a subject performs the same activity in similar but varying ways. The second type of interference is created by moving Object 2 randomly along its rail, while Object 1 is rotating. This simulates the scenario in which an adjacent subject's motion causes interference on the monitored subject. We configure the DMA with 150 random patterns as the transmitter, which is sufficient to achieve perfect classification accuracy for our sensing task. We measure the received signal at the monopole antenna, which is a 150-dimensional complex-valued time-series, where each dimension corresponds to the received signal of a particular DMA pattern.

### Sensing Performance

In the evaluation, we aim to recognize the exact status of Object 1 from the four motion states with different angular speeds, and from the non-motion state. The metric *accuracy* is used to measure the performance. We use a sliding window to separate the 150-dimensional time series into data segments, and label them with the actual status of Object 1. For each segment, we calculate the variances in both signal phase and amplitude, and feed them as features to the SVM for classification. The final classification results are obtained using 10-fold cross-validation. We randomly select an *m*-dimensional measurement ($m \leq 150$) from the original 150-dimensional input to study how the accuracy is affected by the number of DMA patterns being used. Moreover, we also apply different sliding-window lengths (*win*) during the segmentation to examine how the accuracy trades off with the sensing latency.

The results are given in Fig. 5. We are interested in the classification accuracy one can achieve with different levels of antenna pattern diversity. First, limited diversity leads to poor accuracy. For instance, in the amplitude only scenario, given a window size of 3 s, with single- and three-antenna patterns, we achieve only 84 and 88 percent accuracy, respectively. These settings are similar to the cases where a single-antenna device and a triple-antenna device are used for sensing. Indeed, with both amplitude and phase information, a single-antenna pattern can achieve over 94 percent accuracy in recognizing four movement patterns (i.e., an aluminum object rotates at four angular speeds). However, in scenarios where the "activities of interest" are more complex, for example, fine-grained and miniature human activity recognition, the pattern diversity of the DMA has a unique advantage. As shown for all the scenarios, the sensing accuracy increases with the number of antenna patterns used. Second, the antenna pattern diversity of DMA is helpful when both low sensing latency (i.e., small *win*) and high recognition accuracy are required. As indicated in Fig. 5, with a minimum window length of 3, we can achieve 100 percent accuracy by fusing the signal from the 150 DMA patterns. This demonstrates the advantage of the proposed DMA-based solution in practical application scenarios, for example, elderly fall detection and intruder detection,

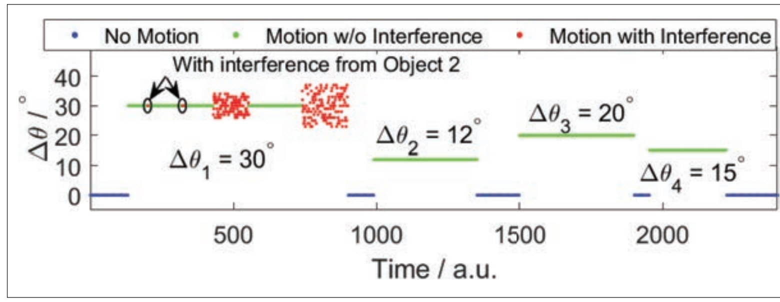


**Figure 4.** Object 1 is controlled to rotate at four different angular speeds $\Delta\theta$. In some periods, interference is introduced by adding noise to $\Delta\theta$ or by moving Object 2 along its rail.

(a) Amplitude

| win \ m | 1 | 3 | 5 | 10 | 20 | 50 | 100 | 150 |
|---|---|---|---|---|---|---|---|---|
| 15 | 90.51 | 93.42 | 96.35 | 97.12 | 99.52 | 100.00 | 100.00 | 100.00 |
| 10 | 88.91 | 91.82 | 95.92 | 96.55 | 98.91 | 100.00 | 100.00 | 100.00 |
| 5 | 87.35 | 90.15 | 94.10 | 95.75 | 98.30 | 99.45 | 100.00 | 100.00 |
| 3 | 84.35 | 88.15 | 92.20 | 94.80 | 98.10 | 99.25 | 99.80 | 100.00 |

(b) Amplitude + Phase

| win \ m | 1 | 3 | 5 | 10 | 20 | 50 | 100 | 150 |
|---|---|---|---|---|---|---|---|---|
| 15 | 97.92 | 98.65 | 98.75 | 99.35 | 100.00 | 100.00 | 100.00 | 100.00 |
| 10 | 96.45 | 96.65 | 98.22 | 98.72 | 99.92 | 100.00 | 100.00 | 100.00 |
| 5 | 94.81 | 95.42 | 97.95 | 98.21 | 99.45 | 99.95 | 100.00 | 100.00 |
| 3 | 94.15 | 94.91 | 97.35 | 97.55 | 99.25 | 99.85 | 99.85 | 100.00 |

**Figure 5.** Classification accuracy (%) given the different number of DMA patterns *m* and different sliding-window lengths *win*. The accuracy increases with *m* and *win*.

where a near-zero false positive rate and a short response time are required.

## Challenges and Directions

### Challenges in DMA Design and Implementation

A fundamental limitation of the DMA used in this study is its form factor: it is 3D printed with a printed circuit board (PCB) attached to it manually. For a more practical implementation, one could envision an entirely PCB-based device: a planar 2D DMA where the cavity is implemented using a deformed via cage. Another shortcoming of the current design is its ability to generate solely random patterns. While random patterns simplify the design and fabrication process, in some cases, it is beneficial to generate patterns with sculpted characteristics. To reach such capabilities, one needs to develop analytical modeling of the 2D DMA and study the characteristics of different DMA configurations.

### Challenges in DMA Control and Optimization

**Adaptive and Optimal Configuration:** The antenna pattern diversity of the DMA provides a high-dimensional channel measurement to improve the sensing performance. Intrinsically coupled to this capability is the challenge in ensuring high system efficiency and low measurement redundancy. For instance, instead of using all possible DMA configurations to probe the wireless channel, is

DMA's capability also allows pushing the performance boundary of fine-grained classification systems that require a higher resolution in separating the channel variations due to multi-subjects or multi-body parts movements. Given this potential, we envision using the DMA as a basis for a set of advanced applications, such as 3D body movement recognition and 3D facial expression recognition.

it possible to adaptively tune and select the most efficient ones? A possible solution is to develop learning-assisted real-time configuration control. For instance, the system can incorporate reinforcement learning [12] to learn an optimal control policy from observed DMA measurements, and thus it can learn and select the most useful configurations at runtime.

**Dynamic Signal Aggregation:** Another associated challenge is the design of a processing mechanism that can *properly assess and compare the sensing quality of different DMA patterns*, and can *dynamically aggregate them based on the estimated quality in runtime*. This is essential as different antenna patterns are unequal in signal resolvability and sensing performance. Moreover, the performance changes dynamically with the sensing conditions and is hard to pre-estimate without actual channel measurements. A possible direction is to design a metric to quantify the sensing quality of individual patterns and design a quality-aware framework to aggregate the high-dimensional channel measurements dynamically based on the metric.

**Feature Generalization:** Another research challenge is to effectively capture a set of generalized features from the high-dimensional measurements of the DMA. One approach is to exploit convolutional neural networks (CNNs) to extract a set of generalized time-frequency domain features from the measurements of different DMA configurations. CNNs are well known for their ability and robustness in learning data representation from high-dimensional input [13], and recently have been applied in wireless sensing [6]. Moreover, by using transfer learning [14] together with CNNs, we can adopt the low-level features learned from an old environment (user) to augment the learning task for a new environment (user). Thus, we can improve the classifier for diverse environments and users.

### Challenges in End-to-End System Design

**Robustness to Environment and User Changes:** An intrinsic challenge in RF sensing is to address the performance variations that result from the environment and user changes. The pre-trained patterns may change if the DMA is deployed in a new environment or used by a different user. Thus, the system will degrade in performance without frequent retraining and updates. According to wireless communication theory, changes in both *environment* and *antenna pattern* will lead to changes/diversity in the receiving signal. From the machine learning perspective, it is impractical to collect a large training dataset that covers all possible environmental dynamics (e.g., collecting wireless signals at many physical locations). Instead, a potential solution is to leverage the antenna pattern diversity of the DMA to generate prolific, high-dimensional channel measurements that mimic the impact of environmental dynamics on the receiving signal. In other words, for a given sensing application (e.g., human activity recognition), one can learn *a set of common features* that is shared among different DMA antenna patterns. The learned features should be robust against the signal diversity due to the changes in either the antenna pattern or the environment.

**Different Configurations of the Antenna Pair:** A promising future direction is to study how different antenna combinations affect the sensing performance. It is possible to use the DMA as both a transmitter and a receiver, and by combining their radiation pattern diversities, we can further improve the measurement diversity and system performance. Another research question that needs to be answered is how different antenna deployments (i.e., antenna positioning) affect performance. For instance, we need to establish how to deploy the antenna pair to achieve the largest sensing coverage without sacrificing the performance. Moreover, we will study how the relative position of the antenna pair affects the sensing performance. If we can have the transmitter and the receiver on a single device, we can potentially reduce the manufacturing cost and deployment complexity.

### New Applications

DMA has a unique advantage in improving the performance of multi-object sensing and fine-grained classification systems. Existing solutions in object tracking usually rely on complex antenna arrays to improve the tracking resolution [15]. In contrast, by spatially combining the diverse radiation patterns provided by a pair of *M*-pattern DMA transceivers, we can probe the wireless channel in $M \times M$ different ways. Thus, by extracting the uncorrelated channel measurements captured by different DMA configurations, we can decompose the signal variations due to different paths. Similarly, DMA's capability also allows pushing the performance boundary of fine-grained classification systems that require a higher resolution in separating the channel variations due to multi-subjects or multi-body-part movements. Given this potential, we envision using the DMA as a basis for a set of advanced applications, such as 3D body movement recognition and 3D facial expression recognition.

## Conclusion

In this article, dynamic metasurface antenna-based sensing is envisioned to pave the way for future low-complexity and low-cost wireless sensing systems. Leveraging the antenna pattern diversity and programmability of a custom DMA, we have demonstrated the feasibility of fine-grained RF sensing without spatial and frequency diversities. To fully realize our concept, we identify several challenges and future directions. We believe that the radiation pattern diversity gives the DMA a unique advantage for multi-object tracking and fine-grained classification systems.

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Guohao Lan received his B.E. degree in software engineering from Harbin Institute of Technology, China, in 2012, his M.S. degree in computer science from KAIST, South Korea, in 2015, and his Ph.D. degree in computer science and engineering from the University of New South Wales, Australia, in 2018. He is currently a postdoctoral research associate with the Department of Electrical and Computer Engineering, Duke University, Durham, North Carolina. His research interests include wireless sensing and mobile computing systems.

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Maria Gorlatova is an assistant professor of Electrical and Computer Engineering and Computer Science at Duke University. She received her Ph.D. in electrical engineering from Columbia University, and her M.Sc. and B.Sc. (Summa Cum Laude) degrees in electrical engineering from University of Ottawa, Canada. Her research is in architectures, algorithms, and protocols for emerging pervasive technologies. She spent two years at Princeton University's Electrical Engineering Department as an associate research scholar and an associate director of the Princeton University EDGE Lab. She is a recipient of the 2011 ACM SenSys Best Student Demonstration Award, the 2011 IEEE Communications Society Award for Advances in Communications, and the 2016 IEEE Communications Society Young Author Best Paper Award.