Participatory 3D Scanning and Modeling of Cities and Buildings Using 5G mm-Wave Smart Phones

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***Abstract*—Millimeter-wave (mm-Wave) frequency bands are a key technology enabler for the ultra-high data rates of 5G cellular networks, and it is fully expected that 5G smart phones will be equipped with mm-Wave network interfaces. Interestingly, millimeter transmissions have utility beyond communication; previously they been used extensively for short-range radar detection and ranging. We envisage a future in which each person carries a smart phone equipped with mm-Wave which can opportunistically scan the adjacent environment and share the results in a participatory manner to allow accurate 3D models to be constructed and maintained. Applications for such low-cost modelling are numerous and include navigating smart cities and buildings, as well as accident prevention in factories. In this article we provide a brief review of mm-Wave, its detection properties, and the basics of 3D scanning and modeling. We introduce a system architecture to enable participatory scanning based on mm-Wave and show results from experiments to demonstrate its feasibility. A variety of research challenges must be solved in order to realize our vision, and we expound on these with a view to stimulating research on this compelling opportunity.**

***Index Terms*—Millimeter-wave, radar detection, 5G, smart cities, smart buildings, participatory sensing.**

I. Introduction

MILLIMETER Wave (mm-Wave) is defined as the range of frequencies between 30-300 GHz and is an integral part of the 5th generation (5G) mobile communication network [1] to provide multi-Gb/s data rates. During the World Radiocommunications Conference (WRC) 2015, the ITU proposed a list of 8 frequency bands between 24 GHz and 86 GHz to be used in 5G, shown as orange in Fig. 1. In addition, many national regulatory agencies released about 9 GHz bandwidth in the unlicensed 60 GHz frequency range (shown as green in Fig. 1). It is expected that future 5G-enabled smart devices, including smart phones, will be equipped with mm-Wave technology.

Of special interest is that mm-Wave has been used in the past for radar detection, and it can be used for detecting objects roughly larger than 5 cm (to be precise, the size of detectable objects depends on the frequency). Historically it was used for long-range radar and in the last few decades, it has been in use for short-range radar, in particular, for object sensing and relative speed measurement in vehicles and for harmful object detection in airport security scanners [2].

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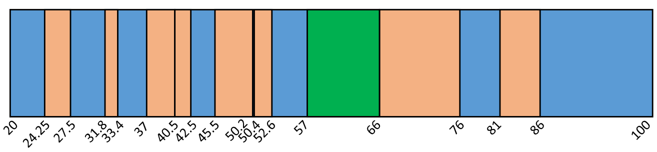

Fig. 1. mm-Wave frequency bands proposed by ITU for 5G (orange) and the unlicensed ISM band (green). The unit of numbers is GHz.

We envisage a future in which smart phones are equipped with mm-Wave technology with a primary purpose for communications but which can also be used by the phone to scan its physical environment. We hypothesise that this scanned data can be used to make and update 3D models of the environment, including inside buildings and in smart cities. Having a 3D model of the indoor and outdoor environments makes it possible to offer a plethora of new services, including guiding firefighters in smoke-filled buildings, and helping vision-impaired people avoid obstacles. Inspired by the concept of participatory sensing [3], we propose an innovative approach in which users provide mm-Wave radar data on a voluntary basis, which is then fused to provide the 3D models. This has the benefit of sourcing data from many individuals, thus increasing spatial accuracy, and on a continuous time basis, thus ensuring that models can track changes in the physical environments over time.

In this paper we expound on our vision for participatory sensing of the environment using mm-Wave. We outline a suitable system architecture and show results from a set of experiments to demonstrate feasibility.

The rest of this paper is organized as follows. Key applications are presented in Section II. In Section III, we summarize the main properties of mm-Wave technology. Section IV provides a scientific background on 3D modeling. The proposed system architecture is shown in Section V, followed in Section VI by supporting results. In Section VII we discuss the main challenges to be addressed by the research community in realising our vision. Finally, Section VIII concludes this paper.

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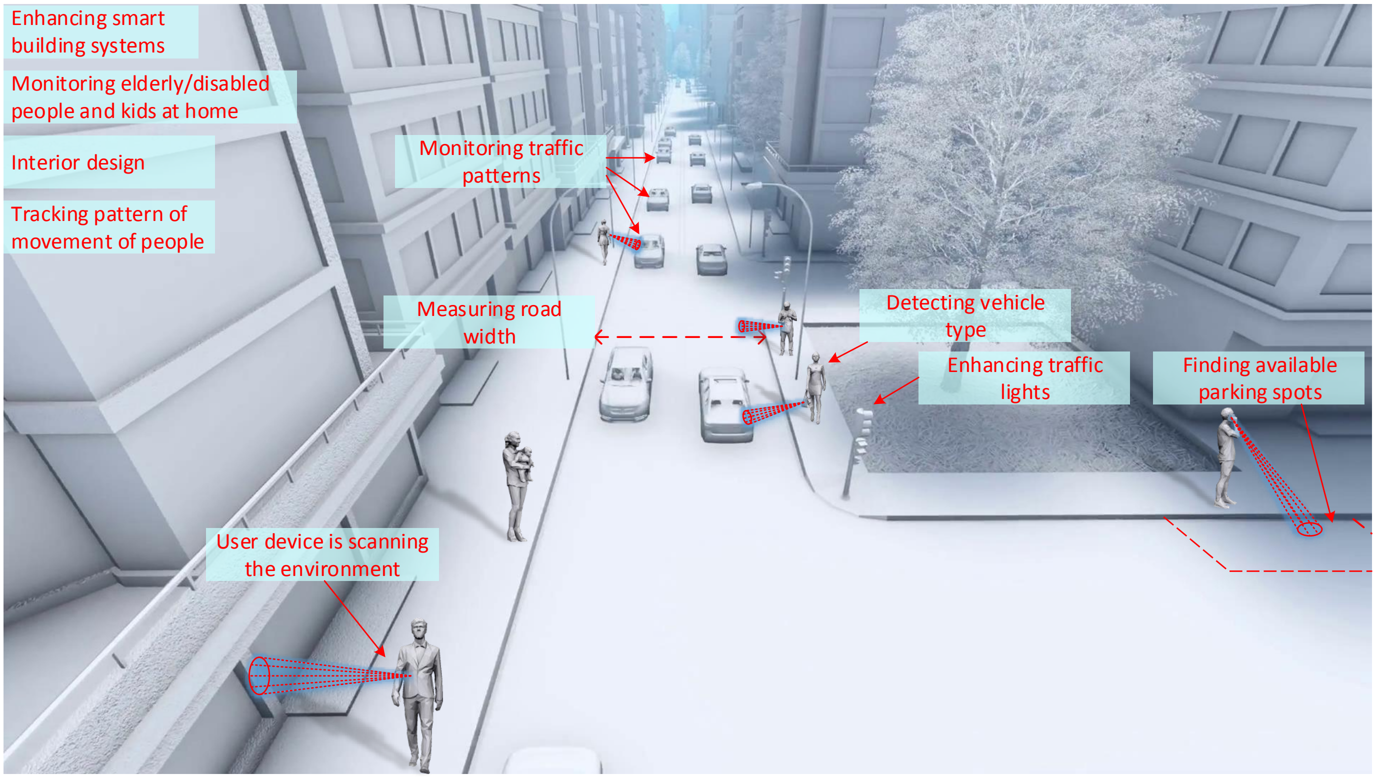


Fig. 2. Applications of mm-Wave 3D scanning/modeling (made using 3D models of Kanistra Studio and DMG Vision and used with their permissions).

II. Applications

In 2002, nobody could imagine that just 5 years later a new generation of mobile phones would have global positioning system (GPS) circuitry and Internet connection capability by which an online map will be accessible through mobile phones, showing the real-time location of users on a map, augmented by location-based services. We believe that the addition of mm-Wave to future smart phones will inspire a similar leap forward.

In the context of smart cities, the availability of a real-time accurate 3D model can seed many new services; Figure 2 highlights some example applications. The pattern of traffic and movements of people can be tracked, by which the traffic lights can be enhanced. The available parking spots can be found. The vehicle type can be detected to be used by the online maps to show the proper route suitable for each vehicle. The maps can also measure road width and slopes to include them in paths suitable for each vehicle. The smart building systems can make use of the 3D model of the buildings, so for example to monitor elderly/disabled people and kids. An interior designer can use the 3D model of houses in their designs. The following subsections provide three case studies.

A. Case Study 1: Obstacle Avoidance and Guidance for Vision-Impaired People

mm-Wave radar sensor has being used in vehicles to avoid accidents. It can be used with a similar approach to assist people who are vision-impaired by warning them of any obstacle or hazard in their way. A more advanced application within their smart phone can make use of available 3D model of the cities to help them find their way and avoid obstacles, thus to make the cities and indoor environments, such as inside buildings, airports and hospitals more suitable and safe for them. Similarly, naturally dark areas such as caves and mines can be scanned and modeled for people to enhance their visibility.

B. Case Study 2: Enhanced Placement and Maintenance for IoT devices

The Internet of things (IoT) is seen as the key enabler of the next generation industrial revolution, which is commonly known as Industry-4. Billions of devices and sensors communicate through the Internet, to gather and process large volume of data and make enhanced decisions. The placement of devices in the physical environment is today a labor-intensive process, requiring walk-through of rooms and factories etc. Having a 3D model of the environment would assist in planning the placement of IoT devices, including feeding into systems for estimating wireless connectivity, by accounting for obstacles. Furthermore and significantly, the participatory nature of the solution could provide the basis for tracking changes in the physical environment that may have an impact on sensing or communications. Accurate 3D models can also assist in planning other utilities, including cable ducts and pipes.

C. Case Study 3: Guidance for Emergency Responders

Firefighters and police officers responding to an emergency in a building often suffer from a lack of information on the internal layout. For firefighers this is especially of concern, given that the presence of dense smoke will substantially cloud their vision. For modern commercial buildings it may be possible to provide the original layout when the building was constructed, at least including interior walls and doorways. However, furniture and any reconfiguration will not be known. A mm-Wave participatory system would provide such details, in an up-to-date manner, including for a broad range of buildings, both small and large.

III. Millimeter-wave Technology

Looking for methods to enable higher data-rates for wireless/mobile communications beyond 6 Gb/s for ultra high datarate demanding applications, researchers and engineers considered use of higher frequencies between 30-300 GHz known as mm-Wave as one of the most promising solutions in recent years. The use of smart phones and mobile data traffic will be increased so that an average mobile user will download around 1 terabyte of data annually by 2020 [4]. This will increase the use of mm-Wave technology for communication purposes. The global mm-Wave technology market was accounted for \$0.27 billion in 2015 and is expected to reach \$2.89 billion by 2022 growing at a CAGR of 40.5% [5].

mm-Wave channels have some featured properties [6]:

- The power degrades drastically with distance. Therefore, to compensate for this power degradation, use of directional antennas are common.
- The multipath effect is weak and can be neglected. So, the channel response is more stable and the compensation for channel impairments is easier.
- The mm-Wave is blocked by human body and any obstacle larger than 5 cm. It also does not penetrate through wall.
- It has a short wavelength enabling engineers to fabricate a large number of antenna elements within a chip or board.
- Larger bandwidth is available compared with regular sub-6 GHz frequencies which makes ultra high bit-rate communication possible.

The development of antenna beamforming and beamsteering techniques has changed the nature of wireless communication in mm-Wave to having a directional antenna in which its direction can be steered toward the receiver antenna electronically within less than 1 millisecond [7].

While there exist some debates between large telecom companies on whether to use mm-Wave in 5G access networks because of the costs involved for reasonable coverage, recent successful experiments over these frequency bands by the same companies reveal the fact that mm-Wave will be one of the main components of 5G.

Besides communication, mm-Wave technology has being used for radar detection. Normally, radar can measure range (from wave propagation delay), velocity (from Doppler frequency shift), and angular direction (from antenna pointing or antenna array layout). It is also possible to detect hand gestures with the aid of AI [8]. While the long-range radar distance measurement is mainly based on transmission of impulses and measuring the difference between the time the pulse transmitted and the time it is reflected back from objects and received, the short-range radar systems use other approaches to achieve higher precision. There are multiple approaches on radar range detection, some of them are explained with details in [2]. While each of these approaches have different pros and cons, the frequency modulated continuous wave (FMCW) is the most popular approach in short-range radar detection. A new trend of research tries to use wireless LAN or 5G signals for the positioning and localization purposes. These approaches can be classified into two categories: based on received signal, and based on reflected signal. In the first category, the position of the transmitter is estimated based on the information in the received signal, such as the angle of arrival and received signal strength. In the second category which is similar to the radar concept, the reflected signal is analyzed to extract information related to the position of the objects in the environment (See [9] as an example). While the first category focuses on localizing the transmitter, the second approach can detect any object.

No matter which radar detection approach is used, one main requirement of radar detection is simultaneous transmission and reception of the electromagnetic wave. In the other word, the radio-frequency (RF) circuitry and antenna system should support two-way transmission and reception of the signals. However, most wireless communication systems work in half-duplex operation mode, which means that they are designed in such a way that they can only transmit or receive at a given time, and not both. In recent years, a considerable research is done to design full-duplex operation. Because of duplicating the channel utilization, full-duplex operation is considered as one of the key enablers of the 5G. So, to make this 3D modeling of the environment possible, the 5G smart devices should be equipped with a full-duplex wireless chip, or with one of the mm-Wave short-range radar detection chipsets such as FMCW. As the trend of current research shows feasibility of full-duplex operation, it is highly probable that the smart devices are equipped with this technology. Besides, including a mm-Wave radar detection component in the smart devices is rather reasonable based on the small cost it incurs to their production.

IV. 3D Modeling of Environment

3D scanning and modeling is the act of mapping an object, structure, or area, and describing it in the form of x, y, and z coordinates – a format known as a *point-cloud*. There are different techniques for 3D scanning, but below we introduce a few of them which are more popular.

- *Light detection and ranging (LIDAR)*: LIDAR is a sensor which uses lasers to build a 3D model of the environment. It is widely used for creating accurate topological maps.

- *Digital photogrammetry*: Similar to human visual system, this method takes multiple photographs which are mathematically intersected to create accurate 3D coordinates.
- *Infrared or structured light 3D scanning*: Uses projected light or infrared and a camera system to shoot light onto the surface of an object, creating a pattern of stripes of light. Distortions in the pattern are then used to recreate the object surface geometry.
- *mm-Wave radar*: It uses radar techniques with mm-Wave beamforming and beamsteering antenna arrays. It is not as precise as the other methods, for example, the details of the face of human cannot be captured. So, it preserves privacy.

The field of 3D scanning and modeling is well-studied by the researchers and engineers and lots of products are available in the market. Challenges such as registering different 3D models created from the scans of different angles to make a single model, dealing with imprecise scans and how to make a precise model from imprecise scans, and efficient methods for processing data are addressed in the literature and there exist lots of solutions for each problem [10].

Before 3D models are obtained from the acquired data, many processing steps are needed. The first of these is preprocessing of the data. The scanned data must be transformed into an appropriate coordinate system and into a format that is suitable for further processing. For example, it is often desirable to convert the scanned data into raster models. Removal of noise is another example of preprocessing. It is then followed by specific processing steps, including: registration, neighborhood selection, outlier removal, tangent plane estimation, tangent plane orientation, feature point detection, segmentation, surface fitting and object detection [11].

Almost all available 3D scanning and modeling products in the market use laser or infrared for two reasons: These technologies are more accurate and can model the details of objects in the order of millimeter, and they are cheaper than mm-Wave. So, at first it seems more reasonable to use laser or infrared and install a scanning device on a car to go around the cities to make precise 3D model of cities. However, there are three problems with this approach: It is highly expensive, there is no electronically beamsteering approach for laser and infrared and they need mechanical devices to full scan the environment, and the models made will be offline models and cannot be updated in real time. Another suggestion is to equip smart phones with laser or infrared sensors. However, this makes smart phones more expensive while mm-Wave is already there for communication purpose. Also, laser and infrared are basically blocked when they are in the pocket/purse of people, while mm-Wave can continue scanning the environment when they are in the pockets. Again, the problem with lack of electronically beamsteering lasers or infrared exists here.

V. System Architecture

To have a better understanding of 3D modeling system architecture, we identified some of the main components in

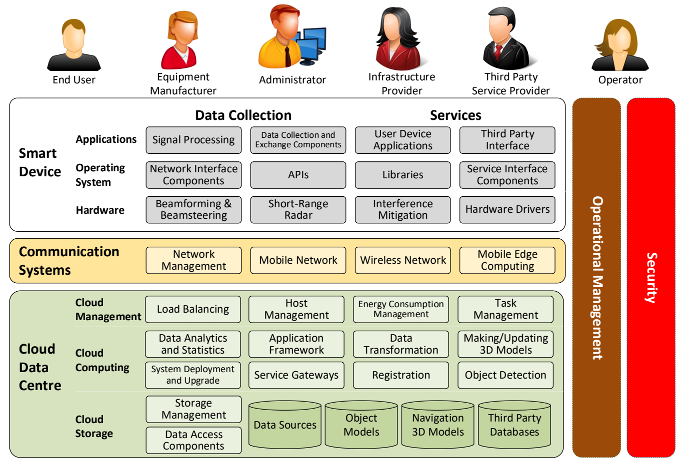


Fig. 3. System architecture for 3D modeling of environment using smart devices.

Fig. 3. The engaging components belong to three parts: smart devices, communication systems, and cloud data center. In smart devices, different components at the hardware, operating system and the applications layer are needed. In the hardware layer, beamforming and beamsteering, short-range radar, interference mitigation, and hardware drivers are of the most important components that should be designed and added to the smart phones. In the application layer, two sets of components are needed: software applications for data collection such as signal processing and data collection and exchange components, and applications developed for end user services and interfaces for third party service providers. Operating systems should also be equipped with interfaces and libraries for both data collection and end user services.

End user devices communicate with the cloud services through communication systems, such as wireless networks and mobile networks. These networks have their own network management components. With the advent of mobile edge computing (MEC), a good contribution to enable low latency updates to 3D-models can be made by the processing units of mobile edge network, for example, in cases where there is a need for urgency.

To offload computations and storage from user devices, cloud data centers are needed, which include components at three levels: cloud management, cloud computing and cloud storage. The main components of cloud management are load balancing, host management, energy consumption management, and task management. These components orchestrate cloud operation. At the cloud computing level, all required tasks for 3D modeling based on the data collected by user devices are done. The main components are data analytics and statistics, system deployment and upgrade, application framework, service gateways, data transformation, registration, making/updating 3D models, and object detection. The cloud storage includes the functions and databases for storing models. They include: storage management and data access components. The main databases are data sources, object

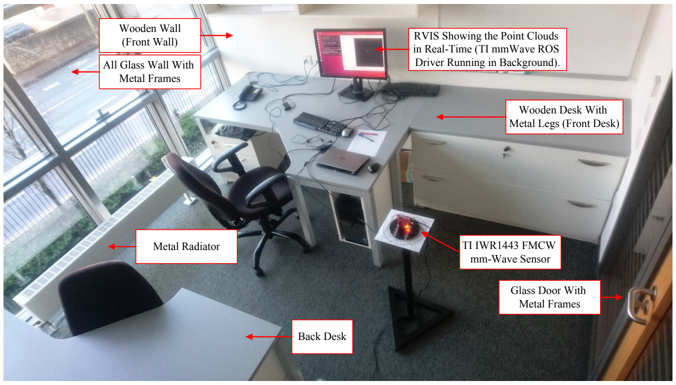


Fig. 4. Experimental setup for 3D scanning and modeling of an office using an FMCW mmWave sensor.

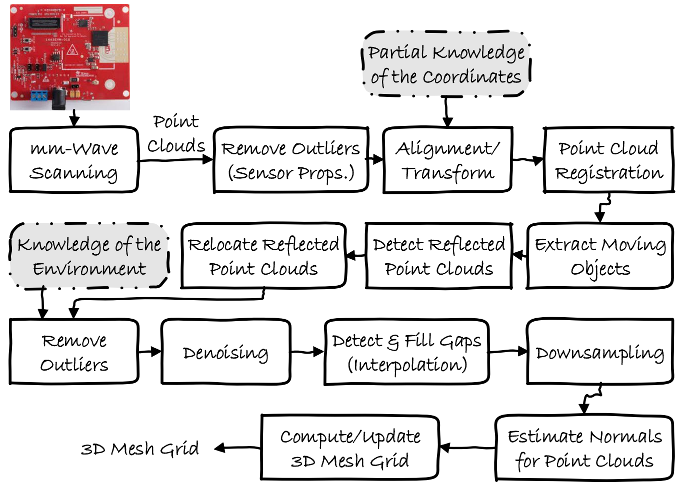


Fig. 5. Block diagram of the offline 3D scanning and modeling process.

models, navigation 3D models, and third party databases.

All layers of the system will require integrated security and operational management. End users, equipment manufacturers, system administrators, infrastructure providers, third party service providers and network operators will be the main contributors of the whole system, each benefit and contribute from different angles.

VI. Feasibility Experiments

In our prior work, we conducted a series of laboratory experiments to assess the feasibility of using mm-Wave devices to provide object detection, using IEEE 802.11ad mm-Wave signals to build a 2D model of an indoor environment [12]. In this section, we present the results of experiments that explore making a 3D model of an office using FMCW mm-Wave sensors. For the scanning part of the experiment, we use a IWR1443 sensor [13] which is a single-chip 76-to-81GHz mm-Wave sensor integrating microcontroller and hardware accelerator. We expect that future smart phones will be equipped with either a full-duplex mm-Wave communication RF transceiver or an FMCW enabled chipset, which can be simply added to the RF transceiver circuitry. Figure 4 shows the experimental setup we used for our measurements. We installed the mm-Wave sensor on a small revolving turntable with a 360° full scale protractor over a height-adjustable stand. The sensor board is controlled by a Linux machine using the related drivers. The RVIZ open-source visualization software [14] and ROS melodic distribution software package [15] are used to visualize the point-clouds captured by the mm-Wave sensor. We put the sensor at 82 different locations and heights in the office environment of Fig. 4. We also changed the scanning plane of the sensor for different measurements. At each location, we rotated the sensor face toward different directions in 10° steps and recorded the measured point-clouds in a `.bag` file. We created a total of 2952 `.bag` files, incorporating 111,484 points.

The layout of the office can also be read from Fig. 4. The left side of this office is composed of a complete glass wall with metal frames. Both glass and metal are good reflectors for mm-Wave frequency radiation. The front and back walls are composed of wood panels. An average size whiteboard is installed on the front wall. The right side wall is also composed of wood, but it also includes a glass door with wood and metal frames and margins. Two sets of office desks which are symmetric in shape are also located in the office. The dimensions of this office are $Width \times Length \times Height = 3.48 \times 3.60 \times 2.89$ m. By using a confined space such as this office we were able to focus on understanding the basic requirememts and challenges for mm-Wave sensing.

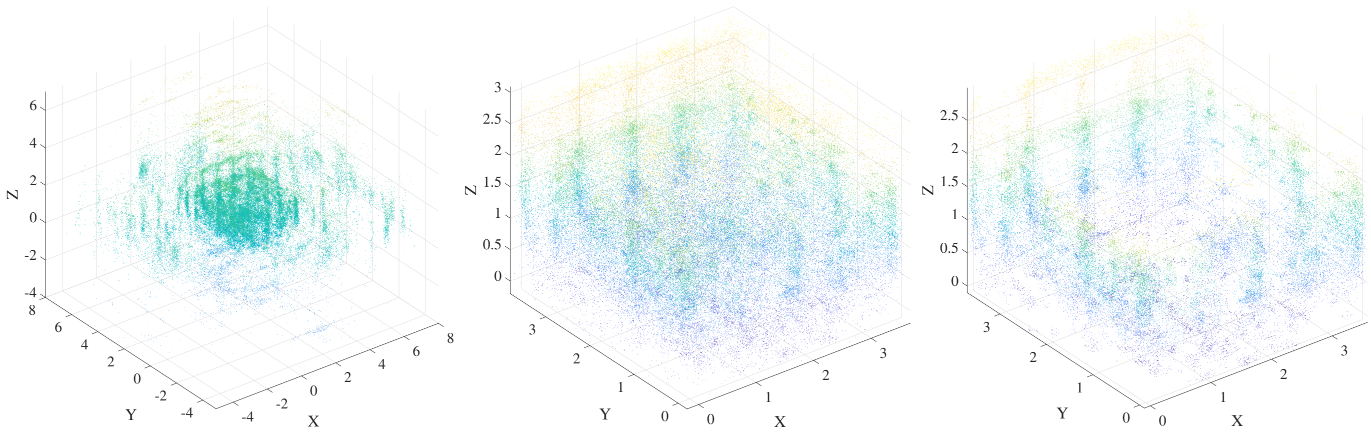
Figure 5 shows the block diagram of our offline 3D scanning and modeling process. It starts by mm-Wave scanning using the mm-Wave sensor and the ROS package. We save the measured point-clouds as a `.bag` file using *rosbag* tool [16]. We convert all the `.bag` files into `.pcd` files by writing a *batch shell script* which uses the `bag_to_pcd` command [17]. In the second part of our process, we remove some outlier points based on the sensor properties. For example, we remove all points which are too close to the sensor (which were the reflections from the stand), or outside a predefined horizontal or vertical angle of arrival.

As we know the exact location of the scanning sensor, we align the point-clouds captured at time t_{n+1} to those captured at time t_n by point-cloud transformation operations. When using a smart phone or real-time scanning, we would start with the first scan at time t_0, continue with the second scan at time t_1, assuming the movement of the smart phone is known, and by having access to the gyroscope information. This is counted as the partial knowledge of the coordinates shown in Fig. 5. But, in our current offline measurements, we know the exact coordinates. In our offline alignment process, we use two transformations as follows.

Rotation: We align all the point-cloud coordinates measured at angle α to the coordinates measured at angle 0°:

$$P_0 = \mathbf{R}.P_\alpha, \tag{1}$$

where $P_\alpha = [x_\alpha, y_\alpha, z_\alpha]^T$ denotes the coordinates of the point-cloud captured at angle α and they are rotated to achieve



(a) All point-clouds aligned (b) Point-cloud after inverse reflection (c) Point-cloud after removing outliers & denoising

Fig. 6. Point-clouds generated by the FMCW mm-Wave sensor and after point-cloud processing.

$P_0 = [x_0, y_0, z_0]^T$ which is the coordinates of the point-cloud at angle 0. $\mathbf{R}$ is the rotation matrix of $-\alpha$ around the Z axis given by:

$$\mathbf{R} = \begin{bmatrix} \cos(\alpha) & -\sin(\alpha) & 0 \\ \sin(\alpha) & \cos(\alpha) & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{2}$$

Transformation: During our measurements, we put the sensor in 5 different positions: XY, XZ, inverse XZ, YZ, and inverse YZ planes. We use the following four transformations to transform all the coordinates to the XY plane, respectively.

$$\mathbf{T_{XZ}} = \begin{bmatrix} 0 & -1 & 0 \\ 0 & 0 & -1 \\ 1 & 0 & 0 \end{bmatrix}, \quad \mathbf{T_{XZ,i}} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix},$$
$$\mathbf{T_{YZ}} = \begin{bmatrix} 0 & 0 & -1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix}, \quad \mathbf{T_{YZ,i}} = \begin{bmatrix} 0 & 0 & 1 \\ 0 & -1 & 0 \\ 1 & 0 & 0 \end{bmatrix}. \tag{3}$$

and multiply the relevant transformation matrix by the coordinates of each point-cloud. Among 82 locations of measurements, 53 measurements were done in XY plane, 5 in XZ, 9 in inverse XZ, 7 in YZ, and 8 in inverse YZ planes.

The next step in Fig. 5 is the registration of point-clouds. In real-time participatory scanning by the smart phones, this would include registering a moving point-cloud to a fixed one based on the iterative closest point (ICP) algorithm [18] (or similar approaches). However, in our current processing, as we already know the exact coordinates at this step, we simply merge the point-clouds.

After registration, a set of points in the registered point-clouds which move over time can be detected and extracted for further processing. These moving points can represent human, animals, cars, or other moving objects. In our current offline processing, we do not extract moving objects. Figure 6–a shows the resulting registered point-clouds from all 82 scans. In the central region of this figure, a cube can almost be seen around the origin which is the office of Fig. 4.

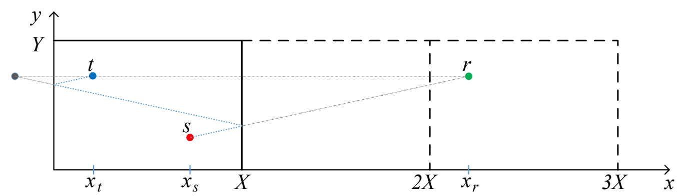
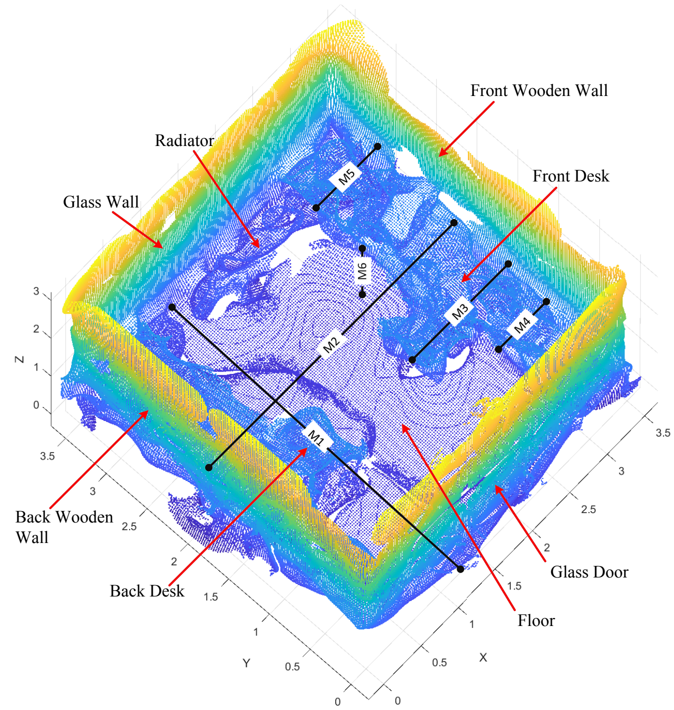


Fig. 7. Multiple reflections of target object t from side walls received by sensor s which shows it at coordinate r.

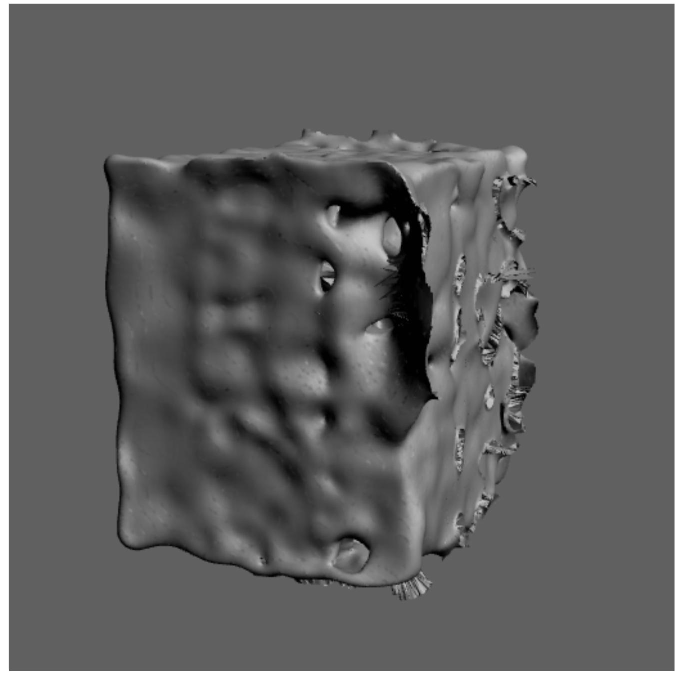
In [12] we report our observation on how mm-Wave follows Newton's law of light reflection in wireless communications signals. In our experiments with FMCW mm-Wave sensors, we also observe similar properties. Indeed, part of point-cloud points outside the office are reflections from the inside objects. These are shown outside the office region in Fig. 6–a. In particular, all points beyond $Y = 3.60$ m on the left side of the figure are located outside of the office which apparently incorrect, as there is nothing outside of our third floor office left-side windows. Figure 7 shows an example of double reflections by the side walls of the target object t received by sensor s. In this example, the sensor shows target t at r which is outside the office $\{(x, y)|x \in [0, X], y \in [0, Y]\}$. The next step in the processing of point-clouds in Fig. 5 is to distinguish such multiple reflections from direct reflections of an object. In this paper, we initially assumed all the points outside the office are incorrect reflections, and relocate them back to their correct locations. However, this is not accurate, as we observed that some points outside the office are actually correct reflections from outside objects. To relocate the points outside the office to their original locations, we use the following formula for dimension X and repeat it similarly for dimensions Y and Z:

$$x_t = \begin{cases} 2X\left(\lfloor \frac{x_r}{2X} \rfloor + 1\right) - x_r, & \text{if } (x_r \bmod 2X) > X \\ x_r - 2X\left(\lfloor \frac{x_r}{2X} \rfloor + 1\right), & \text{o.w.} \end{cases} \tag{4}$$

where $\lfloor . \rfloor$ denotes the floor function. In Eq. (4) we assume all the reflections come from the walls or ceiling or floor, which



(a) Top corner view



(b) 3D interactive object of the resulting grid model which can be viewed and rotated if you open this paper's PDF file using Adobe Reader.

Fig. 8. 3D mesh grid model built from point-cloud using RIMLS algorithm.

is not necessarily true. Indeed, we may have reflections from other objects. But, we apply this assumption for the sake of simplicity. Figure 6–b shows the resulting point-cloud after relocating the reflections to inside of the office. The windows frames are apparent on the left side of this figure.

The next step in the processing of point-clouds in Fig. 5 is to remove outliers within the free space of the office. These outliers are mainly from human bodies and some moving objects such as chairs. In the participatory scanning application, these outliers can be detected by continuous scanning and using techniques such as median filters to remove the points where they only appear in one or a few measurements. The points from reflections of fixed objects such as wall and windows appear in multiple scans and they will be kept. Other points can be removed. In our experiments, we used the knowledge of the physical environment dimensions to remove the outliers from the free space of the office. This information will be available after the first scan in the participatory scanning application. The resulting point-cloud after removing outliers is shown in Fig. 6–c.

We then reduce the noise of point-clouds using the open-source software Meshlab [19]. The next step is to detect and fill the gaps using interpolation techniques. We skip this step as our future research. However, in participatory scanning application, we expect that most of such gaps are filled by continuous scanning over time. Now, we downsample the point-cloud to enhance the performance and accuracy of the 3D model. We then compute the normals of the points of the

TABLE I
NUMBER OF POINTS IN THE POINT-CLOUD AFTER DIFFERENT PROCESSING STEPS

Scanning (Average)	Alignment	Removing Outliers	Denoising	Downsampling
37	111,484	55,550	49,514	4,000

point-cloud. Table I shows the number of points in the point-cloud after different stages of Fig. 5.

Finally, we compute the mesh grid using the robust implicit moving least squares (RIMLS) algorithm [20]. The resulting mesh grid is shown in Fig. 8–a. We remove the ceiling in this mesh to be able to see inside the model. The color used in this figure is dependent on the Z axis values. Walls, ground, and desks are apparent in this figure. The radiator on the left side of our office beside the window is also modeled partly. As we do not detect and fill the gaps, some of them remain in the final model. A 3D interactive object of this model is shown in Fig. 8–b and can be viewed and rotated if you open this paper's PDF file using Adobe Reader which is a free software.

It is worth noting that we made this model with only 82 mm-Wave scans, still precise enough to detect objects. However, in participatory scanning, we expect to have many more number of scans and the 3D models improve over time by having more scans from user devices at different angles and locations.

The sizes of the resulting model at different parts match the physical sizes in the office. Table II shows some measurements from the model depicted in Fig. 8 compared to the actual sizes

TABLE II
MEASUREMENT PRECISION IN THE FINAL 3D MODEL

	M1	M2	M3	M4	M5	M6
Actual Size (cm)	360	348	128	61	83	75
3D Model Size (cm)	360	85	125	55	75	75
Absolute Error (cm)	0	3	3	6	8	0

measured physically in the office. The average measurement error is about 3.3 cm for the numbers of this table which shows the high precision of the final model.

VII. CHALLENGES AND OPEN RESEARCH AREAS

In this section we discuss key research challenges that pertain to the use of smart phones to form 3D models of environment using mm-Wave technology.

Point-cloud registration is a known problem but in mm-Wave, we work with a small number of points compared to other sensors' generated point-clouds where they produce millions of points. The effectiveness of existing approaches is yet to be explored and even new methods may be needed to be designed that can work with large numbers of smaller point clouds.

Referring to Fig. 5, detecting and extracting moving objects, distinguishing reflected points from correctly located ones and finding their reflecting sources, aligning point-clouds with partial information from the environment, removing outliers, customized point-cloud downsampling, and detecting and filling gaps in point-clouds are also open problems.

Processing the big-data generated from the reflections collected by millions of smart devices and using them to update the 3D model or make it more precise is another main challenging problem. In particular, when we try to combine the information from different types of devices with different antenna patterns, with different precisions, and with different methods (e.g., some use IEEE 802.11ad signals and some other use FMCW or other short-range radar approaches).

Finally, privacy is a significant issue, not least due to revealing the interior layout of buildings. Certainly for commercial settings such as factories, such concerns can be overcome in the interest of business prerogatives.

VIII. CONCLUSION

Inspired by the concept of participatory sensing, we propose to use smart phones equipped with mm-Wave technology as a short-range radar sensor, enabling the construction and continuous update of 3D models for smart buildings and cites. We out;ine a system architecture model, identifying each of the key required components, along with experimental results to demonstrate feasibility of using mm-Wave for object detection. The idea of participatory sensing for 3D modeling is innovative, and raises numerous technical, privacy and ethical challenges. We identify several key technical topics that merit research. We hope that our paper will encourage technology researchers to get involved in dealing with the challenges in different layers of the system architecture, and others to examine participatory incentivisation and implications that will arise as future smartphones gain more extensive sensing capabilities.

REFERENCES

[1] R. E. Hattachi and J. Erfanian, "NGMN 5G Initiative White Paper," White Paper, NGMN Alliance, Feb. 2015. [Online]. Available: https://www.ngmn.org/5g-white-paper/5g-white-paper.html

[2] G. L. Charvat, *Small and Short-Range Radar Systems*. Boca Raton, FL, USA: CRC Press, 2014.

[3] D. Estrin, K. M. Chandy, R. M. Young, L. Smarr, A. Odlyzko, D. Clark, V. Reding, T. Ishida, S. Sharma, V. G. Cerf, U. Hlzle, L. A. Barroso, G. Mulligan, A. Hooke, and C. Elliott, "Participatory sensing: applications and architecture [internet predictions]," *IEEE Internet Computing*, vol. 14, no. 1, pp. 12–42, Jan 2010.

[4] M. Agiwal, A. Roy, and N. Saxena, "Next Generation 5G Wireless Networks: A Comprehensive Survey," *IEEE Communications Surveys Tutorials*, vol. 18, no. 3, pp. 1617–1655, 2016.

[5] (07 Sep 2017) Millimeter wave technology market 2017 global trend, segmentation and opportunities forecast to 2022. [Online]. Available: https://goo.gl/NTmS9h

[6] H. Ajorloo and M. Manzuri-Shalmani, "Modeling Beacon Period Length of the UWB and 60-GHz mmWave WPANs Based on ECMA-368 and ECMA-387 Standards," *Mobile Computing, IEEE Transactions on*, vol. 12, no. 6, pp. 1201–1213, June 2013.

[7] H. Ajorloo and M. T. Manzuri-Shalmani, "Throughput modeling of distributed reservation protocol," *IEEE Transactions on Mobile Computing*, vol. 15, no. 2, pp. 503–515, Feb 2016.

[8] J. Lien, N. Gillian, M. E. Karagozler, P. Amihood, C. Schwesig, E. Olson, H. Raja, and I. Poupyrev, "Soli: Ubiquitous gesture sensing with millimeter wave radar," *ACM Trans. Graph.*, vol. 35, no. 4, pp. 142:1–142:19, Jul. 2016.

[9] P. Kumari, J. Choi, N. Gonzlez-Prelcic, and R. W. Heath, "IEEE 802.11ad-based radar: An approach to joint vehicular communication-radar system," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 4, pp. 3012–3027, April 2018.

[10] D. Rex and S. Stoli, "Applications of 3d laser scanning in a production environment," M. Eng. thesis, Department of Product and Production Development, Chalmers University of Technology, Gothenburg, Sweden, 2014.

[11] S. B. Walsh and J. F. Hajjar, "Data processing of laser scans towards applications in structural engineering," Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, Tech. Rep. NSEL-015, Jun. 2009.

[12] H. Ajorloo, C. J. Sreenan, A. Loch, and J. Widmer, "On the feasibility of using IEEE 802.11ad mmWave for accurate object detection," in *The 34th ACM/SIGAPP Symposium On Applied Computing*, ser. SAC 2019. ACM, Apr. 2019, to be published.

[13] Texas Instruments. (2018) IWR1443: Single-chip 76-to-81GHz mmWave sensor integrating MCU and hardware accelerator. [Online]. Available: http://www.ti.com/product/IWR1443

[14] Open Source Robotics Foundation. (2018) RVIZ: 3D visualization tool for ROS. [Online]. Available: http://wiki.ros.org/rviz

[15] ——. (2018) ROS melodic morenia. [Online]. Available: http://wiki.ros.org/melodic/

[16] ——. (2018) The rosbag command-line tool. [Online]. Available: http://wiki.ros.org/rosbag/Commandline

[17] ——. (2018) PCL (point cloud library) ROS interface stack. [Online]. Available: http://wiki.ros.org/pcl_ros

[18] Y. Chen and G. Medioni, "Object modeling by registration of multiple range images," in *Proceedings. 1991 IEEE International Conference on Robotics and Automation*, April 1991, pp. 2724–2729 vol.3.

[19] P. Cignoni, M. Callieri, M. Corsini, M. Dellepiane, F. Ganovelli, and G. Ranzuglia, "MeshLab: an Open-Source Mesh Processing Tool," in *Eurographics Italian Chapter Conference*, V. Scarano, R. D. Chiara, and U. Erra, Eds. The Eurographics Association, 2008. [Online]. Available: http://www.meshlab.net/

[20] A. C. Öztireli, G. Guennebaud, and M. H. Gross, "Feature preserving point set surfaces based on non-linear kernel regression," *Computer Graphics Forum*, vol. 28, pp. 493–501, 2009.