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DOI
10.1007/978-3-031-34960-7_35

Publication date
2023

Document Version
Final published version

Published in
Bioinformatics and Biomedical Engineering - 10th International Work-Conference, IWBBIO 2023, Proceedings

Citation (APA)
Fioranelli, F., Guendel, R. G., Kruse, N. C., & Yarovoy, A. (2023). Radar Sensing in Healthcare: Challenges and Achievements in Human Activity Classification & Vital Signs Monitoring. In I. Rojas, O. Valenzuela, F. Rojas Ruiz, L. J. Herrera, & F. Ortuño (Eds.), *Bioinformatics and Biomedical Engineering - 10th International Work-Conference, IWBBIO 2023, Proceedings* (pp. 492-504). (Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics); Vol. 13920 LNBI). Springer. https://doi.org/10.1007/978-3-031-34960-7_35

Radar Sensing in Healthcare: Challenges and Achievements in Human Activity Classification & Vital Signs Monitoring

Francesco Fioranelli(✉), Ronny G. Guendel, Nicolas C. Kruse, and Alexander Yarovoy

Microwave Sensing Signals & Systems (MS3) Group, Department of Microelectronics, TU Delft, Delft, The Netherlands
f.fioranelli@tudelft.nl
https://radar.tudelft.nl/

Abstract. Driven by its contactless sensing capabilities and the lack of optical images being recorded, radar technology has been recently investigated in the context of human healthcare. This includes a broad range of applications, such as human activity classification, fall detection, gait and mobility analysis, and monitoring of vital signs such as respiration and heartbeat. In this paper, a review of notable achievements in these areas and open research challenges is provided, showing the potential of radar sensing for human healthcare and assisted living.

Keywords: Radar sensing · radar signal processing · machine learning · human activity classification · vital signs monitoring

1 Introduction

Radar is a technology conventionally associated to applications in the context of defence and security to monitor objects located at rather long distances. More recently, radar sensors are broadly used in autonomous vehicles for perception of multiple objects at distances of a few tens of meters, leveraging on their robustness to low-visibility weather and light conditions, if compared to cameras and lidar [1,2].

Besides these more conventional usages of radar, there is an increasing body of studies in the literature demonstrating the potential of radar sensing technologies in the context of human healthcare [3–6]. More specifically, these studies can be broadly categorized into three macro-areas:

– **Monitoring of vital signs**, typically including respiration rate and heartbeat. The principle behind this application is the capability of radar to detect the small physiological movements of the thorax and abdomen due to the respiration cycle and the beating of the heart [7–10]. More recently, research also investigates the usage of radar for other vital signs, such as the arterial pulse wave due to circulation in blood vessels [11], and the combination/fusion of multiple vital indicators to assess higher-level physiological functions, such as sleep stages and quality [12,13].

I. Rojas et al. (Eds.): IWBBIO 2023, LNBI 13920, pp. 492–504, 2023.
https://doi.org/10.1007/978-3-031-34960-7_35

– **Human activity recognition** (HAR), which can include the prompt detection of critical events such as falls, but also the more general pattern of usual activities an individual performs in their home environment. This can help assess the general fitness level and everyday physical activities, as well as the presence of outliers or anomalies that, if repeated, may be signs of physical and/or cognitive decline. In literature, HAR includes the monitoring and classification of movements and activities such as walking, sitting, standing, bending, crouching, carrying objects, and (quasi-)static postures while standing, sitting, or sleeping [14–21]. These basic motions can also be considered in combination to form higher-level activities, such as food preparation, cleaning, or personal hygiene, which constitute the expected daily activities of healthy subjects living independently at home.
– **Gait analysis and gait parameter extraction**, which can include the identification of impaired vs normal gait with radar sensing, such as episodes of frozen gait, limping, dragging feet, as well as the quantification from the radar signatures of gait-related parameters that would otherwise require a visit to a specialized gait laboratory [22–25]. The emphasis on gait analysis is related to the fact that more irregular and slower gait patterns may indicate a worsening in the individual's physical and cognitive health.

The aforementioned applications share the approach to use radar sensors and radar data to monitor physiological quantities and processes that can help form an overall '*health picture*' of subjects, and where needed spot critical events and/or anomalies. The assumption is that radar has the potential to be well-embedded in home environments, with the objective to unlock forms of proactive care and diagnostics that alert medical professional of possible problems before the subjects themselves succumb to illness, become bedridden, and may then require costly and invasive hospitalization.

One may ask: why radar as a sensor for healthcare applications and not others? The potential advantage of radar sensing comes from its non-intrusive, contactless capability to measure small and large movements and postures of subjects [3,26,27]. Hence, individuals do not need to carry, wear, or interact with electronic devices, which can provide an advantage for users' compliance, especially for those affected by cognitive impairments. Additionally, it is important to highlight that radar sensing does not generate optical images or videos of subjects and their private environments at home; this can provide an advantage in terms of perceived privacy infringement and help users' acceptance.

It is important to highlight that the word 'radar' in the context of the aforementioned healthcare applications includes in reality many different types of hardware architectures and operational processing parameters. An in-depth discussion on these aspects goes beyond the scope of this paper and the readers are referred to review papers such as [3,5,15], amongst others.

In the remainder of this article, a brief overview of the basic principles of radar signal processing in healthcare applications is provided in Sect. 2, with representative results and outstanding research challenges discussed in Sect. 3. While the discussion in this section remains at a general high level, additional technical details for each challenge are presented in the provided references. Finally, a brief conclusion is drawn in Sect. 4.

2 Principles of Radar Signal Processing in Healthcare

The working principle of any radar system is based on transmitting and receiving sequences of electromagnetic waves, whose amplitude and/or frequency is modulated according to suitable waveform patterns. These waveforms are transmitted into the environment, propagate in open-air, and are reflected back to the radar by objects present in the area under test. By digitizing these received backscattered waveforms, one can extract information on the objects of interest. For a parallel in terms of working principles, one can make a comparison with echolocation in animals, such as bats or dolphins navigating in their living environments and hunting for prey. However, they utilize acoustic waves (i.e., ultrasound) rather than electromagnetic waves as it is the case for man-made radar systems.

The basic architecture of a radar system comprises of a transmitter and receiver block to generate, condition, and receive electromagnetic waves, antennas that act as the transducers to/from open-air propagation, and a digital block to process and store the radar data with suitable signal processing techniques, briefly outlined later in this section. While a detailed discussion on radar architectures goes beyond the scope of this paper, two main families of radar architectures have been mainly used in the literature for healthcare applications [28]. One includes the so-called CW (Continuous Wave) radars, with simpler architectures and processing capable of measuring the velocity of moving objects (e.g., the bulk walking velocity of a person) but not their location. The other family includes radars whose waveform is modulated in frequency to occupy a certain band (either pulsed Ultra Wide Band, UWB, radars, or Frequency Modulated Continuous Wave, FMCW, radars); the notable implication is that with these radars the distance of objects can also be measured together with their velocity. Recently, radars with multiple transmitters/receivers (MIMO, multiple input multiple output radars) are used to also estimate the angular position of objects of interest in azimuth and/or elevation.

For all the applications mentioned in Sect. 1, the detection in space and the characterisation over time of the movements of body parts of the subjects are crucial. This includes the very minute movements of chest and internal organs for vital signs monitoring, as well as larger-scale movements of limbs and the whole body for activity classification and fall detection. Hence, the typical signal processing operations on radar data for healthcare aim to characterise the subject's posture and movements in three domains: *range*, as the physical distance at which the person and their body parts are located with respect to the radar; *time*, intended as the evolution of the position of the person or their body parts; and *velocity*, as the speed and regularity at which such changes over time happen. As mentioned before, with modern MIMO radars the *angular* position can also be estimated, which can be very important to separate different subjects present together in the field of view of the radar, or even differentiate body parts of a single subject.

It is important to highlight that radar systems measure velocities via the Doppler effect, i.e. the change/shift in the frequency of the received radar waveforms induced by the movement of objects. As a simple example, we can think of a person sitting and facing a radar while breathing, hence with chest moving back and forth during the respiration cycle. This will induce a positive Doppler shift when the chest is moving towards the radar as more electromagnetic wavefronts will be scattered back to the radar in a given time unit; on the contrary, the Doppler shift will be negative when the chest is moving away from the radar. Therefore, measuring velocity with radar implies measuring the frequency components/modulations of the received radar waveforms. This can be accomplished using Fourier analysis, as done in many other fields of engineering (e.g., acoustics, mechanical vibrations), and specifically using the Fast Fourier Transform algorithm (FFT).

Figure 1 shows a simplified signal processing chain for an example of data where a person was walking back and forth in front of a radar system.

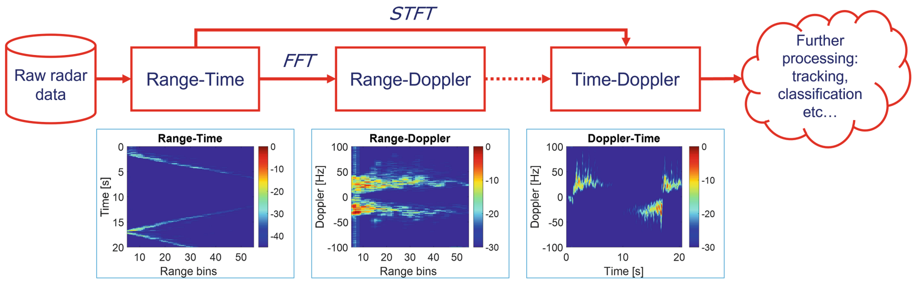

Fig. 1. Simplified signal processing chain for radar data, with examples of Range-Time, Range-Doppler, and Doppler-Time patterns for a person walking back and forth in front of a radar operating in the X-frequency band.

The processing chain starts from raw radar data, i.e., the temporal sequence of the digitized samples of the received radar waveforms. Such data are normally structured into a matrix, in which each radar waveform will include range bins, i.e., digitized samples along one dimension of the matrix that are related to the physical distance of possible targets; the sequence of waveforms along the other dimension of the matrix can be associated to the concept of physical time. This matrix is often referred to as *Range-Time-Intensity (RTI)* matrix. As the person was walking back and forth in front of the radar, a diagonal zig-zag pattern is visible in the RTI image of Fig. 1, with the 'signature' of the person moving first away from the radar (i.e., the range bin index increases over time), and then back towards the radar (with the range bin indexes decreasing over time). As discussed, an FFT operation is used to estimate the velocity of objects of interest via the Doppler effect. By applying this FFT across the sequence of radar waveforms, i.e., the time dimension of the RTI matrix, a new matrix is generated, the *Range-Doppler (RD)* matrix. An example of RD is the middle picture of Fig. 1, with both positive and negative Doppler contributions due to the person walking towards the radar (positive Doppler) and away (negative Doppler) in the considered unit of time. The RD matrix characterizes the overall velocity components present across the (relatively) long observation time of the whole measurement, but it is difficult to map the precise time when each movement happened. For this, a different processing approach is needed, the Short Time Fourier Transform (STFT). This approach applies multiple FFT operations on the data across shorter, possibly overlapped time windows. Each FFT produces one vector with the dimensions of Doppler/velocity, and by placing such vectors one next to each other in their temporal order, a Doppler vs time 2D matrix is generated, the so-called '*spectrogram*'. In Fig. 1, positive and negative Doppler contributions are visible in the pattern of the spectrogram. Each contribution has a central, more intense signature denoted by red and yellow colour due to the movement of the torso and main body, with additional less intense streaks around the main signature denoted by light blue colour and physically attributable to the limbs. This is a typical pattern for a person walking, with the bulk movement contribution due to the torso and main body moving, and additional oscillating movements of the arms and legs. As these movements from the limbs produce smaller, additional Doppler frequencies around the main bulk Doppler, they are called '*micro-Doppler*' in the radar literature [29,30].

The importance of micro-Doppler in the context of healthcare applications comes from the fact that each specific activity, movement, or type of gait will exhibit its specific micro-Doppler pattern or signature. Thus, to achieve human activity classification it is possible to use machine learning techniques to 'teach' algorithms to recognize these patterns as well as to utilize this information to support tracking multiple people in the scene. A selection of representative results is reported in the following section.

3 Representative Results and Open Challenges

Representative results and open challenges from the literature in the context of healthcare applications of radar-based sensing are discussed in this section.

1. *What is the most suitable representation and format of the radar data to characterize or infer healthcare-related information?* Conventionally, most studies use Doppler-time representations generated by the STFT, as explained in the previous section. This allows to study the temporal patterns of Doppler modulations due to the different body parts moving [14,29]. As Doppler modulations are directly related to the velocity of the body parts, algorithms operating on this data representation can characterize human movements, from the small ones related to vital signs, to the larger movements due to gait and/or complex activities. These micro-Doppler patterns can then be exploited as input to classification pipelines based on machine learning to

learn the relevant information, including neural networks with various architectures, or more conventional classifiers such as Support Vector Machines (SVM) [5,31].

A couple of notable examples of micro-Doppler signatures are shown in this section. Figure 2 shows the spectrograms of six human activities recorded with a radar operating at 5.8 GHz, the same frequency as Wi-Fi networks commonly used indoors. The six activities included sitting on a chair, standing up from a chair, bending to tie shoelaces, bending to pick up a pen, crouching to the floor and standing back up, and finally a simulated frontal fall. One can see that each activity has a distinct pattern of positive/negative Doppler components over time, that can be potentially learnt by algorithms for automatic classification.

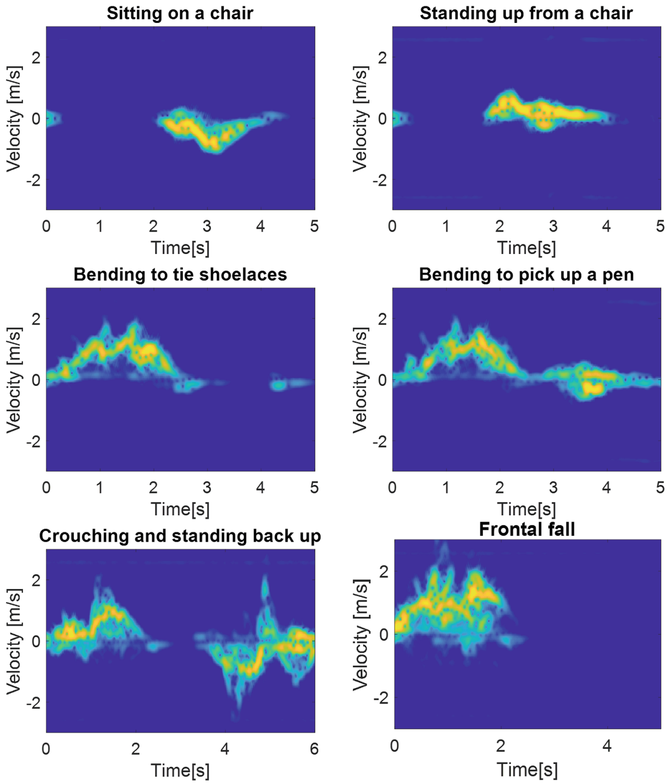

Fig. 2. Example of six Velocity-Time (spectrogram) patterns for six human activities performed by the same volunteer and recorded by a 5.8 GHz radar. It should be noted that these activities were performed in a simplified manner in isolation, with the volunteer starting and ending the movement in a stationary posture.

Figure 3 shows another example of a spectrogram for vital signs monitoring, specifically respiration. In this case, a volunteer was sitting in front of a UWB radar operating in the X-frequency band and performing different respiration patterns on purpose, namely normal breathing, holding breath, deep exhalation, and simulated fast breathing. The different breathing patterns can be easily recognized 'by eye' in the spectrogram, and its envelope can be used to estimate the breathing rate in normal, semi-stationary conditions, as well as the presence of anomalous or irregular patterns.

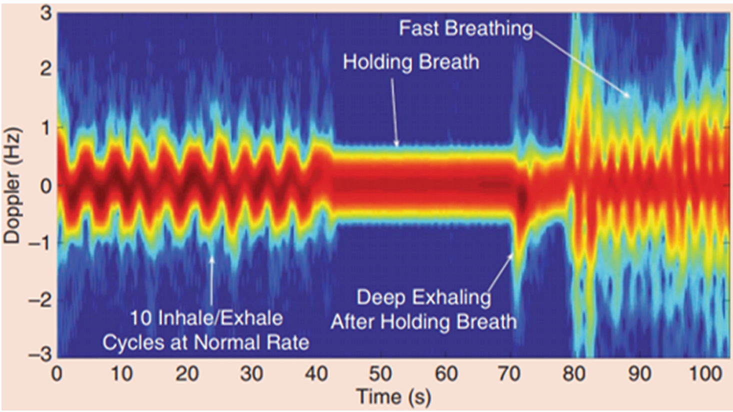

Fig. 3. Spectrogram for a person sitting on a chair at about 60 cm from the radar and simulating different respiration patterns. Specifically, the subject was asked to perform 10 cycles of normal respiration followed by a long period of holding breath and then fast breathing. The radar used for this test worked in the X-frequency band.

However, beyond these examples of 2D spectrograms, radar data can take very diverse representation formats combining into a tensor the dimensions of range or distance, Doppler or velocity, angular information in azimuth and/or elevation, and time. Furthermore, radar data are typically complex-valued, unlike optical images. Hence, they can be represented with their real & imaginary values or magnitude & phase [32–35].

An outstanding research question remains the identification of the most suitable radar data format for a given application and a desired classification algorithm. This also includes the possibility of fusing different data representations and their salient features to maximize performances, and the robustness of any proposed approach and choice to the diversity of environments and individual movement patterns.

2. *How to analyze radar data for HAR that present continuous and diverse sequences of activities?* Studies in radar-based HAR began with the analysis of separated motions and actions performed and collected in isolation, as if they were sort of 'snapshots', whereas in reality human activities are performed continuously. They appear as a seamless sequence, with duration and

transitions between the different motions not being predefined. Furthermore, such sequences are diverse, in the sense that they may include a mixture of full-body actions (e.g., walking, vacuum cleaning the room), actions involving movements of limbs while remaining on the same location (e.g., sitting, picking up an object from the floor), and broadly stationary intervals with small or no movements (e.g., reading a book while sitting, watching TV). These sequences are also highly diverse depending on the subject's gender, age, physical condition, and environmental constraints from surrounding furniture and objects [36–38]. This undoubtedly adds additional complexity in the task of learning the salient information related to the activities being performed.

As a visual example of such diversity, Fig. 4 shows six velocity/time patterns (spectrograms) for the same continuous sequence of five activities performed by six different subjects. Notable aspects are: i) how diverse the signatures appear for the different subjects, despite the sequences being nominally labelled as exactly the same activity-wise; this would set an interesting classification challenge to train automatic algorithms with these diverse data with the same nominal set of labels; ii) how challenging it can be to clearly identify the transitions in order to segment the different activities, i.e., where one stops and a new one starts [39].

For this reason, the formulation of approaches for segmenting, interpreting, and classifying these continuous sequences of human activities that may also include data portions for vital signs extraction and gait parameters analysis is an open research challenge.

3. *How to effectively and wisely use deep learning techniques for radar-based healthcare applications?* Similar to plenty of other disciplines in science and engineering, deep learning approaches are increasingly used for radar data, including for healthcare applications discussed in this paper [5, 31].

   As a typical example of this trend, neural network architectures have been proven as an effective tool for the classification of patterns in radar signatures for HAR. These architectures include Convolutional Neural Networks (CNNs) and recurrent networks such as Long-Short Term Memory (LSTM) and Gated Recurrent Units (GRUs), as well as their combinations, to classify bi-dimensional and temporal patterns in the radar data. Additional architectural choices include Auto-Encoders (AEs) to perform unsupervised feature extraction; Generative Adversarial Networks (GANs) to generate synthetic radar data to complement experimental datasets; and attention-based Transformer architectures [5, 40–45]. However, while deep learning techniques have clear advantages in their ability to learn patterns and features that cannot be easily captured with conventional approaches, their usage also poses practical challenges to address. First, the need to have datasets that are large (in order to train deep architectures with many hyperparameters), well labelled (in order to use supervised learning approaches), and representative (in order to capture enough diverse subjects and environments with their specific multipath phenomena and clutter signatures, so that the classification networks can generalise well to new people and situations).

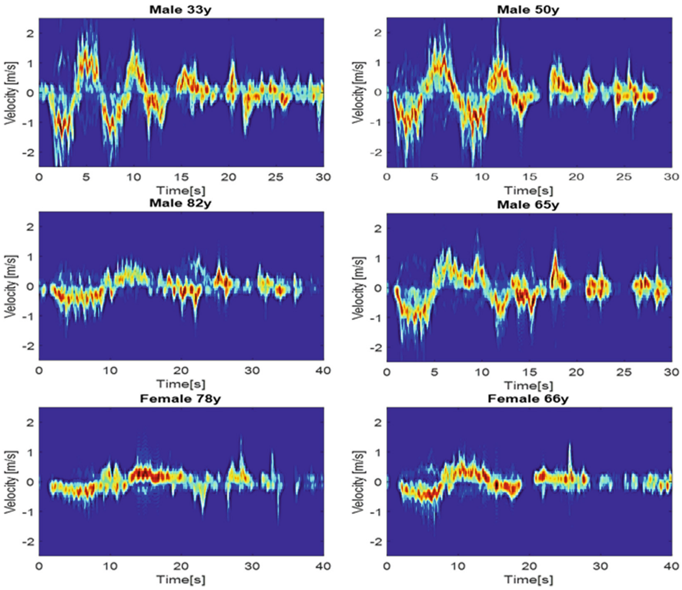

Fig. 4. Radar spectrograms of the same sequence of five daily activities (namely walking back and forth, sitting on a chair, standing up, bending down and coming back up, and drinking from a cup) performed by 6 subjects of different age, gender, physical conditions. The radar operated at 5.8 GHz carrier frequency.

To the best of our knowledge, a dataset with the aforementioned desired characteristics that is publicly shared and accepted by the radar research community as 'the benchmark dataset' does not exist at the moment. However, some steps have been taken to address this challenge of data scarcity by increasingly sharing datasets, as in the several examples reported in [46], or the relatively large dataset our research groups shared in [47,48]. While these activities are still fragmented at the level of the initiative of each individual research group, they still represent a positive sign to help further develop deep learning techniques in this context. With established datasets, one would be able to perform a deep, comprehensive statistical study to compare the different relevant techniques on the same data, scenario, and radar system.

Another important challenge related to the utilization of deep learning techniques in the context of radar-based healthcare comes from the often difficult interpretation and explanation of the decisions made by the neural networks and their rationale. The importance of explainable approaches combined with the aforementioned issue of data scarcity can discourage the usage of deep data-driven end-to-end architectures, even if they have proved very effective in other research domains such as image and audio processing. On the other hand, this challenge can be turned into an opportunity to incorporate physics-based information into the networks. This can leverage both aspects of electromagnetic scattering & propagation, as well as human kinematics, since both are phenomena that can be well characterized a priori with models and equations, which do not need to be learnt from the data since they are well understood from physics and human physiology.

4. *How should a classification algorithm manage the situation of receiving unforeseen data?* This is the so called "open-set" problem [49,50], for which a typical example in the context of radar-based HAR is the occurrence of a movement or activity pattern that was not present in the training data. A closely related aspect to account for, is the fact that many critical, potentially life-threatening activities that a classifier should always recognize (e.g., fall instances) are in a sense part of these unexpected, unforeseen data. This is because they cannot be instigated on purpose to generate representative training data, thus leading to datasets that can be potentially unsuitable to train for robust performances and to deal with the actual critical cases appearing in the test set. The development of robust techniques to deal with these cases remains an open research question.
5. *How can radar be integrated into a wider suite of sensors for healthcare?* For healthcare applications such as those presented in this work, it is expected that the combination of data from multiple sensors located in future smart home environments will yield better performances than using each sensor in isolation. This is because each technology has its own distinctive advantages and disadvantages [26,27], thus a proper synergy in a multimodal fashion can be beneficial. Radar is no exception to this idea, and its acceptance in the perhaps not immediately obvious context of healthcare can be facilitated by its usage together with other sensors that are more familiar to the end-users. An open research challenge for this is the formulation of algorithms for data processing and sensor management to combine information from different, heterogeneous sensors. Incidentally, these approaches can also include networks of multiple radar sensors [24,47], either with similar radars looking at the scene under test from different aspect angles, or with radars operating at different carrier frequencies to 'perceive' complementary characteristics of the objects of interest due to the different probing waveforms.

4 Conclusions

This paper provides a detailed overview of recent developments in the field of radar sensing for healthcare, along with the associated research challenges. Notably, radar technology has allowed contactless monitoring of vital signs such as respiration and heartbeat, as well as the classification of human activity patterns, including fall detection and gait monitoring/analysis through parameter extraction. Nevertheless, research challenges remain in radar signal processing and machine learning including the most modern deep learning techniques for these applications. Specifically, researchers are investigating the most promising approaches for extracting essential information from radar data and formulating effective, robust, and scalable classification algorithms for diverse subjects and activities in indoor environments.

Acknowledgments. The authors thank the many students and collaborators for their contributions to the data collection and processing, especially Dr J. Le Kernec at the University of Glasgow. Financial support from UK EPSRC (grant EP/R041679/1 *INSHEP*), Dutch Research Council NWO (grant NWO KLEIN *RAD-ART*), and Dutch Government Sector Plan is also acknowledged.

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