Radar sensing for human healthcare: challenges and results

(1)Francesco Fioranelli, (2)Julien Le Kernec

(1)Microwave Sensing Signal and Systems (MS3), Department of Microelectronics, TU Delft, Delft, The Netherlands
(2)James Watt School of Engineering, University of Glasgow, Glasgow, UK
F.Fioranelli@tudelft.nl

Abstract—**In this paper, radar sensing in the domain of human healthcare is discussed, specifically looking at the typical applications of human activity classification (including fall detection), gait analysis and gait parameters extraction, and vital signs monitoring such as respiration and heartbeat. A brief overview of open research challenges and trends in this domain are provided, showing that radar sensors and sensing can play a significant role in the domain of human healthcare.**

Keywords—radar, radar signal processing, machine learning, human activity classification.

I. INTRODUCTION

While radar is a technology traditionally associated to defence applications, and more recently to autonomous vehicles, research in radar for healthcare scenarios has attracted considerable interest and achieved significant progress in recent years [1-4]. Specifically, applications of radar in the healthcare domain can be categorised in three macro-areas:

- Human activity recognition (HAR), including fall detection, which was originally one of the first applications of radar in the domain of healthcare. HAR include monitoring and classifying activities and movements of human subjects in their home environments, including but not limited to walking, sitting, standing, bending, crouching, carrying objects [5-8]. These primitive movements can also be combined in higher-level activities, such as food preparation, cleaning, or personal hygiene, that represent expected routine activities of healthy subjects living independently at home.

- Gait analysis, whereby radar signatures are used to identify normal and impaired gait, such as episodes of limping, dragging feet, and frozen gait [9-11]. This focus on gait is based on the evidence that slower and more irregular gait patterns can be correlated to worsening health conditions, both physically and mentally.

- Vitals signs, typically including respiration and heartbeat as the small physiological movements traditionally studied with radar sensing [12]. Recent research is also looking at other vital signs, such as the pulse due to blood circulation [13], and combination of these vital signs to for example check sleep stages and quality [14].

All these applications have in common the idea of using radar sensors and data to monitor physiological quantities and phenomena that contribute to portray an overall "health picture" of the subjects and to spot anomalies and/or critical events. This with the potential to be performed in home environments, unlocking proactive care before the subjects become too ill and require hospitalisation.

But why radar as a sensor for healthcare? The advantages of radar sensing comes from its contactless and non-intrusive nature. The subjects do not need to wear or carry or interact with devices, which can be an advantage for users' compliance, especially for those affected by cognitive impairments. Radar sensors do not generate plain images or videos of people and their environments, which can be an advantage for users' acceptance in term of privacy.

In the remainder of this article, a brief overview of open research challenges and trends in the domain of radar for healthcare are discussed (section II), and some conclusions drawn (section III).

II. SOME CHALLENGES AND RESULTS

Open challenges common to the three applications cited in section I for radar in healthcare are discussed here.

1. Investigating the *most suitable format and domain of the radar data* to describe and infer healthcare-related information. Originally the most significant data format was the Doppler-time representation, originating from the application of time-frequency distributions to the radar data, typically Short Time Fourier Transform (STFT) and its absolute value, the spectrogram. This enables to characterise the so-called "micro-Doppler signatures", the patterns of Doppler modulations in the radar echoes caused by the movement of body parts of a human subject [5, 15]. As Doppler frequency is directly related to the velocity of the moving body parts, understanding and classifying micro-Doppler signatures allows to describe human movements, from the large movements due to gait and complex activities, to the small movements associated to vital signs (with examples shown in Fig. 1 and 2 in this section). These micro-Doppler signatures are then used as input to classification pipelines based on machine learning to extract the relevant information, including neural networks with various architectures [3]. However, radar data can span a variety of formats beyond simple 2D spectrograms, across the multidimensional space of range/distance, Doppler/velocity, time, and angular information in elevation or azimuth. Additionally, unlike optical images, radar data are complex, hence representable in real-imaginary or absolute value & phase planes [16-18]. Identifying the most suitable radar data representation for the specific classification problem and to be paired with specific classification algorithm or neural network remains an interesting open question.

2. While research in radar-based HAR started with the investigation of separated activities and movements performed and recorded in isolation, human kinematic is in reality continuous. Activities appear as *a seamless continuous sequence, where transitions and durations between different movements are not pre-defined*. These sequences are diverse, in a sense that they include a mix of full-body movements, limb-only movements, walking gait, and stationary intervals, and they are also highly dependent on the subject, for example their physical conditions, gender, age, constraints from surrounding objects and furniture [19-21].

    Fig. 1 shows six radar spectrograms (velocity vs time 2D patterns) for the same continuous sequence of 5 activities performed by 6 different subjects. One can see a) the diversity of the signatures from subject to subject despite the sequences being labelled activity-wise as the same, which would pose an interesting challenge to train classification algorithms; and b) the difficulty to identify clearly where separate activities start and stop at the transitions. Approaching the segmentation and interpretation of these continuous sequences of human activities, which also include gait and vitals, is a current challenge.

3. As in many other fields of science and engineering, *deep learning techniques* are increasingly used in radar, including the healthcare applications discussed in this paper [3]. Specifically, neural networks used to classify patterns in the radar signatures and spot possible anomalies are the main example. Typical network architectures include Convolutional Neural Networks (CNNs) and recurrent networks such as Long-Short Term Memory (LSTM) and Gated Recurrent Units (GRUs) to

classify bi-dimensional and temporal patterns in the radar data. Other architectures include Auto-Encoders (AEs) to perform unsupervised feature extraction and Generative Adversarial Networks (GANs) to generate synthetic radar data to complement experimental datasets [3, 22-23].

However, using deep learning techniques emphasised practical challenges to address. First the need of datasets that are large (to train deep architectures with many hyperparameters), labelled (to use supervised learning approaches), and representative (including enough diverse subjects and environments with their clutter and multipath phenomena so that the classification algorithm can generalise well to new people and situations). While some steps have been made by the radar research community to share datasets and generate a common benchmark as done for image or audio processing (see some shared datasets in [24-26] for example), these initiatives are still too fragmented to address the challenge of data scarcity.

Another challenge related to using neural networks in this context comes from the difficulty in interpreting and explaining the reasoning and decisions made by the classification algorithms. The drive for explainable algorithms and the issue of data scarcity appear to discourage the usage of deep, data-driven end-to-end architectures despite their proven capabilities in other research domains. Yet, this challenge can turn into an opportunity by incorporating mode/physics-based information into the classification algorithm pipeline. Both electromagnetic propagation/scattering and human kinematics are not arbitrary phenomena but can be well described by models and a-priori information that do not need to be learnt from scratch by sifting through a very large dataset.
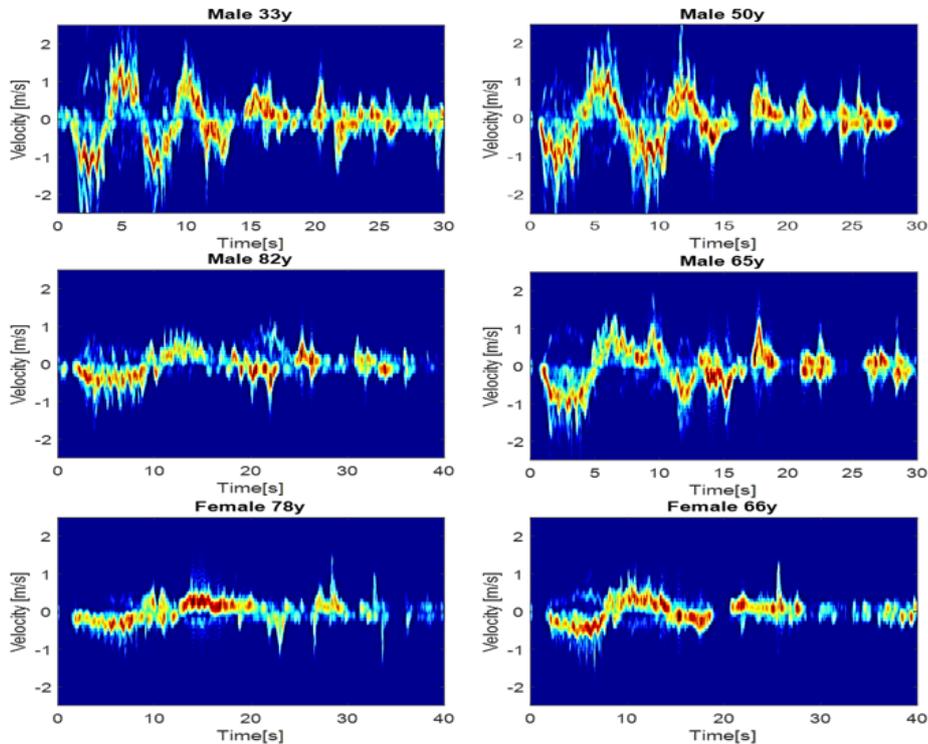

Fig. 1. Radar spectrograms of the same sequence of daily activities (namely walking back and forth, sitting on a chair, standing up, bending down and coming back up, and drinking from a cup) performed by six subjects of different age, gender, and physical conditions. The radar used operated in the C-band (carrier frequency of 5.8 GHz).
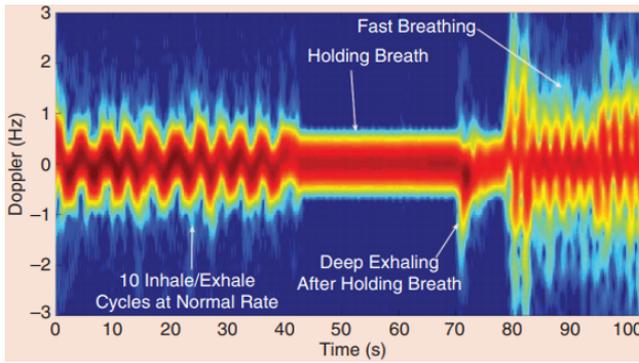
Fig. 2. Inspired from [1]: Radar spectrogram for a person sitting on a chair at approximately 60 cm from the radar and simulating different respiration rates and patterns. Specifically, the subject was asked to perform 10 cycles of normal respiration followed by a long period of holding breath and then fast, accelerated breathing. The radar used for this tes operated in the X-band, within the Ultra Wide Band (UWB) spectral region.

4. Managing the *"open-set" problem* [27] consisting in the presence of an activity or movement that was not present in the training data for the classification algorithm. How should a good classification algorithm react to this unforeseen situation? In part related to this is also the fact that many critical events or activities the classifier should always identify (e.g. fall events) are rare and cannot be instigated on purpose to generate training data, which leads to training datasets unbalanced and potentially unsuitable.

5. Considering radar as "*a sensor in a wider suite of sensors*". In healthcare applications as those discussed in this paper, it is very likely that better performances can be achieved by combining in a multimodal fashion radar and other sensors in future smart home environments. Each sensing technology comes with distinctive advantages and disadvantages, and their synergy, where possible, can produce a better result than the individual usage of each sensor. As a very simplistic example, Fig. 3 shows classification accuracy obtained to classify 6 different activities for a dataset with 15 participants as test subjects, when radar information is combined together with that from a wrist-worn wearable sensor. It can be seen that adding radar data to the pool of information to tackle the HAR problem enables to increase the classification accuracy and reduce the variability of performances for each individual participant. The challenge to address is to formulate algorithms for information combination and fusion across the diverse sensors, which incidentally can also include different models of radar sensors (for example radar operating at very different carrier frequencies, which will "see" the scene under test very differently due to the different scattering mechanisms at play as a function of the wavelength).
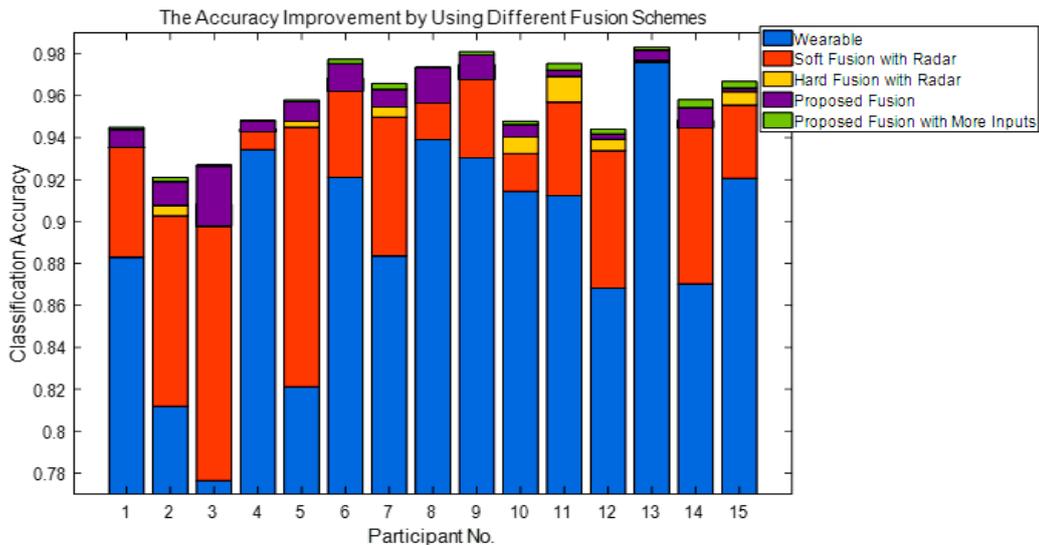

Fig. 3. From [21]: Accuracy obtained by Bi-LSTM network classifier for continuous sequences of human activities using multimodal inputs, namely data from wrist-worn wearable (blue) fused with descriptors derived from radar spectrograms (different colours). The results are presented for each participant considered as unseen test subject to validate the classifier's performances (Leave One Person Out validation approach)

III. Conclusions

In this paper, a short overview of challenges in the domain of radar sensing for human healthcare is discussed. Specific applications include the detection and classification of human activities, including critical events such as falls, the analysis of gait patterns and related parameters, and the contactless monitoring of vital signs such as respiration and heartbeat. The challenges are common to these applications and broadly span both the radar signal processing domain of how to process the data in the best way for these applications, and the machine learning domain of how to infer information from the radar data and how to design classification algorithms that are robust and generalizable across large, diverse groups of subjects and environments with their clutter and multipath.

REFERENCES

[1] F. Fioranelli, J. Le Kernec and S. A. Shah, "Radar for Health Care: Recognizing Human Activities and Monitoring Vital Signs," in IEEE Potentials, vol. 38, no. 4, pp. 16-23, July-Aug. 2019.

[2] J. Le Kernec et al., "Radar Signal Processing for Sensing in Assisted Living: The Challenges Associated With Real-Time Implementation of Emerging Algorithms," in IEEE Signal Processing Magazine, vol. 36, no. 4, pp. 29-41, July 2019.

[3] S. Z. Gurbuz and M. G. Amin, "Radar-Based Human-Motion Recognition With Deep Learning: Promising Applications for Indoor Monitoring," in IEEE Signal Processing Magazine, vol. 36, no. 4, pp. 16-28, July 2019.

[4] E. Cippitelli, F. Fioranelli, E. Gambi, and S. Spinsante, "Radar and RGB-depth sensors for fall detection: A review," IEEE Sensors J., vol. 17, no. 12, pp. 3585–3604, June 2017.

[5] Y. Kim and H. Ling, "Human Activity Classification Based on Micro-Doppler Signatures Using a Support Vector Machine," in IEEE Transactions on Geoscience and Remote Sensing, vol. 47, no. 5, pp. 1328-1337, May 2009

[6] M. G. Amin, Y. D. Zhang, F. Ahmad, and K. C. D. Ho, "Radar signal processing for elderly fall detection: The future for in-home monitoring," IEEE Signal Process. Mag., vol. 33, no. 2, pp. 71–80, Mar. 2016.

[7] X. Li, Y. He, F. Fioranelli and X. Jing, "Semisupervised Human Activity Recognition With Radar Micro-Doppler Signatures," in IEEE Transactions on Geoscience and Remote Sensing, 2021.

[8] A. Gorji, H. -U. -R. Khalid, A. Bourdoux and H. Sahli, "On the Generalization and Reliability of Single Radar-Based Human Activity Recognition," in IEEE Access, vol. 9, pp. 85334-85349, 2021.

[9] F. Wang, M. Skubic, M. Rantz and P. E. Cuddihy, "Quantitative Gait Measurement With Pulse-Doppler Radar for Passive In-Home Gait Assessment," in IEEE Transactions on Biomedical Engineering, vol. 61, no. 9, pp. 2434-2443, Sept. 2014.

[10] A. K. Seifert, M. G. Amin and A. M. Zoubir, "Toward Unobtrusive In-Home Gait Analysis Based on Radar Micro-Doppler Signatures," in IEEE Transactions on Biomedical Engineering, vol. 66, no. 9, pp. 2629-2640, Sept. 2019.

[11] H. Li, A. Mehul, J. Le Kernec, S. Z. Gurbuz and F. Fioranelli, "Sequential Human Gait Classification With Distributed Radar Sensor Fusion," in IEEE Sensors Journal, vol. 21, no. 6, pp. 7590-7603, 15 March15, 2021.

[12] C. Li, P. Mak, R. Gómez-García, and Y. Chen, "Guest editorial: Wireless sensing circuits and systems for healthcare and biomedical applications," IEEE J. Emerg. Sel. Topics Circuits Syst., vol. 8, no. 2, pp. 161–164, June 2018.

[13] Y. Oyamada, T. Koshisaka and T. Sakamoto, "Experimental Demonstration of Accurate Noncontact Measurement of Arterial Pulse Wave Displacements Using 79-GHz Array Radar," in IEEE Sensors Journal, vol. 21, no. 7, pp. 9128-9137, April 2021.

[14] H. Hong et al., "Microwave Sensing and Sleep: Noncontact Sleep-Monitoring Technology With Microwave Biomedical Radar," in IEEE Microwave Magazine, vol. 20, no. 8, pp. 18-29, Aug. 2019.

[15] F. Fioranelli, H. Griffiths, M. Ritchie and A. Balleri (Eds.), *Micro-Doppler Radar and its Applications*, The IET Press, 2020.

[16] R. G. Guendel, F. Fioranelli and A. Yarovoy, "Phase-Based Classification for Arm Gesture and Gross-Motor Activities Using Histogram of Oriented Gradients," in IEEE Sensors Journal, vol. 21, no. 6, pp. 7918-7927, March 2021.

[17] T. Scarnati and B. Lewis, "Complex-Valued Neural Networks for Synthetic Aperture Radar Image Classification," 2021 IEEE Radar Conference (RadarConf21), 2021, pp. 1-6.

[18] D. A. Brooks, O. Schwander, F. Barbaresco, J. Schneider and M. Cord, "Complex-valued neural networks for fully-temporal micro-Doppler classification," 2019 20th International Radar Symposium (IRS), 2019, pp. 1-10.

[19] A. Shrestha, H. Li, J. Le Kernec and F. Fioranelli, "Continuous Human Activity Classification From FMCW Radar With Bi-LSTM Networks," in IEEE Sensors Journal, vol. 20, no. 22, pp. 13607-13619, 15 Nov.15, 2020.

[20] P. Chen et al., "Multi-view Real-time Human Motion Recognition Based on Ensemble Learning," in IEEE Sensors Journal, 2021.

[21] H. Li, A. Shrestha, H. Heidari, J. Le Kernec and F. Fioranelli, "Bi-LSTM Network for Multimodal Continuous Human Activity Recognition and Fall Detection," in IEEE Sensors Journal, vol. 20, no. 3, pp. 1191-1201, Feb 2020.

[22] M. S. Seyfioğlu, A. M. Özbayoğlu and S. Z. Gürbüz, "Deep convolutional autoencoder for radar-based classification of similar aided and unaided human activities," in IEEE Transactions on Aerospace and Electronic Systems, vol. 54, no. 4, pp. 1709-1723, Aug. 2018.

[23] B. Erol, S. Z. Gurbuz and M. G. Amin, "Motion Classification Using Kinematically Sifted ACGAN-Synthesized Radar Micro-Doppler Signatures," in IEEE Transactions on Aerospace and Electronic Systems, vol. 56, no. 4, pp. 3197-3213, Aug. 2020.

[24] Fioranelli, F. , Shah, S. A. , Li, H., Shrestha, A., Yang, S. and Le Kernec, J., Radar sensing for healthcare. Electronics Letters, 55(19), pp.1022-1024. (doi:10.1049/el.2019.2378).

[25] D. Gusland, J. M. Christiansen, B. Torvik, F. Fioranelli, S. Z. Gurbuz and M. Ritchie, "Open Radar Initiative: Large Scale Dataset for Benchmarking of micro-Doppler Recognition Algorithms," 2021 IEEE Radar Conference (RadarConf21), 2021, pp. 1-6.

[26] M. Ritchie, R. Capraru, and F. Fioranelli, "Dop-NET: a micro-Doppler radar data challenge,"Elec-tronics Letters, vol. 56, no. 11, pp. 568–570, May 2020.

[27] Y. Yang, C. Hou, Y. Lang, D. Guan, D. Huang, J. Xu, "Open-set human activity recognition based on micro-Doppler signatures", *Pattern Recognition*, vol. 85, 2019, pp. 60-69.