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Challenges and results

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Radar sensing for human healthcare: challenges and results

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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 sensing, 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 great 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 relates to 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, and sleep posture [5-9]. 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, frozen gait [10-12]. 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 [13]. Recent research is also looking at other vital signs, such as the pulse due to blood circulation [14], and combination of these vital signs to check higher level physiological functions, for example sleep stages and quality [15-16].

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.

There are several types of radar architectures used for healthcare in the literature. While a detailed discussion on this goes beyond the scope of this paper, the main difference lies in the possibility to measure range/distance, enabled by FMCW/UWB radar in contrast to simpler CW radar. But why radar as a sensor for healthcare? The advantage 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. Furthermore, 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, 17]. 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 [18-20]. Identifying the

most suitable radar data representation for the specific classification problem and for usage with specific classification algorithms or neural networks remains an interesting open question, as well as finding the best combination of different features and data representations to reap the benefits of each of them.

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, e.g., their physical conditions, gender, age, constraints from surrounding objects and furniture [21-23].

   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, interpretation, and assessment of these continuous sequences of human activities, which may 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 of this trend. Typical network architectures include Convolutional Neural Networks (CNNs) and recurrent networks such as Long-Short Term Memory (LSTM) and Gated Recurrent Units (GRUs), or their combinations, 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, 24-25].

   However, the increasing usage of deep learning techniques emphasises 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 [26-28] 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 networks. The drive for explainable algorithms and the issue of data scarcity appear to discourage the usage of deep, fully 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.

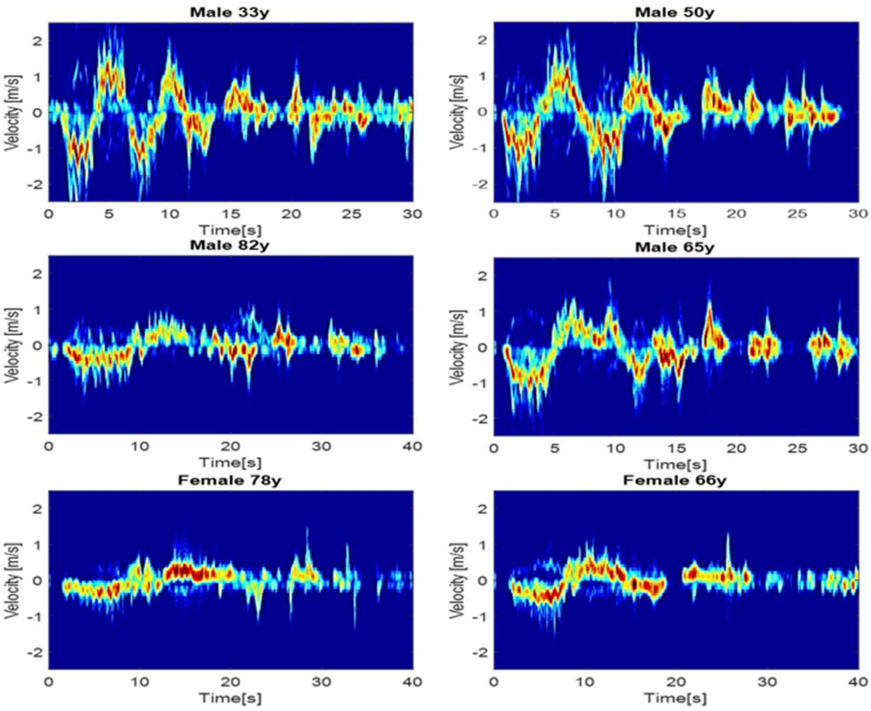

Fig. 1. Radar spectrograms of the same sequence of daily activities (namely walking back and forth, sitting on a chair, standing up, bending down and coming back up, and drinking from a cup) performed by 6 subjects of different age, gender, physical conditions. The radar operated at 5.8 GHz carrier frequency.

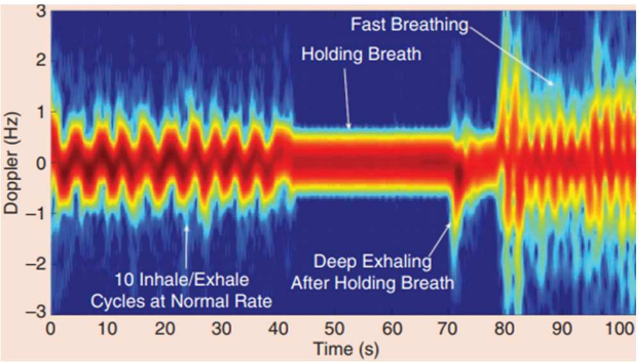

Fig. 2. Inspired from [1]: Spectrogram for a person sitting on a chair at ~60 cm from the radar and simulating different respiration rates and patterns. Specifically, the subject was asked to perform 10 cycles of normal respiration followed by a long period of holding breath and then fast, accelerated breathing. The radar used for this test operated in the X-band, within the Ultra Wide Band (UWB) spectral region.

4. Managing the *"open-set" problem* [29] 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 that may be 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 an initial simple example, Fig. 3 shows the 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 helps 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).

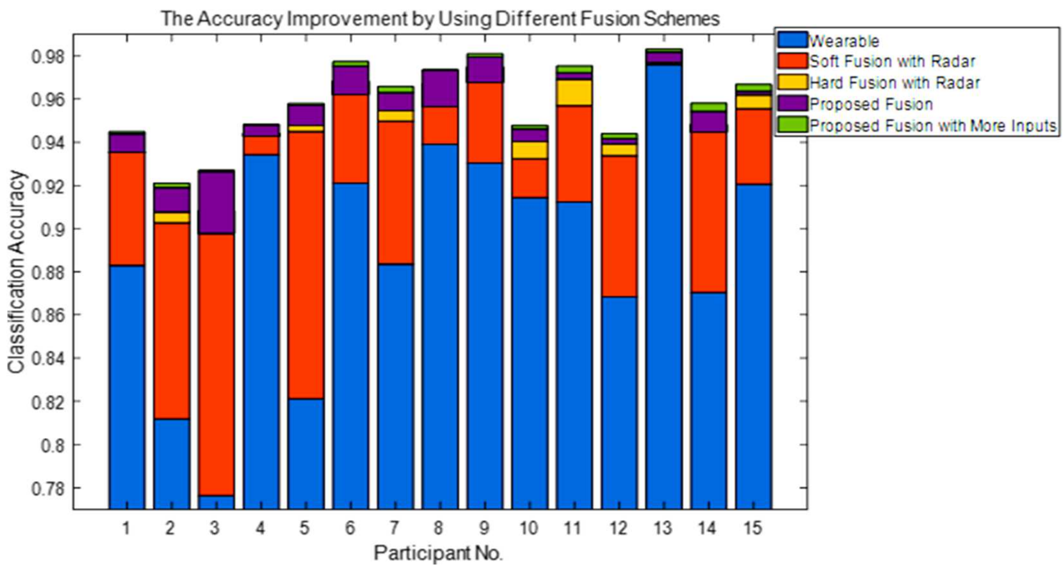

Fig. 3. From [23]: Accuracy obtained by Bidirectional-LSTM network classifier for continuous sequences of human activities using multimodal inputs, namely data from wrist-worn wearable (blue) fused with descriptors derived from radar spectrograms (different colours for different fusion techniques). The results are presented for each participant as unseen test subject to validate the classifier's performances (Leave One Person Out validation approach). Note that *soft* fusion is a weighted fusion between sensors; *hard* fusion is implemented via a recall combiner; *proposed* fusion is an implementation of hard fusion with the results of soft fusion used as an additional classifier.

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.

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