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Fioranelli, Dr Francesco, Shah, Dr Syed Aziz, Li1, Haobo, Shrestha, Aman, Yang, Dr Shufan and Kernec, Dr Julien Le (2019) Radar sensing for healthcare. Electronics Letters, 55 (19). pp. 1022-1024. ISSN 0013-5194

DOI: https://doi.org/10.1049/el.2019.2378

Publisher: Institution of Engineering and Technology (IET)

Version: Accepted Version

Downloaded from: https://e-space.mmu.ac.uk/624441/

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Radar sensing for healthcare

- PDF
546.72Kb
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- **Source:** Volume 55, Issue 19, 19 September 2019, p. 1022 – 1024
DOI: 10.1049/el.2019.2378 , **Print ISSN** 0013-5194, **Online ISSN** 1350-911X

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Published 05/08/2019

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Abstract

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Although traditionally associated with defence and security domains, radar sensing has attracted significant interest in recent years in healthcare applications. These include the monitoring of vital signs such as respiration, heartbeat, and blood pressure, analysis of gait and mobility levels, classification of human activities to promptly detect critical events such as falls, as well as the evaluation of fitness and reactivity levels. The attractiveness of radar against alternative technologies such as wearable sensors or cameras lies in its contactless capabilities, whereby people do not need to wear, carry, or interact with any additional device, and plain images of people and private environments are not recorded. In this letter, we discuss some of the most recent achievements and outstanding research challenges related to radar applications in healthcare and present some results from our work at the University of Glasgow, including a dataset of radar signatures of human activities that are openly shared with the wider community.

Introduction

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To support a rapidly aging population, future healthcare provision will extensively use technology to provide care in private home environments, avoiding hospitalisation, and preserving as much as possible the independence of people in their own living environments (“assisted living for healthy ageing”). Furthermore, continuous monitoring with new technologies will enable the timely identification of incoming health problems, allowing a “proactive and pre-emptive” approach rather than only reacting after serious symptoms have emerged.

Radar technologies have been proposed in recent years for healthcare applications [1 – 3], thanks to their capability to identify and track the presence of people and their movements, from bulk movements of the whole body to micro-scale movements of individual body parts. Compared with alternative technologies (wearable, video, or ambient sensors [4]), radar does not record plain images of the subjects or environments (helping with potential privacy concerns) and does not require the users to wear, carry, or interact with additional devices (helping with potential issues of acceptance and compliance).

Despite the recent interest and progress, outstanding research challenges remain, which can be broadly summarised into two main directions and themes:

- Finding and extracting the relevant information from the radar data. Depending on the specific application, the challenge is to develop and apply signal processing techniques that can retrieve the relevant information, for instance the respiration or heart rate, or more complex information such as the pattern of movements over time associated to specific human activities, or the quantitative parameters associated to human gait, such as stride length and symmetry.

- Validating the proposed techniques in realistic environments and scenarios, involving representative users. Most research work in this domain is often validated with a small group of subjects (tens or less than ten at times), typically relatively young students in controlled laboratory environments, hence not very representative of actual home environments and potentially older subjects. Any identification/classification algorithm based on machine learning for this context needs to be validated with relevant data, and most likely be able to adapt and be fine-tuned as additional data becomes available thanks to long-term monitoring. As the specific signatures of individuals change over time (for example a specific subject may become slower in certain movements, but that is not necessarily associated to critical health conditions). Also related to this validation challenge is the current lack of a large shared dataset of relevant radar signatures, equivalent to what for example the "ImageNet" dataset could be for the image processing research community. This means that single research groups often work on proprietary, relatively small datasets, with the risk of generating overfitted solutions that cannot be easily scaled or ported to more generic and realistic conditions.

Typical radar signal processing

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All typical radar signal processing approaches in the context of healthcare aim to characterise the signatures of interest in three domains: range (the physical distance to the radar), time (the evolution of the subject's location and position over time), and velocity (of the bulk body motion, and of the finer, smaller movements of individual body parts, all measured through the Doppler effect and the induced frequency shift); these three dimensional characteristic for the radar data is sometimes referred to as the "radar cube" [2 – 3]. Very recently, with the widespread development of compact radar systems with multiple receiver channels also driven by the automotive sector [5], a 4th relevant dimension is also added, the angular direction or angle of arrival, which can be inferred comparing signals received by the different receiving channels thanks to the emerging availability of multi-channel/MIMO (Multiple Input Multiple Output) compact radar systems, especially at mm-wave frequencies.

Both measurements of velocity and of angle of arrival are typically performed using Fast Fourier Transform (FFT) and its Short Time variant (STFT). Figure 1 presents an example of the typical signal processing chain for the case of a person walking back and forth in front of the radar. The starting point is the temporal series of received raw data. This can be organised into a matrix containing radar pulses repeated according to the Pulse Repetition Frequency (PRF) over the measurement time, where each pulse contains range bins associated with the physical distance of possible targets. This Range-Time image can be used for analysis and classification of human activities. For example, the diagonal zig-zag pattern shown in Figure 1, is associated with walking back and forth in front of the radar, with the intensity colour peak located at higher range bins as the person moves away, and back to lower range bins as the person comes back towards the radar.

A single FFT can then be applied across the time dimension of the Range-Time image to obtain a Range-Doppler image, to characterise the macro-movement of the target. For example, in Figure 1 we can see both positive (person walking towards the radar) and negative (person walking away) Doppler. To characterise the velocity and movements of individual body parts over time ("micro-Doppler" signatures), STFT is used to generate "spectrograms", Time-Doppler plots. The example in Figure 1 shows less intense (light blue) streaks around more intense (red and yellow) contributions, for both positive and negative Doppler. The former is related to the oscillations of limbs while walking, whereas the latter to the bulk movement and slight oscillation of the human torso while walking. Although STFT is the most used time-frequency distribution to characterise micro-Doppler signatures, several alternatives have been proposed based on Wavelets, Empirical Mode Decomposition, and other distributions [2 – 3].

Finally, data from previous steps and machine learning are used to enable algorithms to automatically identify patterns specific of activities of interest or extract desired healthcare related parameters.

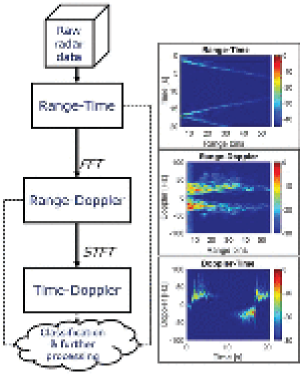

Fig. 1

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Fig. 1

Example of typical data formats for radar sensing for human activities identification.

Example of results

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Some examples of representative results obtained by our group are reported in this section, with additional results in the review papers [1 – 3] and references within.

Figure 2 shows the spectrogram (time-velocity pattern) for a sequence of 6 actions performed one after other, namely walking back and forth, sitting on a chair, standing back up, bending down to pick up an object, coming back up, and drinking water in a few sips while standing. Two research challenges arise, namely the automatic identification of the different activities and their potential combinations (how can an automatic system discriminate between them?), and their separation through processing the continuous stream of data, where detecting the transitions between activities can be rather challenging (where does one or more activities start and end?).

Figure 3 shows the same sequence of six activities performed by 6 different subjects with gender, age, and physical conditions diversity (4 male and 2 female subjects, age span from 33 to 82 years old). Although all the people were asked to perform exactly the same activities, the radar spectrogram can appear very different in terms of its spread across the velocity axis (linked to how fast the subjects move) and shape of the signature (linked to the different ways different people move about when performing even nominally identical activities). Here the significant research challenge is the capability to learn and adapt to the diversity of the signatures for different subjects and environments, as well as managing changes that may happen in individuals' signatures as their health conditions evolve.

The radar used for both these experiments was a Frequency Modulated Continuous Wave (FMCW) radar operating at 5.8 GHz with 400 MHz bandwidth and 1 ms chirp duration.

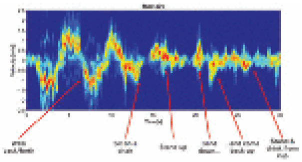

Fig. 2

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Fig. 2

Radar spectrogram (in normalised log scale) of a sequence of six activities performed one after the other by a 33-year-old male subject.

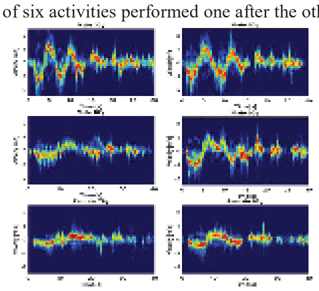

Fig. 3

Click to view

Fig. 3

Radar spectrograms (in normalised log scale) for the same sequence of 6 activities performed by 6 different subjects with gender and age diversity.

Figure 4 shows results for breathing detection. These compare three cases: empty room (the “control” case), a person sitting on a mat in the room and breathing normally (the “breathing” case), and a person holding their breath to simulate its loss due to some medical reason. Two features related to the strength and regularity of the recorded radar signals were extracted and plotted. These are sufficient to satisfactorily separate the three cases, which is promising for future validation of the approach to not only identify presence/absence of respiration but also quality and possible anomalies.

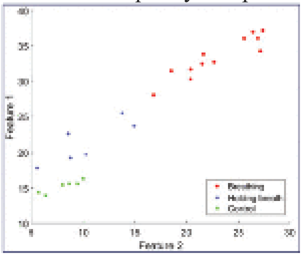

Fig. 4

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Fig. 4

Radar-based detection of presence/absence of respiration with two features extracted from segments of data of 20s duration each.

Conclusions

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Radar sensing has been attracting interest for healthcare applications, but outstanding challenges in this research domain remain [1 – 3], such as:

- Translating classification techniques from the analysis of individual, separated activities (images) into the analysis of a more realistic, continuous, and uninterrupted sequence of actions (temporal series) to be processed in real-time leveraging on “sparse” or “on-edge” computation.
- Incorporating additional information from recent mm-wave compact radar systems, providing very fine spatial resolution and beamforming and direction of arrival information. This will enable systems to resolve echoes from different body parts directly in the range domain, and the multi-occupancy problem of simultaneous multiple subjects with overlapping signatures.
- Validating any proposed technique by including realistic environments and procedures beyond controlled laboratory spaces, involving representative end-users ensuring diversity of age, gender, and physical conditions. This is necessary to develop algorithms and systems capable of dealing with such diversity and enact effective “transfer learning” and usage of data collected in heterogeneous conditions.

Related to this latter point is the lack of a comprehensive shared radar dataset that different researchers and groups can use for common benchmarking. Collecting and labelling good quality radar data is generally onerous and requires time/resource investment that may discourage free data sharing, although the need for this is increasingly seen positively within the scientific community.

As a contribution, we want to share a relatively large dataset collected at the University of Glasgow with the support of the UK EPSRC, which we believe is one of the first in the radar community in this domain [6]. The dataset includes human activities such as those mentioned in figure 2 and 3, collected by the same FMCW C-band radar and performed by over 50 subjects in 9 different locations. An interesting feature is the inclusion of radar signatures collected in environments outside controlled university spaces, in common rooms of residential establishments provided by external collaborators. Far from being perfect or universally comprehensive, we hope that this can provide a common set of data to try novel signal processing algorithms and classification techniques applied to radar data in this domain. The dataset is accessible at the reference provided in [6] and will be updated with additional data as the project develops until its end in October 2020.

Acknowledgements

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The authors acknowledge support from the UK EPSRC (grant EP/R041679/1) and Scottish Innovation Centre CENSIS for this work, and the precious collaborations of NG Homes Glasgow, Age UK West Cumbria, AngelMonitors.

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