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Fioranelli, Francesco; Zhu, Simin; Roldan, Ignacio

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Student Highlight: Benchmarking Classification Algorithms for Radar-Based Human Activity Recognition

***Francesco Fioranelli*, *Simin Zhu*, *and Ignacio Roldan*, TU Delft, 2628 CD Delft, The Netherlands**

Human Activity Recognition (HAR) with radar sensors has recently attracted great interest from many researchers. Initially started with a focus on fall detection, the scope has been broadened to characterize more in general patterns of activities of daily living of vulnerable individuals. This has the objective of looking not only at critical events, such as indeed falls, but also at more subtle changes and anomalies in the way each individual walks and performs daily activities, changes that can be linked to worsening physical and/or cognitive conditions.

One may ask: Why use radar technology for HAR? An advantage is the contactless sensing capabilities of radar, whereby locations and movements of people and their different body parts can be inferred without them actively wearing, carrying, or interacting with any sensors. This can be helpful for users' compliance, especially for users that might forget to carry sensors with them or recharge their batteries. Furthermore, radar technology does not record plain optical images or videos of individuals and their private environments. This aspect can be beneficial for the "end-users' perception" of this technology in terms of privacy.

Despite a significant and still increasing body of research in radar-based HAR, an important limiting aspect is the lack of a large, commonly accepted dataset for benchmarking of algorithms. Each individual research group often uses their own dataset, collected with proprietary radar sensors and typically involving a group of volunteers—very often students, which is inevitably small in terms of the number of people and number/realism of the activities collected.

Authors' current address: Francesco Fioranelli, Simin Zhu, and Ignacio Roldan are with the Department of Microelectronics, TU Delft, 2628 CD Delft, The Netherlands (e-mail: F.Fioranelli@tudelft.nl, S.Zhu-2@tudelft.nl, I.RoldanMontero@tudelft.nl).
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However, the radar community is increasingly tackling this problem and adopting practices of "open access" to data, which are very much the standard now in the image and audio processing communities. Examples of such practices include the organization of classification challenges on common datasets at the IEEE and IET radar conferences (e.g., IET Radar Conference 2020, IEEE Radar Conference 2022), and the public release of datasets such as the following.

1) The "Open Radar Initiative" [1] was presented at the 2021 IEEE Radar Conference to promote within the radar community the sharing of datasets for classification algorithm benchmarking. Available: https://doi.org/10.1109/RadarConf2147009.2021.9455239
2) The dataset of "Radar signatures of human activities" released by the radar researchers in the Communication Sensing and Imaging (CSI) group at the University of Glasgow [2], [3] is among the first datasets in radar-based HAR to be publicly shared and has been downloaded already more than 1,000 times. Available: https://researchdata.gla.ac.uk/848/
3) The "DopNet" dataset released by the UCL Radar Group [4] and containing radar spectrograms of several human gestures poses an important classification challenge in the field of human–computer interaction. Available: https://github.com/UCLRadarGroup/DopNet
4) The "PARrad" dataset, aimed at recording patients' activities in hospital settings, was released by Ghent University [5]. Available: https://sumo.intec.ugent.be/parrad
5) The data released by the Computational Intelligence for Radar Laboratory, at the University of Alabama Tuscaloosa [6] provides several datasets. Available: https://github.com/ci4r
6) The "OPERAnet" dataset, by the University of Bristol and UCL, contains multimodal data for HAR from sensors including Wi-Fi network interface cards, passive Wi-Fi implemented on software-defined radio platforms, UWB radars, and vision plus infrared data

from Kinect sensors [7]. Available: https://www.nature.com/articles/s41597-022-01573-2#Sec8

7) The "People Gait" dataset described and analyzed in [8] contains 3D radar point clouds of 95 volunteers walking along fixed and unconstrained trajectories to study gait-based people identification. Available: https://github.com/mmGait/people-gait
8) The dataset presented in [9] and focuses on vital signs, in which extended recordings with a 24-GHz radar synchronized with reference medical devices in clinical settings are included. Available: https://www.nature.com/articles/s41597-020-00629-5#Sec19
9) The dataset presented in [10] focuses on radar-based monitoring of respiration for premature infants in the neonatal intensive care environment. Available: https://radarmimo.com/contactless-radar-based-breathing-monitoring-of-premature-infants-in-the-neonatal-intensive-care-unit/
10) The dataset of "Continuous human activities recorded with a distributed radar network" was recently released by our group at TU Delft [11]. This dataset contains continuous sequences of human activities recorded with a distributed network of five simultaneously operating radar sensors. Available: https://doi.org/10.4121/16691500.v3

While not exhaustive, this list represents some of the most recent and most used datasets in the field of radar-based HAR and more in general radar-based human monitoring.

Linked to the increasing availability of datasets for radar-based HAR, in this Student Highlights contribution, we report on a classification project that a group of 23 graduate students performed at TU Delft. The project was part of the educational activities of the *Object Classification With Radar*[1] course, taught within the master's degree in electrical engineering.

The students were asked to work in groups of 2–3 members and to use the University of Glasgow dataset (item 2 in the aforementioned list) to develop the best classification pipeline as possible, by justifying both choices for the preprocessing techniques on the radar data (e.g., time–frequency distributions and cleaning of the signatures), and for the classification algorithms (e.g., the type of the algorithm, the hyperparameters' selection, the training–validation–testing split). This is in line with the intended learning outcomes of the course, aiming to educate the students in both radar signal processing techniques and classification tools based on machine learning and artificial intelligence.

Albeit containing only six activities (namely, walking, sitting down, standing up, picking up an object from the floor, drinking water, and falling, with spectrograms shown in Figure 1), a challenging aspect of this dataset is that it also includes data from actual residents of care homes in multiple environments. These are, for the same given activity, notably different from data collected in laboratory environments with younger individuals, leading to diversity in the different signatures to be accounted for. Additionally, the students were challenged in a competition to test their classification pipelines on a testing dataset with unknown labels to promote the generalization capabilities of their pipelines.

More details on the University of Glasgow dataset can be retrieved in the readme file at the DOI link of [2]. In this file, the characteristics of the radar used for the data collection, the different environments, and the information about the participants' age, height, gender, and dominant hand can be retrieved.

In terms of proposed techniques, all the groups worked on spectrograms as the chosen representation of radar data, considered as the most informative for the problem at hand. The students worked on both classic classification pipelines extracting relevant features and using classifiers such as support vector machines, and on using neural networks, mostly convolutional neural networks.

For the former approaches, the features explored included those that attempt to describe the temporal evolution of relevant information, such as the centroid, the bandwidth, and the upper/lower envelopes of the spectrograms, as well as moments derived from the spectrograms processed as images, such as Chebyshev polynomials. In terms of classification algorithms, it was proven that ensemble approaches that combine together multiple classifiers, such as bagging of different decision trees, can outperform the usage of a single classifier.

For the latter approaches based on neural networks, two important take-home messages were inferred from the students' work. First, given the relatively small size of the dataset, very large and deep networks would run into problems of overfitting compared to smaller, shallower models that were designed from scratch. Second, to address this problem of the small amount of data, strategies of transfer learning from optical images and generation of synthetic data were successfully experimented with. For this last point on data augmentation, it was shown that simplistic translations and geometrical modifications of the spectrograms did not bring consistent advantages, and in some cases made performances even worse by confusing the kinematic behavior of different classes. This might be solved by more advanced data augmentation techniques, such as the usage of generative adversarial networks that were however not explored in these student projects due to limited time.

[1]Course description *Object Classification With Radar*, TU Delft study guide: https://www.studiegids.tudelft.nl/a101_displayCourse.do?course_id=61724

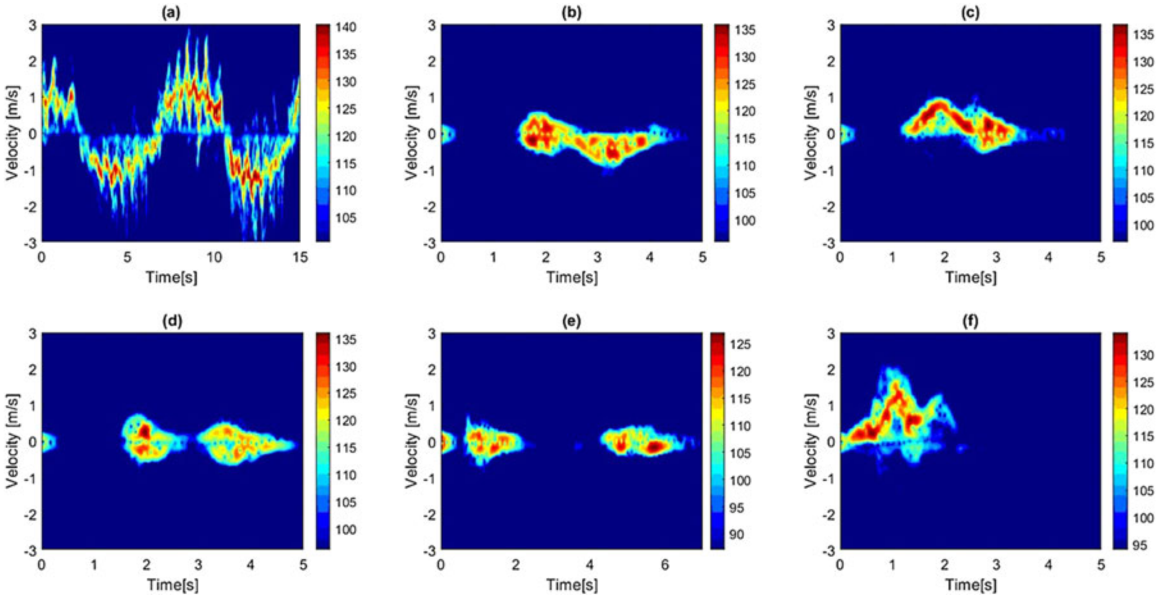

Figure 1.
Examples of spectrograms for the six activities in the dataset “Radar signatures of human activities,” namely, (a) walking, (b) sitting down on a chair, (c) standing up from a chair, (d) picking up an object from the floor, (e) drinking a glass of water, and (f) frontal fall. Note that the *Y*-axis shows the radial velocity calculated from the corresponding Doppler values accounting for the radar carrier frequency of 5.8 GHz.

A notable proposed solution involved the generation of a point cloud from the data, by running a cell averaging constant false alarm rate on range-time and spectrogram plots. This is a quite creative solution for data collected at 5.8 GHz, as point cloud processing is normally applied to data collected with mm-wave MIMO radar, e.g., 60-GHz systems and automotive 77-GHz systems. Furthermore, the radar had a single transmitter and receiver with no angular measurement capabilities; hence, the resulting point cloud had only four features containing range, Doppler, received power, and time instant information. Nevertheless, this representation combined with a network designed to work on point clouds—in this case, a simple PointNet—provided very promising results. Part of the processing and network development for this approach was performed within the Seminar series of Computer Vision by Deep Learning offered by TU Delft.[2]

The highest performances in terms of F1 score on the unlabeled test dataset were achieved by two groups of students, group #5 (Jurgen Wervers and Bob van Nifterik) who achieved 79% and group #7 (Mujtaba Hassan, Yanwen Chen, and Victor Oliveira) who achieved 88%. The reports and algorithm code generated by these two groups has been publicly shared.[3] A typical example of reported misclassification was the confusion between the “picking up” and “drinking water” activities, as in both cases, the participants had to extend their body and arm to take an object and then move it closer to their bodies, ending up in very similar micro-Doppler signatures.

In conclusion, while this student activity was performed at a small scale and with educational rather than research aims, we are happy to report it to the AESS readership, as we believe that such initiatives with open datasets sharing and classification algorithm benchmarking are beneficial for the wider radar research community.

[2]https://github.com/SimmyZhu/CS4245_Project
[3]https://github.com/SimmyZhu/TUD-EE4675-Project-2022

REFERENCES

[1] 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,” in *Proc. IEEE Radar Conf.*, 2021, pp. 1–6, doi: 10.1109/RadarConf2147009.2021.9455239.

[2] F. Fioranelli, S. A. Shah, H. Li, A. Shrestha, S. Yang, and J. Le Kernec, “Radar signatures of human activities,” in *Proc. Asian Conf. Innov. Technol.*, 2019, pp. 1–4, doi: 10.5525/gla.researchdata.848.

[3] F. Fioranelli, S. Aziz Shah, H. Li, A. Shrestha, S. Yang, and J. Le Kernec, “Radar sensing for healthcare,” *Electron. Lett.*, vol. 37, no. 9, pp. 1022–1024, 2019, doi: 10.1049/el.2019.2378.

[4] M. Ritchie, R. Capraru, and F. Fioranelli, “Dop-NET: A micro-Doppler radar data challenge,” *Electron. Lett.*, vol. 56, pp. 568–570, 2020, doi: 10.1049/el.2019.4153.

[5] G. Bhavanasi, L. Werthen-Brabants, T. Dhaene, and I. Couckuyt, "Patient activity recognition using radar sensors and machine learning," *Neural Comput. Appl.*, vol. 34, pp. 16033–16048, 2022, doi: 10.1007/s00521-022-07229-x.

[6] S Z. Gurbuz, M. M Rahman, E. Kurtoglu, T. Macks, and F. Fioranelli, "Cross-frequency training with adversarial learning for radar micro-Doppler signature classification (Rising researcher)," *Proc. SPIE*, vol. 11408, 2020, Art. no. 114080A, doi: 10.1117/12.2559155.

[7] M. J. Bocus et al., "OPERAnet, a multimodal activity recognition dataset acquired from radio frequency and vision-based sensors," *Sci. Data*, vol. 9, 2022, Art. no. 474, doi: 10.1038/s41597-022-01573-2.

[8] Z. Meng, "Gait recognition for co-existing multiple people using millimeter wave sensing," *AAAI Tech. Track: Appl.*, vol. 34, no. 1, pp. 849–856, Apr. 2020.

[9] S. Schellenberger et al., "A dataset of clinically recorded radar vital signs with synchronised reference sensor signals," *Sci. Data*, vol. 7, no. 1, Sep. 2020, Art. no. 291, doi: 10.1038/s41597-020-00629-5.

[10] G. Beltrão et al., "Contactless radar-based breathing monitoring of premature infants in the neonatal intensive care unit," *Sci. Rep.*, vol. 12, 2022, Art. no. 5150, doi: 10.1038/s41598-022-08836-3.

[11] R. Guendel, M. Unterhorst, F. Fioranelli, and A. Yarovoy, "Dataset of continuous human activities performed in arbitrary directions collected with a distributed radar network of five nodes," *4TU.ResearchData*, 2021, doi: 10.4121/16691500.v3.