# Radar-Based Hierarchical Human Activity Classification

*Xingzhuo Li[1,2], Francesco Fioranelli[3], Shufan Yang[1], Olivier Romain[4], Julien Le Kernec[1,4,5*]*

[1]*James Watt School of Engineering, University of Glasgow, Glasgow, UK*
[2]*Glasgow College – UESTC, University of Electronic Science and Technology of China, Chengdu, China*
[3]*MS3-Microwave Sensing Signals and Systems, TU Delft, Delft, The Netherlands*
[4]*ETIS – Signal and Information Processing lab, University Cergy-Pontoise, Cergy, France*
[5]*School of Information and Communication, University of Electronic Science and Technology of China, Chengdu, China*
**Julien.lekernec@glasgow.ac.uk*

**Keywords**: CLASSIFICATION, HUMAN ACTIVITY RECOGNITION, HUMAN MICRO-DOPPLER, MACHINE LEARNING.

## Abstract

Worldwide the ageing population is increasing, and there are new requirements from governments to keep people at home longer. As a consequence assisted living has been an active area of research, and radar has been identified as an emerging technology of choice for indoor activity monitoring. Activity classification has been investigated, but is often limited by the classification accuracy in the most challenging yet realistic cases. This paper aims to evaluate and improve the accuracy in classifying six commonly performed indoor activities from the University of Glasgow open dataset. For activity classification, the selection of features to discriminate between activities is paramount. Activity classification is usually done as one vs all strategy with one classifier and a set of features to distinguish between all the activities. In this paper, we propose to optimise the feature selection and classifier choice per activity using a hierarchical classification structure. This strategy reached 95.4% accuracy for all activities and about 100% for walking, opening the field for personnel recognition.

## 1. Introduction

Elderly care or assisted living for human activity monitoring has attracted much interest in maintaining people at home longer. The primary care units are not designed to take care of chronic patients in high numbers, and for less concerning situations that require monitoring but not hospitalisation, there is interest in monitoring people remotely at their homes [1-3]. The primary function is to detect critical events such as fall and alert carers for a swift response to the emergency [4].

Additionally, people can utilise the feedback from such systems to monitor their health status, and this could enable interventions to build better habits through gamification.

Currently, many activity monitoring methods [2, 5-11] are based on cameras and wearables. Cameras are sensitive to lighting conditions, obstructions and are perceived by the users as invading their privacy. Wearables, on the other hand, can be easily forgotten, broken, and may require difficult operation for cognitively impaired people. Radar monitoring presents advantages in contactless remote sensing and insensitivity to light conditions. Its ability to capture backscattered signals from humans in motions opens the field to a more private way of observing patients indoors without requiring patient compliance or handling. Features can be extracted from the processed signals for human activity classification.

In this paper, we propose to improve the classification accuracy with a hierarchical one versus scheme. Furthermore, we provide an analysis of the performance improvement and the key features involved in improving classification.

This paper is organised as follows. Section 2 describes the state-of-the-art in radar activity classification. Section 3 presents the methodology from data collection to the classification algorithms. The results will be discussed in section 4. In section 5, we will provide conclusions and further work required.

## 2. State-of-the-art

Activity classification with radar is a very active field of research. In [6], the authors show that the majority of human activity classifications are based on micro-Doppler (mD) signatures as they reflect the kinematic characteristics of human motions. A variety of features can be extracted from the mD signatures including but not limited to physical features, transform-based features and speech-inspired features. In [2], the authors thoroughly reviewed radar-based human activity classification with different radar data domains and their associated classification algorithms, highlighting the problems of supervised learning with selecting salient features for robust classification. Examples of works which implement feature selection for radar-based human activity classification include [12-17]. In this paper, instead of using one multiclass model to classify all the activities, a custom hierarchical classification structure is designed in sequential stages of one-versus-all classification models. Different classification algorithms and different features can be selected separately to optimise each model to discriminate the different activities.

## 3. Methodology

### *3.1. Data Collection*

The activities are recorded using an Ancortek SDR-580AD. It transmits a Frequency-Modulated Continuous Wave (FMCW) signal with 400 MHz instantaneous bandwidth centred at 5.8 GHz, and 1 ms repetition period. The data collection was

performed at the University of Glasgow and two elderly care homes in the UK [18]. Sixty subjects (21-98 years old) were recorded while performing activities labelled A*X* as follows walking A1, sitting down A2, standing up A3, drinking water from a cup A4, picking an object from the floor A5, and falling forward A6 with each action repeated thrice. In total, the database contains 1080 signatures.

### 3.2. *Signal pre-processing*

The signal pre-processing reshapes the raw complex data before the application of FFT to extract the range information. The data matrix is reshaped into 128×N where 128 is the number of samples per sweep, which is also the size used for FFT and N is the number of chirps. To remove static targets/clutter, an infinite impulse response notch filter removes the DC component. In order to reduce the noise in the mD signature, the range bins of interest are limited to the include only the size of the room for the implementation of STFT using a 0.2s hamming window with 95% overlapping factor for the extraction of the time-varying mD signatures (Figure 1). The micro-motions around the torso from feet and other body parts are visible. Those patterns will be leveraged to discriminate between different activities by extracting salient features. To obtain the cadence velocity diagram, an FFT is performed on the entire spectrogram for every Doppler bin in the time direction.

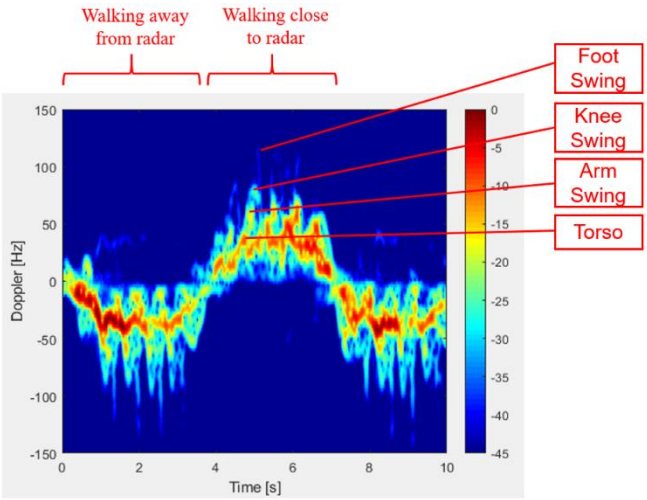


Figure 1: The mD-time signature for walking A1

### 3.3. *Feature extraction*

All the features calculated are listed in Figure 2 and based on prior work in [19-24]. The extracted features consist of empirical features indicating the physical properties; image-based features directly extracted from the mD signatures; and transform-based features indicating periodicity as other physical meanings. Specifically:

- The mean and deviation of the centroid and bandwidth are used to locate the centre of mass and spread of the mD signatures for different actions analysing the micro-motions of limbs. These are salient for walking A1 as the Doppler shift from the torso is relatively steady, and the mD signature presents a wider bandwidth caused by swinging limbs.
- The entropy and energy curve (mean/deviation/trapezoidal numerical integration) are used to follow the energy variations for different movements. If an activity shows a random and sudden intense movement, e.g., falling A6, they reflect a widespread energy curve and larger entropy, and thus can be an evident characteristic for classification.
- The skewness reflects the symmetry/asymmetry of the histogram of the mD signatures. Typically, patterns of continuous activities, e.g., walking A1 present uniform distributions. Activities have symmetric motions such as drinking A4; first raising the arm up and then putting the arm down. On the contrary, sitting down A2 and standing up A3 are more asymmetric.
- The binary feature uses the mean pixel value of all walking samples as the reference threshold value and converts the mD signatures into a binary figure where anything above the threshold is white. The area of the mD signatures waveform is calculated to reflect the shape and intensity of the motion.
- Singular Value Decomposition (SVD) reduces the feature-space dimensionality of the mD signature complex matrix. It is able to extract physical parameters such as the velocity, periodic properties of the mD signature. -After obtaining the vectors V and U, the mean and standard deviation of these two vectors are calculated as features.
- CVD features are extracted to leverage periodicity characteristics of different parts of the body and help classify activities with periodical motions from others.

| | Micro-Doppler Spectrogram Feature | Number |
|---|---|---|
| Energy features | Entropy of Spectrogram | 1 |
| | Energy Curve of Spectrogram | 3 |
| Physical features | Centroid of Spectrogram | 2 |
| | Bandwidth of Spectrogram | 2 |
| Image-based features | Binary Feature of Spectrogram | 1 |
| | Skewness of Spectrogram | 1 |
| | Cadence Velocity Diagram Feature | |
| Periodical features | Step Repetition Frequency | 1 |
| | Step Repetition Frequency Band Peak | 2 |
| | Singular Value Decomposition Feature | |
| Periodical and physical features | Mean and variance of singular vectors | 12 |

Figure 2: extracted feature set

### 3.4. *Classification algorithm*

To obtain a reference for the results and choose the most suitable algorithms, some commonly known machine learning methods such as decision trees, naïve Bayes, K-nearest neighbour and support vector machine (SVM) are used for multiclass classification. The M-fold cross-validation method is chosen to split the data into the training and test sets. It randomly splits the samples into M groups, and for each test, one group will be held as the test data while the others are used for training. The algorithms are therefore trained M times, and the presented accuracy is the average of M tests.

From Figure 2, 25 features are extracted. However, not all the features are salient for all the activities, and some features can be correlated with others, causing redundancy which reduces accuracy. The use of irrelevant features will increase the feature dimension and thus make for more complex algorithms and yield lower performances [25]. Therefore, feature selection is performed to identify the most salient features to

improve the classification accuracy as well as reducing the complexity of the algorithm, cost-effectiveness and providing a better understanding of decision processes [26].

### *3.5. Feature selection*

Feature selection algorithms are divided into 3 categories:

- Filter methods, which look into the intrinsic properties of the features regardless of the training model used.
- Wrapper methods, which test subsets of original features with a classifier and compare their prediction errors.
- Embedded methods, which generate scores of features during the model learning process.

According to the algorithms of these selection methods, filter methods are computationally efficient. Wrapper methods directly evaluate the classification accuracy using different subsets of features. Thus wrapper methods yield better performances than filter methods [27]. In this paper, a sequential backward selection (SBS) is used from the family of wrapper methods for its proven good performances, as shown in [19]. SBS starts with the full feature set and removes one feature at a time to optimise accuracy by testing all the combinations sequentially.

### *3.6. Hierarchy classification structure*

During the evaluation of multiclass models, multiclass and one-versus-all classification methods were considered. From experience, it can be observed that some activities such as walking and sitting down have a high classification accuracy. Therefore, a hierarchical classification structure was designed to improve the performance of the overall prediction. With hierarchical classification, activities which are known to be classified with high accuracy are extracted first, and the following models are trained without those activities previously extracted. Walking and falling are predicted accurately with 99%. From the tests in this paper, ranking from most accurate to least accurate, we obtain walking A1, falling A6, sitting A2, standing A3, picking an object A5 and drinking A4. In total, five models corresponding to each "one vs all" case are trained as shown in Figure 3. SBS feature selection method is also applied to every model to customise the feature sets, making them the most suitable ones for their specific task in the hierarchical classification structure and improve the overall performance.

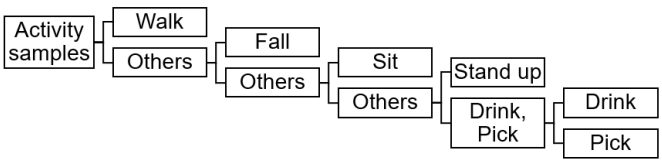


Figure 3: Hierarchy classification structure

## 4. Results

### *4.1. Multiclass classification*

The multiclass classification model is first validated with candidate algorithms using the combination of all the features, CVD features and SVD features listed in Figure 2 and the average classification accuracy after training and cross-validating for 50 times are shown in Table 1. From the initial results, the SVM model with Quadratic kernel performs best with 91.8 % accuracy. Then, the SBS feature selection method is applied to optimise the number of features for maximum accuracy.

| Classification algorithms | Validation accuracy (%) |
|---|---|
| **Decision Tree** | 86.8 (min/max: 84.9/88, var: 0.53 ) |
| **Naïve Bayes** | 86.4 (min/max 85.8/87.6, var: 0.18) |
| **SVM (Quadratic)** | **91.8** (min/max 90.9/93, var: 0.22) |
| **KNN** | 84.6 (min/max: 83/85.8, var: 0.21) |
| **Ensemble** | 90.3 (min/max 88.8/92.2, var: 0.35) |

Table 1: Classification results from the multiclass model

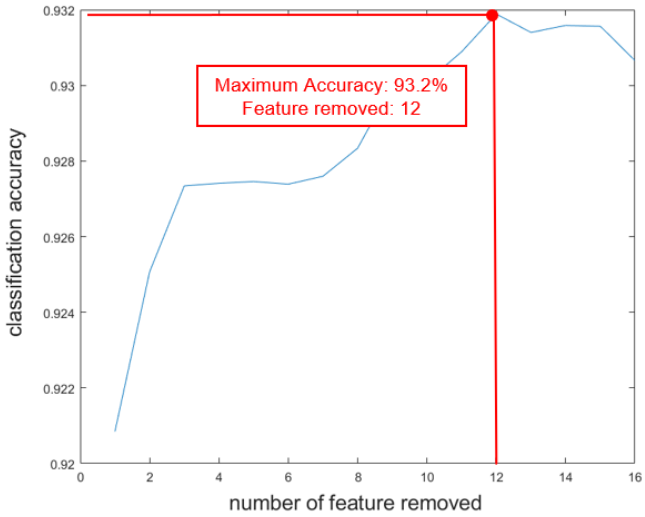


Figure 4: Classification accuracy after feature selection using SBS.

Figure 4 presents the change of classification accuracy by removing redundant features. The classification accuracy first increases when those redundant features are removed and attain maximum accuracy where the best feature combination is reached. In this way, a better and simpler model with accuracy 93.2% is found with the subset of 12 features as shown in Table 2.

| Feature Name | Number |
|---|---|
| **CVD Features** | 3 |
| **Mean of energy curve feature** | 1 |
| **Mean and variance of CVD features** | 8 |

Table 2: Features removed by selection

For step repetition frequency and band peaks in CVD, they describe the most frequently repeated frequency component and its bandwidth in the various activities. While those are essential features for periodic motions such as walking A1, they are not salient for non-periodic activities. The feature which describes the mean value of the energy curve of the mD signature is removed, since activities are chosen in this project such as walking forward and backward A1 Figure 5 (a), picking an object A5 (b) and drinking water A4 (c) all have a recovery transition making the mD signatures, so that have both positive and negative Doppler shifts. The energy curve mean-value is centred at zero and cannot distinguish between mD signatures, whereas the energy curve standard deviation can.

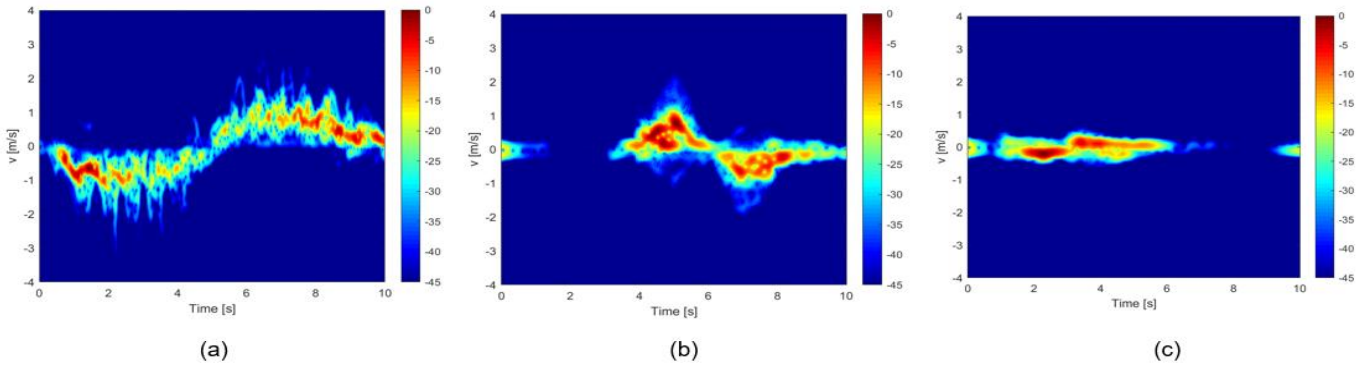

Figure 5 mD signatures of (a) walking A1 (b) picking up an object from the floor A5 (c) drinking from a glass A4

The SVD features have been shown to be useful in distinguishing birds, and unmanned aerial vehicles [28] and classify armed and unarmed personnel in walking [22] which indicates SVD features are able to identify characteristics and properties in long periodic activities. However, while four variances of vector U and V in SVD features are kept as the robust features, another eight features especially all the mean values of SVD features are removed by the feature selection, as they are possibly less useful in the classification of non-periodical and brief actions.

Table 3 shows the confusion matrix of the results from feature selected multiclass activity classification model where labels 1 to 6 represent walking, sitting, standing up, drinking water, picking an object from the floor and fall respectively. It can be observed that some activities such as walking and fall have 99% classification accuracy while drinking only have 85% classification accuracy. These varied classification results are greatly caused by the physical characteristics of different motions. For instance, the periodical characteristic of walking activity can be described by SVD features and CVD features, the intensive and rapid movement from fall can be captured by energy features such as energy curve and entropy. However, the minor motion from drinking (Figure 5c) makes it less distinctive than other activities, and its similarity with picking (Figure 5b) explains 10% of misclassification.

| | | Predicted class | | | | | |
|---|---|---|---|---|---|---|---|
| | | A1 | A2 | A3 | A4 | A5 | A6 |
| True class | A1 | 99% | | | 1% | | |
| | A2 | | 95% | | 3% | 2% | |
| | A3 | | 1% | 93% | 3% | 4% | |
| | A4 | | 1% | 3% | 85% | 10% | 1% |
| | A5 | | | | 8% | 92% | |
| | A6 | | | | 1% | | 99% |

Table 3: Multiclass confusion matrix with feature selection

### *4.2. One-versus-all classification with the hierarchy structure*

From the multiclass confusion matrix (Table 3), some activities show 99% accuracy in one-versus-all classification. Therefore, further one-versus-all model analysis is performed, and a hierarchical classification structure was designed (Figure 3) after model optimisation and feature selection for individual models at each stage. The results are listed in Table 4. From the comparison of the accuracy before and after the feature selection, it can be observed that walking activity A1 can be classified with 100% accuracy, and by using the most suitable models and feature selection methods, falling A6 and sitting A2 activities improved accuracy by 2% while standing A3, picking A5 and drinking A4 improved by 5%, 9% and 4%, respectively. It is worth noting that using the designed structure (Figure 3) with progressively removing the previous classified activity data, the model of the last stage is trained as a one-versus-one classifier which is designed and optimised specifically to distinguish picking A5 from drinking A4 which are the hardest to distinguish from one another. While the optimised hierarchical feature improved by 2%, it is worth noticing that the falling accuracy dropped by 0.6% compared to multiclass and would need to be fixed to reach 100% accuracy as critical events cannot be missed for a practical application or at least not decreasing.

| Activity | Model | Accuracy without feature selection | Accuracy after feature selection | Multiclass Accuracy |
|---|---|---|---|---|
| A1. Walk (model 1) | SVM | 100% | 100% | 99% |
| A6. Fall (model 2) | Linear regression | 96.5% | 98.4% | 99% |
| A2. Sit (model 3) | SVM (linear) | 96.3% | 98.5% | 95% |
| A3. Stand (model 4) | SVM (medium Gaussian) | 90.0% | 95.2% | 93% |
| A5. Pick (model 5) | SVM (cubic) | 84.8% | 94.4% | 92% |
| A4. Drink (model 5) | SVM (cubic) | 86.4% | 90.2% | 85% |
| Overall Classification accuracy | Hierarchical classification | 91.6% | 95.4% | 93.2% |

Table 4: Classification results from one-versus-all models

Table 5 shows the most robust and commonly kept features in the five models after feature selection. The centroid and bandwidth of the mD signatures are key features describing the physical properties of the motions. The skewness indicates the symmetry properties of the mD signatures and SVD features can also infer physical parameters and periodic properties in the mD signatures. Notably, only the standard deviations of the first column data in the vectors U and V in SVD are selected, possibly showing a better ability and higher weight in each vector U and V implying they may store the properties of the motions. Apart from the features in Table 5, other features are

flexibly selected in different models that are specifically suited to discriminate different activities. For instance, in model 1, the CVD features are used to classify walking activity A1, which has salient periodic patterns compared to others. The entropy feature showing the randomness and unpredictability of energy distribution is used in models 2 and 3 to identify falls A6 and sitting actions A2 which involve rapid and intensive motions, but it was removed in classifying relatively slow and more similar activities such as picking A5 and drinking A4. Instead, energy curve features are selected in identifying picking A5 from drinking A4 to describe more detailed motions and changes in energy.

| Feature Name | Number |
|---|---|
| Centroid of spectrogram (mean, variance) | 2 |
| Bandwidth of spectrogram | 2 |
| Skewness | 1 |
| SVD features (variance of U, V) | 2 |

Table 5: The most robust features from the feature selection of 5 models

After the feature selection and the use of hierarchical classification structure, the overall classification accuracy with one-versus-all hierarchical classification structure increases from 91.6% to 95.4% and is also 2% more accurate than using the multiclass model (93.4%). These improvements in classification results can be explained by three reasons.

Firstly, when training the models of the hierarchical structure, the activities which have already been classified in previous models are removed before the training of the next model in the following stages. This is because the models in the first stages are able to identify their focused activities accurately and by removing these recognised data samples which are already redundant can decrease the training complexity and improve the performance in the following stages.

Secondly, by taking advantage of using a multi-stage one-versus-all classification model, each trained model can select the most suitable algorithms and kernels for their specific classification tasks. In this way, model 2 in the hierarchy classification applies linear regression machine learning algorithms to train the model, and other models use SVM with different methods and kernels to obtain the best performance in classifying their corresponding activities.

Thirdly, the feature selection procedure can also be applied separately to these five models, and each model can be customised to work best for the specific activity that needs to be classified.

## 5. Conclusion and Future work

A custom hierarchical structure for activity classification was proposed improving by 2% the result over multiclass accuracy and insight on the role of features in classifying different activities has been presented.

The empirical-based features, transform-based features and image-based features were processed, and a wrapper method (SBS) for feature selection was applied to optimise each stage of the hierarchical classification as well as selecting the best classifier for each one vs all test to maximise performances. The trained multiclass model for six activities reached 93.4%. The hierarchical classification scheme with five feature sets and five classifiers separately selected for the one versus all tests was designed, increasing the classification accuracy to 95.4%.

For further work, while the first three models in hierarchy classification have classification accuracy over 98%, falls A6 should be improved to be at least as good as multiclass the last two models only have 94% and 90% in classifying picking A5 and drinking A4 which have a great impact on the overall accuracy. Therefore, new customised features will be developed, which can capture the key differences and identify these specific activities. For instance, while picking an object from the floor A5 shows a forward bending of the torso, drinking motions A4 can involve a slightly backward bending of the head and upper torso. Furthermore, since picking an object from the floor A5 has a relatively more intensive and larger movement in the range-Doppler data domain. Therefore, more features based on the range-Doppler signature [29] and other domains [2, 30] can be considered to present the difference described in these two activities.

Also, since walking activities were recognised with 100% accuracy, gait analysis could be performed to extract further parameters and features like walking speed and stride length, which are essential indicators showing health conditions as well as providing a biometric measure for personnel recognition [31].

## Acknowledgement

The authors would like to thank the British Council 515095884 and Campus France 44764WK – PHC Alliance France-UK for their financial support.

## References

[1] J. L. Kernec *et al.*, "Radar Sensing in Assisted Living: an Overview," in *2019 IEEE MTT-S International Microwave Biomedical Conference (IMBioC)*, 6-8 May 2019 2019, vol. 1, pp. 1-4, doi: 10.1109/IMBIOC.2019.8777748.

[2] J. Le Kernec *et al.*, "Radar Signal Processing for Sensing in Assisted Living: The Challenges Associated With Real-Time Implementation of Emerging Algorithms," *IEEE Signal Processing Magazine,* vol. 36, no. 4, pp. 29-41, 2019, doi: 10.1109/msp.2019.2903715.

[3] M. Abdur Rahman *et al.*, "A Secure Occupational Therapy Framework for Monitoring Cancer Patients' Quality of Life," *Sensors,* no. 19(23):5258, 2019, doi: https://doi.org/10.3390/s19235258.

[4] M. Terroso, N. Rosa, A. Torres Marques, and R. Simoes, "Physical consequences of falls in the elderly: a literature review from 1995 to 2010," *European Review of Aging and Physical Activity,* vol. 11, no. 1, pp. 51-59, 2014/04/01 2014, doi: 10.1007/s11556-013-0134-8.

[5] E. Cippitelli, F. Fioranelli, E. Gambi, and S. Spinsante, "Radar and RGB-Depth Sensors for Fall Detection: A Review," *IEEE Sensors Journal,* vol. 17, no. 12, pp. 3585-3604, 2017, doi: 10.1109/jsen.2017.2697077.

[6] S. Z. Gurbuz and M. G. Amin, "Radar-Based Human-Motion Recognition With Deep Learning: Promising

Applications for Indoor Monitoring," *IEEE Signal Processing Magazine,* vol. 36, no. 4, pp. 16-28, 2019, doi: 10.1109/msp.2018.2890128.

[7] V. Nathan *et al.*, "A Survey on Smart Homes for Aging in Place: Toward Solutions to the Specific Needs of the Elderly," *IEEE Signal Processing Magazine,* vol. 35, no. 5, pp. 111-119, 2018, doi: 10.1109/msp.2018.2846286.

[8] F. Ahmad, A. E. Cetin, K. C. D. Ho, and J. Nelson, "Signal processing for Assisted Living: Developments and Open Problems [From the Guest Editors]," *IEEE Signal Processing Magazine,* vol. 33, no. 2, 2016.

[9] C. Debes, A. Merentitis, S. Sukhanov, M. Niessen, N. Frangiadakis, and A. Bauer, "Monitoring Activities of Daily Living in Smart Homes: Understanding human behavior," *IEEE Signal Processing Magazine,* vol. 33, no. 2, pp. 81-94, 2016, doi: 10.1109/msp.2015.2503881.

[10] F. Erden, S. Velipasalar, A. Z. Alkar, and A. E. Cetin, "Sensors in Assisted Living: A survey of signal and image processing methods," *IEEE Signal Processing Magazine,* vol. 33, no. 2, pp. 36-44, 2016, doi: 10.1109/msp.2015.2489978.

[11] 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 Processing Magazine,* vol. 33, no. 2, pp. 71-80, 2016, doi: 10.1109/msp.2015.2502784.

[12] C. Ding *et al.*, "Continuous Human Motion Recognition With a Dynamic Range-Doppler Trajectory Method Based on FMCW Radar," *IEEE Transactions on Geoscience and Remote Sensing,* vol. 57, no. 9, pp. 6821-6831, 2019, doi: 10.1109/tgrs.2019.2908758.

[13] C. Ding *et al.*, "Non-Contact Human Motion Recognition Based on UWB Radar," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems,* vol. 8, no. 2, pp. 306-315, 2018, doi: 10.1109/jetcas.2018.2797313.

[14] Y. Lin, J. Le Kernec, S. Yang, F. Fioranelli, O. Romain, and Z. Zhao, "Human Activity Classification With Radar: Optimisation and Noise Robustness With Iterative Convolutional Neural Networks Followed With Random Forests," *IEEE Sensors Journal,* vol. 18, no. 23, pp. 9669-9681, 2018, doi: 10.1109/jsen.2018.2872849.

[15] H. Li, A. Shrestha, H. Heidari, J. Le Kernec, and F. Fioranelli, "Bi-LSTM Network for Multimodal Continuous Human Activity Recognition and Fall Detection," *IEEE Sensors Journal,* vol. 20, no. 3, pp. 1191-1201, 2020, doi: 10.1109/jsen.2019.2946095.

[16] H. Li, A. Shrestha, H. Heidari, J. Le Kernec, and F. Fioranelli, "Magnetic and Radar Sensing for Multimodal Remote Health Monitoring," *IEEE Sensors Journal,* vol. 19, no. 20, pp. 8979-8989, 2019, doi: 10.1109/jsen.2018.2872894.

[17] A. Shrestha, H. Li, F. Fioranelli, and J. Le Kernec, "Activity recognition with cooperative radar systems at C and K band," *The Journal of Engineering,* vol. 2019, no. 20, pp. 7100-7104, 2019, doi: 10.1049/joe.2019.0559.

[18] F. Fioranelli, S. A. Shah, H. Li, A. Shrestha, S. Yang, and J. Le Kernec. *Radar signatures of human activities*, doi: 10.5525/gla.researchdata.848.

[19] H. Li, A. Shrestha, F. Fioranelli, J. Le Kernec, and H. Heidari, "FMCW radar and inertial sensing synergy for assisted living," *The Journal of Engineering,* vol. 2019, no. 20, pp. 6784-6789, 2019, doi: 10.1049/joe.2019.0558.

[20] F. Fioranelli, M. Ritchie, and H. Griffiths, "Performance Analysis of Centroid and SVD Features for Personnel Recognition Using Multistatic Micro-Doppler," *IEEE Geoscience and Remote Sensing Letters,* vol. 13, no. 5, pp. 725-729, 2016, doi: 10.1109/lgrs.2016.2539386.

[21] N. Marinovic and G. Eichmann, "An expansion of Wigner distribution and its applications," in *ICASSP '85. IEEE International Conference on Acoustics, Speech, and Signal Processing*, 26-29 April 1985 1985, vol. 10, pp. 1021-1024.

[22] F. Fioranelli, M. Ritchie, and H. Griffiths, "Classification of Unarmed/Armed Personnel Using the NetRAD Multistatic Radar for Micro-Doppler and Singular Value Decomposition Features," *IEEE Geoscience and Remote Sensing Letters,* vol. 12, no. 9, pp. 1933-1937, 2015, doi: 10.1109/lgrs.2015.2439393.

[23] S. Björklund, T. Johansson, and H. Petersson, "Evaluation of a micro-Doppler classification method on mm-wave data," in *2012 IEEE Radar Conference*, 7-11 May 2012 2012, pp. 0934-0939.

[24] R. Ricci and A. Balleri, "Recognition of humans based on radar micro-Doppler shape spectrum features," *IET Radar, Sonar & Navigation,* vol. 9, no. 9, pp. 1216-1223, 2015.

[25] J. Miao and L. Niu, "A Survey on Feature Selection," *Procedia Computer Science,* vol. 91, pp. 919-926, 2016/01/01/ 2016, doi: https://doi.org/10.1016/j.procs.2016.07.111.

[26] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," *J. Mach. Learn. Res.,* vol. 3, no. null, pp. 1157–1182, 2003.

[27] M. Dash and H. Liu, "Feature selection for classification," *Intelligent Data Analysis,* vol. 1, no. 1, pp. 131-156, 1997/01/01/ 1997, doi: https://doi.org/10.1016/S1088-467X(97)00008-5.

[28] R. I. A. Harmanny, J. J. M. d. Wit, and G. P. Cabic, "Radar micro-Doppler feature extraction using the spectrogram and the cepstrogram," in *11th Eur. Radar Conf.*, 8-10 Oct. 2014 2014, pp. 165-168, doi: 10.1109/EuRAD.2014.6991233.

[29] Y. He, T. Sakamoto, P. Molchanov, A. Yarovoy, F. Le Chevalier, and P. Aubry, "Range-Doppler surface: a tool to analyse human target in ultra-wideband radar," *IET Radar, Sonar & Navigation,* vol. 9, no. 9, pp. 1240-1250, 2015, doi: 10.1049/iet-rsn.2015.0065.

[30] B. Jokanovic, M. Amin, and B. Erol, "Multiple joint-variable domains recognition of human motion," in *IEEE Radar Conf.*, Seattle, USA, 2017 2017, pp. 0948-0952, doi: 10.1109/RADAR.2017.7944340.

[31] L. Lee and W. E. L. Grimson, "Gait analysis for recognition and classification," in *Proceedings of Fifth IEEE International Conference on Automatic Face Gesture Recognition*, 21-21 May 2002 2002, pp. 155-162, doi: 10.1109/AFGR.2002.1004148.