Feature diversity for fall detection and human indoor activities classification using radar systems

A. Shrestha, J Le Kernec*, F Fioranelli*, E. Cippitelli†, E. Gambi†, S. Spinsante†*

**School of Engineering, University of Glasgow, UK (francesco.fioranelli@glasgow.ac.uk)*
†Deparment of Information Engineering, Università Politecnica delle Marche, Ancona, Italy, (s.spinsante@staff.univpm.it)

Keywords: FMCW radar, micro-Doppler signatures, feature extraction, classification, machine learning.

Abstract

This paper presents preliminary analysis of radar signatures for fall detection and classification of human indoor activities, to monitor the daily behaviour of individuals at risk of deteriorating physical or cognitive health. Two datasets of signatures in different environments have been collected, one of which included signatures generated from signals simultaneously collected from a radar and an RGB-D Kinect sensor, on a couple of older individuals. This preliminary analysis shows the potential effectiveness of different features and classifiers, and highlights the need of additional investigation to characterise and exploit the diversity of features and classification methods, in different experimental scenarios with different subjects.

1 Introduction

The problem of monitoring people's activities in indoor scenarios has been addressed by several research works, with the aim of reliably discriminating fall events against other actions and activities, and more in general being able to analyse the daily activities patterns of the monitored subjects [1]. Estimates from the World Health Organisation report that the proportion of people aged over 65 years who fall every year is approximately 28-35%, and 32-42% for those aged over 70 years [2]. Given the increasing proportion of elderly people in Europe, United States, and China, the occurrence of these fall events can pose a significant health and welfare challenge. Apart from the physical consequences and trauma, correlation has been highlighted between the long-lie time spent on the floor after a fall event and the reduction of life expectancy. Technologies for reliable and automatic fall events detection are therefore of significant interest. These systems can also provide additional information to evaluate the general wellbeing of patients, for example how active they are and in which part of the environment they spend their time, as well as how often they perform fundamental activities such as food intake or personal hygiene. Irregularities and anomalies in these patterns could inform carers and health professionals on risks related to deteriorating physical and cognitive capabilities.

Many different types of sensors and technologies have been suggested for this purpose, namely wearable devices such as accelerometers, inertial sensors, and panic buttons, infrared proximity sensors, magnetic and acoustic sensors, video-cameras, RGB-Depth sensors, and radar sensors [3-7]. The interest in radar technologies for indoor monitoring is related to their contactless sensing capabilities, with no need for the users to wear or carry devices or change their habits, and to the insensitivity to light conditions in the environment where the monitored subjects operate. Furthermore, it is expected that limited privacy concerns are associated with radar systems, as no personal images are recorded and there are no specific links between the individuals and their radar data. This is beneficial in addressing users' acceptance issues and potentially deploy radar sensors in parts of the house such as bedrooms and bathrooms where the risk of falling is higher but also privacy issues are more relevant [8]. Regarding exposure to EM radiations, the power level required by radar systems in this context are comparable to those used by conventional Wi-Fi routers or smartphones and involve non-ionizing radiations. Additionally, the perceived risks from radar waves has to be traded off with the advantages of continuous monitoring that these systems can enable, especially for vulnerable people with physical/cognitive impairments.

The majority of radar-based solutions in this context are based on the exploitation of micro-Doppler signatures, i.e. the additional Doppler frequency components on the human radar signature generated by movement of torso and swinging of limbs. These have been used for a variety of applications, including identification of people vs other targets such as vehicles and animals or of potentially armed personnel, and classification of specific individuals based on their walking gait [9-10]. Although the use of radar in the context of fall detection and indoor monitoring provided interesting preliminary results, challenges to be addressed remain. These include the deployment of the radar sensor to avoid occlusions of the monitored subject caused by other people or clutter objects, the compliance of the radar waveform with existing communication and electromagnetic compatibility standard, the dependency of micro-Doppler signatures on the cosine of the aspect angle, hence the possible degradation of the signatures that can invalidate the proposed classification schemes, and the robustness in rejecting false alarms and misclassification events related to similar actions (e.g. falling rather than bending or crouching down) [8]. An additional limitation is the current lack of large and shared databases of signatures to validate the proposed approaches rather than using small, ad-hoc datasets. Furthermore, these ad-hoc datasets are generally collected in semi-controlled laboratory environment and involving mostly young subjects rather than elderly people.

Some of these technical challenges can be addressed by using multiple types of sensors through a sensor fusion approach

[11], with the aim of exploiting complementary advantages of different technologies to overcome the limitations of a single family of sensors. This paper introduces two datasets of signatures of human activities, one of which includes simultaneous radar and RGB-D signatures enabling the investigation of suitable multisensory classification techniques for this context. Preliminary results are presented, regarding the analysis of the radar data, showing promising classification accuracy and referring to the final version of the manuscript for the analysis of the RGB-D data and their joint use. Brief examples of simulated human micro-Doppler signatures generated by motion-capture data are also shown, referring to the final version of the manuscript for a more detailed discussion. These signatures can be used to complement experimental data for comparison and for achieving the very significant amount of data necessary to test some classification techniques, such as those based on unsupervised machine learning or neural networks.

The paper is organized as follows. Section 2 presents examples of preliminary results of simulated human radar signatures. Section 3 describes the experimental setups of the two data collections, with the relevant analysis and some results presented in section 4. Finally, section 5 concludes the paper.

2 Simulation of radar micro-Doppler signatures

The generation of reliable simulated data can complement experimental radar data for improvement of classification methods. In order to try and characterise the contribution of various body parts in the micro-Doppler signatures, two scenarios were simulated: walking towards the radar (~10-15 m – subject 7 motion 5) and crouching facing the radar (~4-5 m – subject 26 motion 9). The human movements are extracted from the Carnegie Mellon motion capture database [12] and read with the HDM05 parser [13].

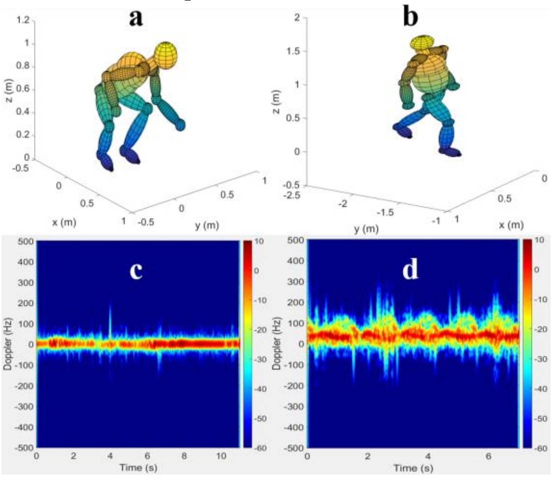

Figure 1. 3D model of a man a) crouching b) walking and the resulting simulated spectrograms for c) crouching and d) walking actions while facing a radar with a carrier frequency of 5.8 GHz and a pulse repetition frequency of 1 kHz

The database motion was shot at 120 frames per second (fps). Using MATLAB basic fitting tool based on 'shape-preserving interpolant', the movements were up-sampled to 1000 fps to match the experimental Doppler sampling rate (PRF 1 kHz). The data was simulated at 5.8 GHz using an adapted approach based on the simulation in V. Chen's book [14] and the radar cross section (RCS) model was superimposed on the skeleton data from the database. The RCS has been modelled with spheres and ellipsoids that have analytical equations taking into consideration incident angles in azimuth and elevation thus resulting in more realistic micro-Doppler signatures as seen in Figure 1 for the 2 scenarios abovementioned and also matches the experimental radar parameters presented in section 3.

3 Experimental setup and data collection

The paper presents the preliminary analysis of radar data collected in two separate experiments. The radar is an off-the-shelf Frequency Modulated Continuous Wave (FMCW) system operating at 5.8 GHz, with bandwidth equal to 400 MHz and chirp duration equal to 1 ms (hence unambiguous Doppler frequency range equal to ±500 Hz, sufficient to capture the whole human micro-Doppler signature for indoor activities). The transmitted power of the radar sensor is approximately +19 dBm, and two linearly polarised Yagi antennas with gain equal to 17 dBi and beam-width of approximately 24° in azimuth and elevation were used.

Dataset 1. The first experiment was performed in an indoor meeting room at the School of Engineering at the University of Glasgow. The room contained several pieces of office furniture (desks, chairs, cupboards, computers), but the radar system had line-of-sight to the targets and was located at a height of approximately 1.2 m pointing at the torso of the subjects. Six different volunteers took part to the data collection, 3 males and 3 females, with age varying between 20 and 30 years. For this collection seven different actions were recorded, namely walking back and forth in front of the radar, sitting on and standing up from a chair, bending to pick up an object from the floor and standing up, making circles with one arm while standing, clapping while standing, pushing (moving one arm fast towards the radar faster, and then slowly backwards), and pulling (basically the opposite of the previous movement). Two 60s long recordings for each activity and for each subject were collected, each of them containing several repetitions of the particular movement under test. Additional data were collected with two of the six subjects facing different aspect angles, namely 30°, 45° and 60° away from the line-of-sight of the radar. This was done to test the effect of the aspect angle parameter on the signatures and on the classification algorithms.

Dataset 2. The second experiment was performed in the laboratory of the Telecommunication Systems Group at the Università Politecnica delle Marche, Ancona, Italy. The same radar sensor and antennas were used, in a similar setup in terms of height of the sensor (approximately 1-1.1 m from the floor) and distances between targets and radar (approximately 2 to 4 m). Ten different actions were recorded, namely walking (A1), walking while carrying an object with both hands (A2), sitting down on a chair (A3), standing up from a chair (A4), bending to pick up a pen (A5), bending to tie shoelaces (A6), drink multiple sips from a glass while standing (A7), extract a mobile phone from pockets and pick up a call (A8), simulated tripping

with frontal fall (A9), and crouching down pretending to check something under a piece of furniture and then coming back up (A10). Three different recordings were collected for each person for each of the 10 activities. In each recording only one repetition of the particular movement considered was collected. The recordings had different durations depending on the activity (from 5 s to 10 s). Seven different subjects took part to this experiment, aged between 23 and 40 years old.
It is known that micro-Doppler signatures can change significantly for the same action at different aspect angles [15], especially at aspect angles that approach 90° to the radar line of sight. Multistatic radar has been suggested as possible solution to approach this issue, where different radar nodes collect simultaneous signatures of the subject from different aspect angles, as well as different classes of sensors that can be more tolerant of the aspect angle issue. For these data, simultaneous recordings of the activities were also collected using the RGB-D sensor Kinect, located in frontal position with respect to the subjects. The joint use of radar and Kinect data to improve fall detection and activities classification performance is beyond the scope of this paper, but these data will enable a detailed investigation of the most effective information fusion techniques. The measurement setup is shown in Figure 2 where both the radar and Kinect sensors are visible.

Figure 2. Laboratory setup for dataset 2.

Additional data were then recorded for the same activities in a sitting room of an actual flat, with two subjects (one 62 years old male and one 58 years old female). These additional data will help investigating differences between signatures of younger and older subjects, in order to assess the robustness of classification approaches developed (mostly) on data from younger subjects in laboratory environments, when processing data from older subjects in realistic home environments.

4. Data analysis and preliminary results

The radar data were processed using a Short Time Fourier Transform (STFT) with a 0.2 s Hamming window and 95% overlap to produce spectrograms. A Moving Target Indication (MTI) IIR filter was applied to the data prior to time-frequency analysis to remove the static clutter contribution from the micro-Doppler signatures. Aside from the spectrogram, time frequency distributions that address the time and frequency resolution trade-off associated with STFT can also be applied. S-methods and bilinear or quadratic transforms [16], mostly a subset of Cohen's class transformations, would also be suitable in this context, although beyond the scope of the analysis presented in this paper.
Figure 3 shows an example of spectrograms for six different actions performed by the same subject as collected in dataset 2. Figure 4 shows four spectrograms for the same action (crouching to look below a piece of furniture and coming back up) performed by four different subjects, one of which (Figure 4d) was significantly older than the other 3. The temporal duration of the signature and the change and extension in positive/negative Doppler appear to differentiate the actions, with the challenge of finding suitable features that can capture these differences effectively and be robust to the variability from one subject to another. Some actions are more similar than others, e.g. the frontal fall in Figure 3e is very similar to the bending action in 3d, presenting a challenge for false alarms in fall detection. Furthermore, the signatures in Figure 3c and 3f could be confused with the actual fall (3e) as well, if the classification algorithm only considers the initial part of the signature. One can also observe in Figure 4 how the same action produces rather different signatures for different subjects, and the fact that the signature for the older subject (Figure 4d) appears to be more limited in Doppler frequency range than for the younger subjects. This may highlight the importance of collecting data from actual older subjects for effective development and validation of classification techniques. This needs to be validated through the collection of a large number of signatures, including older volunteers, to validate the statistical significance of this statement.
Numerical features were then extracted from the spectrograms to perform automatic classifications. These are briefly described here, referring the readers to more detailed description in the references provided:

- Centroid and bandwidth of the signatures, i.e. the centre of mass of the spectrograms and the intensity of the signatures around it. The mean and the standard deviation of these two quantities have been previously used for human micro-Doppler classification [15,17].
- Entropy of the spectrogram image and skewness of the histogram containing the intensity samples. These textural features have been previously used to discriminate human targets from other classes of targets [18].
- Features based on Singular Value Decomposition (SVD), in particular the mean and the standard deviation of the first three vectors of the left (U) and right matrix (V) resulting from the decomposition. These have been previously used for classification of unarmed vs potentially armed personnel and for micro-drones' payloads classification [17, 19].

The feature samples were then processed using different classifiers implemented in MATLAB. These were: Naïve Bayes (NB), diagonal-linear version of the discriminant analysis (DL), Nearest-Neighbour with 7 neighbours (KNN), binary classification tree (CT), support vector machine with radial basis funcitons (SVM), and ensamble method based on random forest/bagged tree (BT). A detailed description of the classifiers goes beyond the scope of this paper, but additional information can be found in [20-21].

When analysing dataset 1, the 60 s long spectrograms were partitioned in 3 s long segments and one sample per feature was extracted from each individual segment. For this dataset ten features were considered as input to the classifier, namely mean and standard deviation of the centroid and bandwidth of the signature, entropy and histogram skewness, and the six features based on SVD. This generated a total of 2460 feature samples (i.e. 246 datasets in total for the 6 people and 7 actions, and ten features). The feature samples set was randomly partitioned in two equal subsets for training and samples, and this process was repeated 50 times to test the validity of the classification approach. The average accuracy was then calculated and the results per class are reported in the confusion matrix in Table 1. The classifier used is a support vector machine (SVM) with cubic kernel, implemented with in MATLAB with one-vs-one approach for multiclass problems [22].

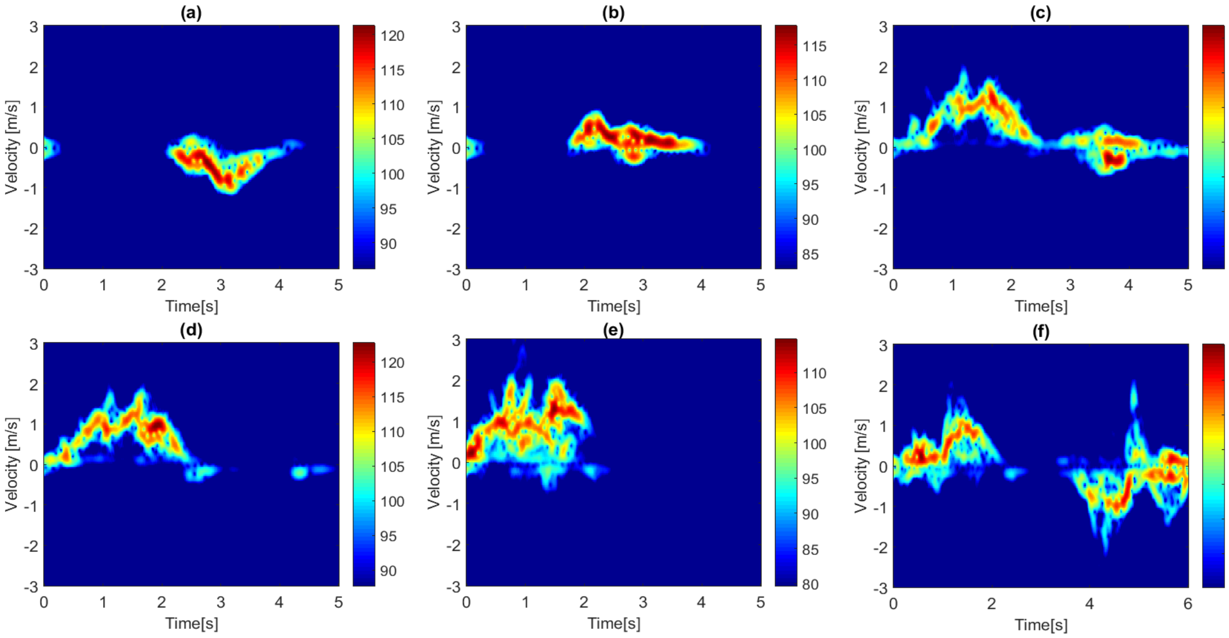

Figure 3. Spectrograms for 6 activities performed by the same subject: (a) sitting on a chair, (b) standing up from a chair, (c) bending and picking up a pen, (d) bending and staying low to tie shoelaces, (e) frontal fall, and (f) crouching to look below a piece of furniture and standing back up

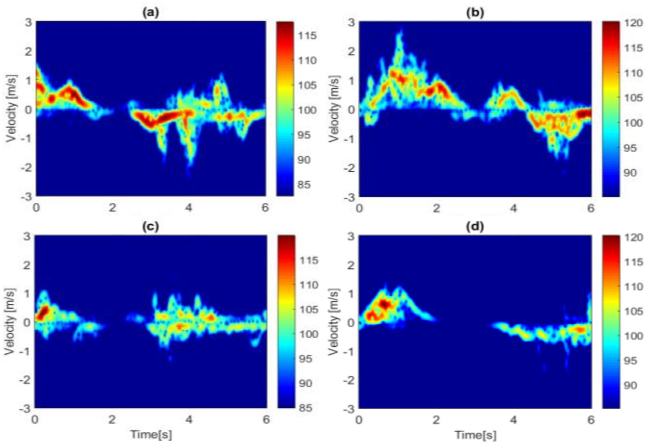

Figure 4. Spectrograms for crouching to look below a piece of furniture and standing back up performed by 4 subjects of different ages

The average accuracy across the seven activites is approximately 94%. The classification accuracy is higher than 90% for each activity considered, with misclassification events spread fairly consistently across the other activities, i.e. there are no obvious pairs of activities misclassified one with each other. It is interesting to observe that the datasets contained recordings colelcted at different aspect angles (0, 30, 45, and 60 degrees), and these have been used jointly for both training and testing. Future work will investigate how using robust the classification method is if testing data include aspect angles not used at training, as for practical applications it will be unfeasible to train the classifier with data from all possible orientation. Furthermore, these preliminary results used the ten available features jointly, whereas it is interesting to explore the diversity in performance obtained with different combination of fetures for different operational parameters, for example aspect angle and Signal-To-Noise Ratio.

When analysing dataset 2, one feature sample was extracted from each spectrogram, generating 270 samples for each feature in total (10 activities, 3 recordings, 9 volunteers). For this datasets 6 features were used as inputs to the classifier, i.e. those based on centorid and bandwidth and the textural features. 80% of the data were used to train the classifier and 20% for testing, repeating this process 50 times with different randomly selected samples for the training and testing process, in order to test the validty and the robustness of this approach. The final accuracy shown is the average across the 50 iterations. Table 1 presents the summary of the classification accuracy obtained with the different classifiers, and Table 2 shows an example of confusion matrix obtained for the SVM classifier. One can see that the best classification accuracy (around 76-77%) is obtained with the BT (bagged tree) and SVM classifiers, whereas simpler classifiers such as DL or KNN yield reduced accuracy. The improved accuracy yielded by BT and SVM may be due to their ensemble-based implementation, whereby different simpler classifiers operating on subspaces of classes are combined together to provide final decisions, whereas the other simpler classifiers operate on the whole features/classes space. Furthermore, it is interesting to investigate where misclassification events happened in the confusion matrix, especially because the activities in dataset 2 were chosen to be similar with one another, and test how effectively false alarms are rejected. For example, it can be seen that A1 and A2 (walking and walking carrying an object) are confused one with each other quite often, and the actual fall (A9) is mostly confused with bending and sitting activities (A4 to A6). This highlights the importance of developing feature extraction techniques capable of rejecting these false alarms and characterising the differences between very similar movements. The activities A7 and A8 performed on the spot (drinking, mobile phone call) present the highest classification result, and they are mostly confused one with another.

Classification accuracy [%]	
NB	67.88
DL	58.28
KNN	60.4
CT	66
BT	77.8
SVM	76.44

Table 1. Classification accuracy for dataset 2 with different classifiers

Accuracy [%]	**Walk**	**Push**	**Pick up item**	**Pull**	**Circle arms**	**Clap**	**Sit/Stand**
Walk	**95.9**	0.5	0.2	0.7	1.3	0.5	0.7
Push	0.2	**94.7**	0.3	1.8	1.2	0.3	1.1
Pick up item	0.4	0.6	**94.2**	1.5	1.9	0.2	0.9
Pull	0.3	4.2	0.3	**91.9**	1.6	0.2	1.2
Circle arms	0.3	1.7	1.6	2	**91.4**	1.2	1.3
Clap	0.3	0.6	0.1	0.1	1.7	**96.5**	0.3
Sit/Stand	0.3	1.5	0.3	1.6	1.6	0.3	**94**

Table 2. Confusion matrix for SVM classifier (cubic kernel) for dataset 1

[%]	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**
A1	**68**	26.4	0	0	5.6	0	0	0	0	0
A2	29.2	**70.4**	0	0	0.4	0	0	0	0	0
A3	0	0	**86**	0	2.4	4.8	0	6.8	0	0
A4	0	0	0	**80.8**	4	9.6	0	0	3.2	2.4
A5	1.6	0	5.6	8.8	**56**	4	0.4	1.2	0	22.4
A6	0	0	0	8.8	8.8	**71.2**	0	0	6.8	4.4
A7	0	0	0	0	0	0	**91.2**	8.8	0	0
A8	0	0	0.4	2	0.4	0	2.4	**92.4**	0	2.4
A9	0.8	0	0	4	3.6	9.6	0	0	**82**	0
A10	5.6	0	0	0	19.6	3.2	0	5.2	0	**66.4**

Table 3. Confusion matrix for SVM classifier (RBF kernel) for dataset 2

5. Conclusions

This paper has presented preliminary results on the analysis of radar data for monitoring of human indoor activities and fall detection. Two datasets collected with different subjects and in different locations have been analysed, using ten different features extracted from the micro-Doppler signatures. Accuracy up to an average of 94% has been achieved using the ten features jointly for one dataset. Large variability in the accuracy has been observed for different features (here based on the centre of mass of the signature, on the SVD decomposition, on image processing techniques), classifiers, scenario dependent parameters (e.g. the aspect angle of the movement with respect to the radar line of sight). This is being investigated in more detail to select the most suitable features and classification approach in each operational scenario, with the perspective of adopting cognitive-radar inspired approaches, whereby the radar system can know or even learn what is more appropriate to do in each condition. Different architectures of neural networks are also considered, for their effectiveness to learn features without human intervention and capabilities to transfer learning across signatures collected in different operational scenarios.

Another element of interest in the data presented here is the simultaneous recording with radar and RGB-D (Kinect) sensors, and the acquisition of signatures of older volunteers in a realistic home environment. These have been only briefly

touched in this manuscript, but future work will explore multi-sensor techniques for improved classification accuracy, and will aim to include more data from older volunteers. This will enable to characterise differences with signatures from younger people and investigate how the classification approach can take these differences into account.
Furthermore, the simulated micro-Doppler signatures presented in section 2 will allow studying the effects of the radar geometry configuration (azimuth, elevation, monostatic, multistatic) and different radar parameters (frequency, bandwidth) on the classification effectiveness.

Acknowledgements

A. Shrestha is supported for his PhD by the UK Engineering and Physical Sciences Research Council (EPSRC) Doctoral Training Award to the School of Engineering.
The authors are grateful to the volunteers who helped with the data collection, in particular A. Angelov (University of Glasgow) and M. Pepa (Università Politecnica delle Marche).

References

[1] 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],” I*EEE Signal Processing Magazine*, vol. 33(2), pp. 25–26, 2016.
[2] World Health Organisation, “*WHO Global Report on Falls Prevention in Older Age*,” 2008.
[3] 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(2), pp. 36–44, 2016.
[4] C. Debes, A. Merentitis, S. Sukhanov, M. Niessen, N. Frangiadakis, and A. Bauer, “Monitoring Activities of Daily Living in Smart Homes: Understanding human behavior,” I*EEE Signal Processing Magazine*, vol. 33(2), pp. 81–94, 2016.
[5] S. C. Mukhopadhyay, “Wearable Sensors for Human Activity Monitoring: A Review,” *IEEE Sensors Journal*, vol. 15(3), pp. 1321–1330, 2015.
[6] I. H. Lopez-Nava and M. M. Angelica, “Wearable Inertial Sensors for Human Motion Analysis: A review,” *IEEE Sensors Journal,* vol. PP, no. 99. p. 1, 2016.
[7] E. Cippitelli, F. Fioranelli, E. Gambi, and S. Spinsante, “Radar and RGB-Depth Sensors for Fall Detection: A Review”, *IEEE Sensors*, vol. 17(12), pp. 3585-3604, 2017.
[8] 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(2), pp. 71–80, 2016.
[9] D. Tahmoush, “Review of micro-Doppler signatures,” *IET Radar, Sonar & Navigation*, vol. 9(9), pp. 1140–1146, 2015.
[10] V. C. Chen, D. Tahmoush, and W. J. Miceli, Eds., *Radar Micro-Doppler Signatures: Processing and Applications*, Institution of Engineering and Technology, 2014.
[11] S. Gasparrini, E. Cippitelli, E. Gambi, S. Spinsante, J. Wåhslén, I. Ohran, and T. Lindh, “Proposal and experimental evaluation of fall detection solution based on wearable and depth data fusion”, *ICT Innovations 2015: Emerging Technologies for Better Living*, vol. 399, S. Loshkovska and S. Koceski, Eds. Cham: Springer International Publishing, pp. 99-108, 2016.
[12] *http://mocap.cs.cmu.edu/*, accessed in February 2017.
[13] M. Müller, T. Röder, M. Clausen, B. Eberhardt, B. Krüger, A. Weber, Documentation Mocap Database HDM05, *Technical report, No. CG-2007-2, ISSN 1610-8892*, Universität Bonn, June 2007.
[14] V.C. Chen, *The micro-Doppler effect in radar,* Artech House, 2011. ISBN: 978-1-60807-057-2
[15] Fioranelli, F., Ritchie, M., Gürbüz, S., Griffiths, H.; ‘Feature diversity for optimized human micro-Doppler classification using multistatic radar’, *IEEE Transactions on Aerospace and Electronic Systems*, vol. 53(2), 640-654, 2017.
[16] Thayaparan, T., Stanković., and Djurović, I., “Micro-Doppler Based Target Detection and Feature Extraction in Indoor and Outdoor Environments*”, Journal of the Franklin Institute*, vol. 345(6), pp 700-722, 2008.
[17] Fioranelli, F., Ritchie, M., Griffiths, H.; “Centroid features for classification of armed/unarmed multiple personnel using multistatic human micro-Doppler”, *IET Radar, Sonar & Navigation*, vol. 10(9), pp. 1702-1710, 2016.
[18] X. Shi, F. Zhou, L. Liu, B. Zhao and Z. Zhang, "Textural feature extraction based on time–frequency spectrograms of humans and vehicles," *IET Radar, Sonar & Navigation*, vol. 9(9), pp. 1251-1259, 2015.
[19] Ritchie, M., Fioranelli, F., Borrion, H., Griffiths, H.; ‘Multistatic micro-Doppler radar feature extraction for classification of unloaded/loaded micro-drones’, *IET Radar, Sonar & Navigation*, vol. 11(1), pp. 116-124, 2017.
[20] T. Hastie, R. Tibshirani, J. Friedman, The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition, *Springer*, 2009.
[21] Breiman, L. Random Forests. Machine Learning 45, *Springer*, pp. 5–32, 2001.
[22] Hsu, C. W., & Lin, C. J., “A comparison of methods for multiclass support vector machines”, *IEEE Transactions on Neural Networks*, *13*(2), 415–425, 2002.