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Filtering Data Bins of UWB Radars for Activity Recognition with Random Forest

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Abstract

The world's population is rapidly aging, leading to an increase in the number of people who need care and a reduction in the number of potential workers who can give that care. Hence, in order to fight this worker shortage, scientific researchers proposed solutions, mainly prototypes, to maintain people at home. These solutions monitor the activities performed by people and can detect anomalies in people's behavior to assist them in a proper way and at the perfect time. In this paper, we propose a solution based on three ultra-wideband radars to recognize activities in a prototype apartment. More precisely, we processed the data provided by the radars with a conventional band-pass filter applied on each bin independently. Then, we extracted several features and performed dimensionality reduction with the help of the SelectKbest algorithm and the principal component analysis. Finally, we tested the proposed approach with Random Forest algorithm and the leave-one-subject-out strategy. The results obtained show an average improvement of approximately 13% accuracy compared to our previous work.

Keywords: Ultra-wideband radar; Band-pass filter; Features extraction; Feature selection; Dimensionality reduction; Activity Recognition

1. Introduction

The aging of the world's population is a serious concern that particularly affects developed countries. Unfortunately, it reaches an unprecedented level and will continue to grow. For example, the Canadian population is currently composed of 9.1% of people aged 65 years old and older and will reach 15.9% by 2050, according to the United Nations [20]. The main reasons explaining this aging of the population are the decline in the birth rate, the improvement in health care and the increase in life expectancy [20]. In addition, this demographic evolution continuously leads to a growing need for supporting older people with, for example, care services and surveillance systems [16, 21]. However, the existing health care infrastructure and human resources available are not enough for assisting all older people in need [16, 21]. Hence, to fight the lack of resources, academic research invests a lot of effort in developing

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sensor-based solutions, relying on the concept of Ambient Intelligence (AmI) [9]. These potential solutions should be installed in the people's homes to prolong home support for semi-autonomous people and, thus, unclog the health care system. More specifically, the main idea behind developing sensor-based solutions is to closely monitor the Activities of Daily Living (ADLs) by recognizing them efficiently. This monitoring should allow detecting people's behaviour anomalies to provide the right assistance (e.g., calling 911) at the right moment (e.g., a fall occurs).

In the literature, we can find three main approaches to recognize human activities. The first one is the video-based approach, exploiting cameras [19]. Cameras provide images or sequences of images, where information is rich to recognize human activities. For example, if a person is brushing their teeth, the camera can provide: an image where the person gets the toothbrush; an image where the person gets the toothpaste; an image where the person puts the toothpaste on the toothbrush; and finally, an image where the person is brushing their teeth with a part of the toothbrush visible. Therefore, recognize the person, the toothbrush, the toothpaste, the toothpaste on the toothbrush, and the toothbrush in the mouth allow identifying the activity as the person is brushing their teeth. For less than one decade, the research exploiting cameras mainly used deep learning algorithms to recognize human activities [19]. Unfortunately, processing this sequence of images is not easy. Indeed, these algorithms need a consequent number of data to be trained correctly. In addition, the camera should be installed at the perfect location in the apartment to catch all key steps of human activities. Finally, people can be reluctant to use cameras, in large part because of privacy concerns [13]. The second approach is the wearable-based one exploiting technologies such as smartwatches or smartphones [14]. Unlike the video-based approach, these technologies can mainly collect data related to the movements performed by a person or their vital signs. However, almost no information about the person's interactions with their environment is provided by wearable devices. Furthermore, although people feel like their privacy is preserved, the major drawback of this approach is that the persons can forget to wear the wearable device, and no monitoring can be carried out [10]. Finally, the third and last approach concerns non-wearable devices (context-based approach), such as audio and ultrasonic sensors, or electromagnetic contacts [8, 3]. In general, these devices are directly installed into the person's environment by using, for example, the walls or kitchen cabinets. Regrettably, using only one type of sensor does not allow reaching good performances for human activity recognition. Therefore, these sensors are often combined and sometimes also combined with wearable devices [5]. The limitation of this approach is the high cost of the entire system [22], which means that we need to find a very expressive non-wearable sensor.

According to the disadvantages related to the use of video-based and wearable-based approaches, we decided to explore the non-wearable solutions by exploiting ultra-wideband (UWB) radars mounted on the apartment's walls of the *Laboratoire d'Intelligence Ambiante pour la Reconnaissance d'Activités* (LIARA). It should be noted that UWB radars are used in numerous applications, such as breathing detection, localization, micro-movement detection, or activity recognition [7, 23, 11, 18]. The main reason for this spread use is the details of the information in the data provided by UWB radars. That is why we selected this technology to recognize ADLs. In this paper, we outperform the results obtained in [12]. Indeed, we reach 59.2% accuracy, while in [12], we only got 46% accuracy for the top-1. To do so, we preprocess the data of UWB radars with a conventional filter (i.e., band-pass filter), but in an unconventional way. Then, we extract many features (e.g., skewness, wavelet coefficients) that we reduce with the SelectKBest algorithm and the principal component analysis (PCA). The dimensionality reduction aims to avoid the overfitting of classification models. Finally, we apply a coarse grid search to find one of the best sets of features and principal components. The observed metric is the accuracy of the successive classifications with the Random Forest (RF) algorithm. Finally, we have to mention that the results in this work have been obtained with the leave-one-subject-out strategy.

The rest of the paper is organized as follows: Section 2 presents the literature about using UWB radars for activity recognition. Section 3 describes the experimental setup. More specifically, the UWB radar and data acquisition during experiments are presented. Section 4 gives details of the proposed approach. Section 5 shows and discusses the results obtained and compares them with those from the previous work. Finally, Section 6 concludes this work and lists some perspectives for future work.

2. Related Work

As mentioned previously, in this paper, we exploit UWB radars to recognize ADLs. Hence, we decided to focus on work that uses UWB radars for human activity recognition. In general, we can observe two axes of work to obtain good results in recognizing human activities with UWB radars. The first one focuses on data processing. The second one is the extensive use of deep learning algorithms.

For example, in [11], the authors proposed a two-stage real-time sleep motion classification from data of a UWB radar. More specifically, they first applied a power burst curve detection to decide whether sleep motions occur. Then, they proposed to reduce the number of parameters of classifiers thanks to the zero-forcing time-frequency method. In other terms, the zero-forcing method cleans the radar spectrum from noise. Finally, the two-stage low-complexity classification is applied. First, if detected, a support vector machine (SVM) classifies sleep motions into two categories: *micro-motion* or *body movements*. Then, three features are extracted from the radar spectrum. The first one is beyond-vital-sign Doppler power. The second is the beyond-vital-sign Doppler information, and the third represents the ratio of beyond-vital-sign Doppler power to total Doppler power. The second stage would rely on the use of the long short-term memory (LSTM) if the SVM classified the event as a body movement. The radar is set 1-1.5 m above the subject. There were ten subjects. The subjects performed 5 activities (*micro-motion*, *lying down*, *getting up*, *turning over*, *waving*). They reached an average accuracy of 97.87% from five-fold cross-validation and 91.50% using the leave-two-subject-out strategy.

In [6], the authors proposed a system for identifying dynamic and static postures of the user in a room of 4 m $\times$ 5 m $\times$ 3 m. The technology used to collect the data was a UWB radar mounted on the wall at the height of 1 m. Also, the proposed system can extract breathing and coughing rates when the user is in a static posture. To do so, they only computed three statistical parameters and used the k-Nearest Neighbours (k-NN) to discriminate between static postures. Finally, they tested the reliability and carried out a fault tolerance of their approach. The movements performed by volunteers are *walking*, *standing up*, *sitting down*, *lying down* and *falling*. The static postures to recognize are *standing up*, *sitting* and *lying*. The performance obtained is greater than 99% accuracy. In addition, respiratory activity and coughing can be extracted from the static postures. The sitting position gives the best results since the person is perpendicular to the coming UWB signal. However, the experiments are not conducted realistically because of the absence of the room's furniture.

The authors in [18] present a fall detection system relying on UWB radar data collected from 99 volunteers. Also, they included five human activities, namely *walking*, *sitting*, *standing*, *picking up objects* and *drinking water*. The approaches exploited are the use of classical machine learning algorithms, such as random Forest (RF), k-NN, SVM, and deep learning algorithms, such as LSTM, bi-directional LSTM (Bi-LSTM) and convolutional neural networks (CNN). The best results were obtained with the CNN algorithm, where the accuracy reached 95.30%. It should be mentioned that a preprocessing stage has been applied to get optimum results. Hence, they used PCA and data augmentation. The dataset was divided into 90% for training instances and 10% for testing instances. Unfortunately, the proposed approach has not been tested with the leave-N-subject-out strategy.

Although the majority of the work in the literature transforms the data of the UWB radar into a radar data cube (RDC) [4] or spectrogram [6] and extracts features for machine learning models, few of them are attempting to improve the data quality. For this latter, numerous works apply the running average to delete the background clutter and static target from the raw data of UWB radars [17]. In this paper, it is the first time that conventional filters have been applied to UWB radar data to the best of our knowledge. Finally, the human activities that we recognize with UWB radar data are very different from the literature and experiments, as described in Section 3, are very realistic.

3. Experimental Setup

In order to capture the maximum of human movements inside the LIARA smart prototype apartment when a person is performing an ADL, three UWB radars were precisely installed to cover as much area as possible, as shown in Figure 1. The radars used are three XeThru X4M200 by Novelda, and the radar's transceiver can operate in the range of 6.0 to 10.2 GHz. The three radars are mounted on the walls, 36 cm above the ground and provides a very high spatial resolution while being a privacy-preserving technology by only sending wave pulses. The pulses are repeatedly sent following a pulse repetition frequency (PRF) of 15.875 MHz. If any object or person disrupts one of them, its energy is reflected at the place of their origin. Then, with the properties of electromagnetic waves, we can estimate the direction and the distance of the reflecting object/person. The pulses can be sent up to approximately 10 m. Thus, with this range, three radars were needed to cover the whole unit.

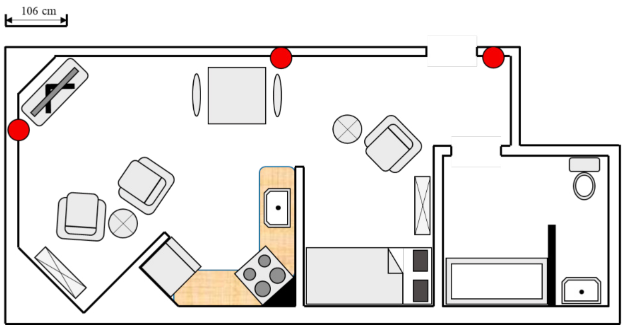

Fig. 1. Plan of the LIARA apartment. Red circles are the location of the UWB radars [2].

The training of the system is based on a multiple subjects data acquisition in order to increase the robustness of the classification for a user related applications. The group of subjects is formed of 10 healthy men aged from 23 to 39 years. The experiments have been conducted under the approbation of a formal ethical board, the Université du Québec à Chicoutimi human research board (2019-202).

The subjects were asked to perform 15 different ADLs listed in Table 1. The experiments have been conducted in the LIARA smart prototype apartment where all the other technologies were previously turned off and the subject was left alone. It is important to mention that the subjects were completely free to perform the activities the way they wanted as they usually do in their daily life. Also, it should be noted that two different participants can do the ADLs in different way and in different locations. For instance, activity such as *take medication* was completed in the bedroom, the bathroom or the kitchen and this can cause many variabilities in our dataset for the same activity. In fact, the particularity of the signals given by the UWB is that they are highly depending on the orientation of the sensors and the proximity of the participants with the sensors. Thus, if the activities are performed in different area, a high variability is observed. Because the duration of each activity is inconsistent, from 30 to 300 seconds, the recording length can differ, as shown in Table 1, and it results in a variation of the numbers of instances. Each participant was asked to perform the 15 ADLs for a total of 150 data acquisitions for our global dataset.

Table 1. List of ADLs.

Activity	Recording duration (*seconds*)	Locations
Drink	30	Table (dining room), kitchen
Sleep	60	Bedroom
Put on a jacket	30	Close to the door of the apartment
Do the housework	120	Everywhere in the apartment
Cook pasta	300	Kitchen (other activities while waiting)
Make tea	180	Kitchen (other activities while waiting)
Do the dishes	120	Kitchen
Brushing teeth	180	Bathroom
Wash hands	30	Kitchen and bathroom
Read a book	120	Living room, table (dining room), Bedroom
Eat	120	Table (dining room)
Walk	30	Everywhere in the apartment
Put on shoes	45	Close to the door of the apartment
Take medication	30	Mostly in the kitchen, bathroom and bedroom
Use a computer	120	Living room, table (dining room), bedroom

4. The proposed approach

In this section, we present the proposed approach to recognize human activities from data provided by three UWB radars mounted on the walls of a prototype apartment. First, to better understand the proposed approach, we need to

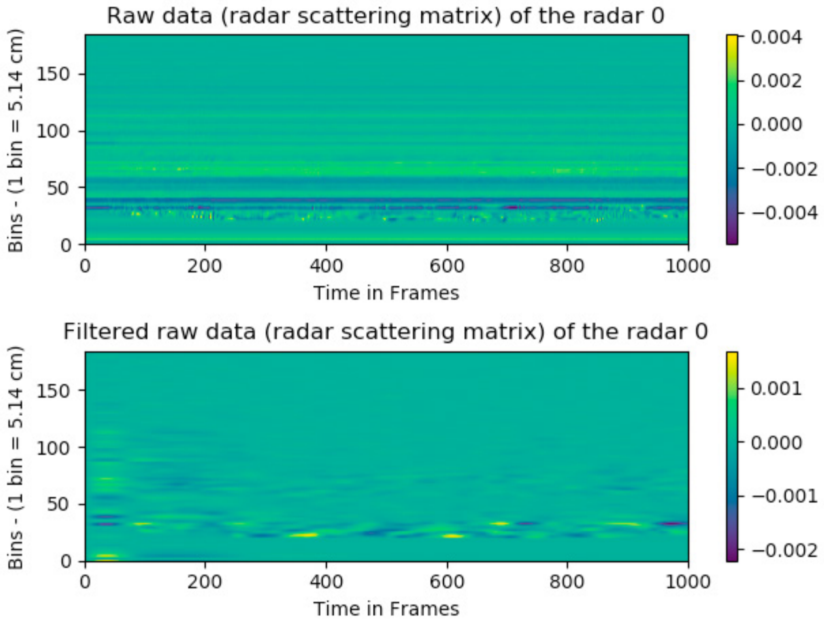

Fig. 2. The raw and filtered scattering matrices of the radar 0.

describe the format of the acquired data. Each UWB radar provides information about human movements made in a half-disc of radius 9.8 meters in front of the radar. The data acquisition of one UWB radar during a specific time interval produced a scattering matrix. The columns of the scattering matrix represent frames. For example, 5 seconds of data acquisition at a sampling rate of 50 frames/s gives 250 frames. We call this axis slow time. Each row of the scattering matrix provides information about human movements at a specific distance in a half-disc in front of the radar. We call this axis fast time. More precisely, a frame is composed of 184 bins, where one bin represents 5.14 cm. Hence, for example, the 50^{th} bin corresponds to information about human movements made between 2.92 and 2.97 meters approximately.

4.1. Preprocessing and data filtering

The first step of the proposed approach consists in preprocessing the raw data. Hence, we applied a band-pass filter to each bin of the scattering matrix provided by a UWB radar during data acquisition. Since we have three UWB radars, there are three scattering matrices. This band-pass filter has been chosen according to frequencies in time series that are not related to human activities, such as noise and clutter. In other terms, it is important to retain only the information associated with the ADLs and thus keep the frequencies in time series located in a humanly possible range. Therefore, we selected a low and high cut-off frequency of 1 Hz and 5 Hz, respectively. The band-pass is then from 1 Hz to 5 Hz. Also, to keep the maximum information from the raw data and reduce as much as possible the clutter and noise, we selected the Butterworth type filter of order 2 among a list of well-known filter types (e.g., Chebyshev type I and II, Elliptic, Bessel) that we tested and compared. In more detail, the filter type and its order have been determined by filtering the raw data of different ADLs and subjects. Then, we observed the filtered data and noted oscillations at the beginning of each bin. We decided to remove these oscillations. It should be mentioned that these oscillations decrease with time and are related to the frequency response of filter types. The Butterworth filter of order 2 is the one with the best frequency response. To remove these oscillations from the filtered data, we decided to cut the first 490 frames. This value was determined by graphical analysis and corresponds to the maximum frame where we still observe oscillations. Because of this data removal, the remaining data was too small to proceed with the next steps for one subject. So, we excluded this participant from the dataset. Figure 2 shows the raw data of a scattering matrix and its filtered version.

Once the data are filtered, we can proceed to the second step of the data preprocessing, namely the dataset creation. To do so, we applied a sliding time window of 15 seconds length with an overlap of 95% between two successive time windows. Since the sampling rate of the data acquisition is 50 frames/s, every instance forming the dataset is thus composed of 750 frames and shares 713 frames with the next one. The shape of one instance is then (750×184×3), where the latter dimension denotes the number of UWB radars. Also, the created instances have been separated using the leave-one-subject-out strategy. In other terms, if we have N subjects, the training of a classifier is done on instances of N-1 subjects, and the remaining subject's data are used to create the testing set. This method produces *N* different main datasets divided into training and testing sets. In this project, we have 9 subjects. The leave-one-subject-out strategy allows testing the generalization performances of a trained classifier.

4.2. Feature extraction

We can now process each created instance by extracting features. In our study case, 17 features have been calculated on each bin of each instance. The features are minimum, maximum, average, median, standard deviation, skewness, kurtosis, mean absolute deviation, waveform length, zero crossing rate, mean crossing rate, squared energies, power spectral density, energy of the level-3 approximation coefficients, and energies of the level-3 to level-1 detail coefficients (approximation and detail coefficients are provided by the Discrete Wavelet Transform). It should be noted that those features have been selected according to the ones commonly used in the literature [1]. The new shape of one instance is (9384x1). More specifically, we have 17 features multiply by 184 bins multiply by 3 UWB radars. As the reader can note, this number of features is too important to train a classifier properly. Indeed, the classifier will have more chances to overfit the training data with this set of features. Hence, we need to reduce this number.

4.3. Feature selection and reduction, and classification

To reduce the number of features, we applied a feature selection relying on univariate statistical tests. More precisely, we used the function SelectKBest from the Scikit-Learn library [15] and defined the Chi-Square test as the parameter for the univariate statistical test. From this test, the Chi-Square statistic is computed between each feature of the training dataset (instances composed of features and the label of each instance). A small value for the Chi-Square statistic means the feature is independent of the classes. On the other hand, a large value means the feature is strongly related to the classes and can provide important information to classify the instances. As the name of the function mentions, SelectKBest will pick the first *K* features of the training dataset with the highest scores. In our case, *K* was found by doing a first grid search from 1000 features to 8000 features with a step of 1000.

Then, we reduced the number of features for each *K* number by applying the Principal Components Analysis (PCA) algorithm. This algorithm computes the covariance matrix between each pair of features to determine if there are redundant information between them. After that, eigenvectors and eigenvalues are calculated from the covariance matrix to identify the principal components. The principal components are linear combinations of the *K* best features in a way that the principal components are uncorrelated. We decided to vary the number of principal components from 10 to 100 for each *K*. We arbitrarily chose the dataset for this grid search where the subject 0 was left out to be the testing set, denoted by LVOO 0. Also, to apply well these two algorithms, it should be mentioned that both are executed on the training set, and the results are applied on the training and testing sets.

Finally, the resulting datasets during the grid search are used to train and test the RF classification algorithm, providing classification accuracy. RF proved its efficiency in [2] because it had the best overall accuracy among three other classifiers, namely k-NN, CART and AdaBoost. RF first selects random samples of instances from our dataset. Then, for each sample of instances, a set of features are randomly picked (e.g., where *k* is the number of features) to construct a decision tree. Each decision tree gives a prediction when it classifies a new instance. The final prediction of the RF classifier is based on a majority vote from all decision tree predictions. In our case, we defined 100 estimators, which correspond to the number of trees we have in the forest.

The best *K* number seems to be around 4000 for less than 50 principal components. Hence, we carried out a second grid search by varying *K* between 3500 and 4500 with a step of 100 and the number of principal components in the range of [10, 50]. The results of the second grid search indicate that the maximum accuracy is obtained when K = 4000 best features are selected. The next step is to select these 4000 best features for each of the 9 LVOO datasets by varying the number of principal components in the range of [10, 100].

It was difficult to find out graphically the best number of principal components. Thus, we computed the average of the obtained accuracies from all LVOO datasets for each number of principal components. Then, the maximum average of accuracies represents the final performances that we reached for ADL recognition.

5. Results and Discussion

The results presented in this section are obtained by the method explained previously. To summarize, the data have been collected at a rate of 50 frames/s. We applied a band-pass Butterworth filter of order 2. We defined a sliding window of 15 seconds length and an overlap of 95%. Hence, 9384 features have been computed from each time window, and 4000 features have been selected with the SelectKbest algorithm. Then, the resulting dataset has been reduced by applying a PCA ranging from 10 to 100 principal components. Each dataset resulting from this last step has been used to train a RF model composed of 100 trees.

The metric used to evaluate the performance of the recognition is the accuracy. The accuracy represents the ratio between the correct predictions and the total instances. In our case, we decided to focus on getting the highest possible results and comparing them to the ones obtained in the previous work to emphasize the filter's effect [12].

As shown in Table II, the RF classifier obtained accuracies fluctuating between 0.47 to 0.72. It should be noted that the best results have been obtained with 33 principal components. In addition, the average of these accuracies represents an increase of 13% comparing the results obtained with the unfiltered data in [12], which vary from 39% to 56%.

Table 2. Accuracies of the ADL recognition for each dataset obtained from the leave-one-subject-out strategy.

Participant ID	Accuracy (Filtered data)	Kappa (Filtered data)	Accuracy (Unfiltered data [12])
0	0.64	0.58	0.45
4	0.72	0.67	0.56
5	0.61	0.56	0.47
6	0.47	0.37	0.41
7	0.61	0.56	0.46
8	0.61	0.55	0.56
9	0.51	0.45	0.43
10	0.62	0.56	0.39
12	0.54	0.48	0.41

Even though the accuracies in the literature are higher than the ones we obtained with the RF classifier, it can be explained by the complexity of the chosen activities. Indeed, the activities were much simpler, such as *walking*, *sitting*, or *standing*. However, in our study, the activities were much complex and have been performed in different locations.

In addition, the confusion matrix of each participant indicates that frequently the activity *walking* is confused with *doing the housework*. It makes sense because *doing the housework* necessarily includes the activity *walking*. Furthermore, *cooking pasta* has the longest recording duration and thus has more instances, affecting at the same time the recognition. Finally, it should be added that the tests performed with the leave-one-subject-out strategy have lower performances than the conventional train-test split.

6. Conclusion

In conclusion, the proposed approach outperforms in recognizing ADLs from UWB radars compared to our previous work [12]. Indeed, we increased the average accuracy by 13%. The main reason for that improvement is the filtering of UWB radar data. More specifically, we filtered each bin of the scattering matrices with a band-pass Butterworth filter.

This work also highlights future improvements that can be made. For example, the confusion of the activities in the kitchen could be reduced by investigating the amount of UWB radars needed and the angle of each one to discriminate the activities properly in a small area with similar movements. Finally, we can also investigate, in more detail, the preprocessing step of UWB radar data to improve the ADL recognition with deep learning algorithms.

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References

[1] Barandas, M., Folgado, D., Fernandes, L., Santos, S., Abreu, M., Bota, P., Liu, H., Schultz, T., Gamboa, H., 2020. Tsfel: Time series feature extraction library. SoftwareX 11, 100456.

[2] Bouchard, K., Maitre, J., Bertuglia, C., Gaboury, S., 2020. Activity recognition in smart homes using uwb radars. Procedia Computer Science 170, 10–17.

[3] Do, H.M., Welch, K.C., Sheng, W., 2021. Soham: A sound-based human activity monitoring framework for home service robots. IEEE Transactions on Automation Science and Engineering .

[4] Erol, B., Amin, M.G., 2018. Radar data cube analysis for fall detection, in: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE. pp. 2446–2450.

[5] Gjoreski, H., Kiprijanovska, I., Stankoski, S., Kalabakov, S., Broulidakis, J., Nduka, C., Gjoreski, M., 2021. Head-ar: Human activity recognition with head-mounted imu using weighted ensemble learning, in: Activity and Behavior Computing. Springer, pp. 153–167.

[6] Hämäläinen, M., Mucchi, L., Caputo, S., Biotti, L., Ciani, L., Marabissi, D., Patrizi, G., 2021. Ultra-wideband radar-based indoor activity monitoring for elderly care. Sensors 21, 3158.

[7] Imphaiboon, P., Kittipiyakul, S., Kaemarungsi, K., Koike, Y., 2021. Effect of obstacle attenuation on human respiratory detection using ir-uwb sensor, in: 2021 9th International Electrical Engineering Congress (iEECON), IEEE. pp. 563–566.

[8] Jiang, W., Miao, C., Ma, F., Yao, S., Wang, Y., Yuan, Y., Xue, H., Song, C., Ma, X., Koutsonikolas, D., et al., 2018. Towards environment independent device free human activity recognition, in: Proceedings of the 24th Annual International Conference on Mobile Computing and Networking, pp. 289–304.

[9] Klimova, B., Valis, M., Kuca, K., 2018. Exploring assistive technology as a potential beneficial intervention tool for people with alzheimer's disease–a systematic review. Neuropsychiatric disease and treatment 14, 3151.

[10] Köping, L., Shirahama, K., Grzegorzek, M., 2018. A general framework for sensor-based human activity recognition. Computers in biology and medicine 95, 248–260.

[11] Lai, J., Yang, Z., Guo, B., 2021. A two-stage low-complexity human sleep motion classification method using ir-uwb. IEEE Sensors Journal 21, 20740–20749.

[12] Maitre, J., Bouchard, K., Bertuglia, C., Gaboury, S., 2021. Recognizing activities of daily living from uwb radars and deep learning. Expert Systems with Applications 164, 113994.

[13] Mulvenna, M., Hutton, A., Coates, V., Martin, S., Todd, S., Bond, R., Moorhead, A., 2017. Views of caregivers on the ethics of assistive technology used for home surveillance of people living with dementia. Neuroethics 10, 255–266.

[14] Nweke, H.F., Teh, Y.W., Al-Garadi, M.A., Alo, U.R., 2018. Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges. Expert Systems with Applications 105, 233–261.

[15] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E., 2011. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research 12, 2825–2830.

[16] Prince, M.J., Wimo, A., Guerchet, M.M., Ali, G.C., Wu, Y.T., Prina, M., 2015. World alzheimer report 2015-the global impact of dementia: An analysis of prevalence, incidence, cost and trends .

[17] Quan, X., Choi, J.W., Cho, S.H., 2020. A new thresholding method for ir-uwb radar-based detection applications. Sensors 20, 2314.

[18] Taylor, W., Dashtipour, K., Shah, S.A., Hussain, A., Abbasi, Q.H., Imran, M.A., 2021. Radar sensing for activity classification in elderly people exploiting micro-doppler signatures using machine learning. Sensors 21, 3881.

[19] Ullah, H.A., Letchmunan, S., Zia, M.S., Butt, U.M., Hassan, F.H., 2021. Analysis of deep neural networks for human activity recognition in videos–a systematic literature review. IEEE Access .

[20] United Nations, D.o.E., Social Affairs, P.D., 2019. World population prospects 2019, volume ii: Demographic profiles (st/esa/ser. a/427) .

[21] Warrick, N., Prorok, J.C., Seitz, D., 2018. Care of community-dwelling older adults with dementia and their caregivers. Cmaj 190, E794–E799.

[22] Yadav, S.K., Tiwari, K., Pandey, H.M., Akbar, S.A., 2021. A review of multimodal human activity recognition with special emphasis on classification, applications, challenges and future directions. Knowledge-Based Systems , 106970.

[23] Yan, B., Giorgetti, A., Paolini, E., 2021. A track-before-detect algorithm for uwb radar sensor networks. Signal Processing 189, 108257.