Activities Recognition and Fall Detection in Continuous Data Streams Using Radar Sensor

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***Abstract*—This student paper presents a Quadratic-kernel Support Vector Machine (SVM) based FMCW (Frequency Modulated Continuous Wave) radar system to recognize daily activities and detect fall accidents. Data collected in this work is divided into two different collection modes, namely, snapshots mode (different activities individually collected in isolation) and continuous activity mode (continuous streams of activities collected one after the other). For the continuous activity streams, a sliding window approach with 4s duration and 70% overlapping has achieved 84.7% classification accuracy and subsequent improvement of 2.6% has been proved by using Sequential Forward Selection (SFS) on six participants to identify an optimal feature set. A 'tracking' graph has been utilized to verify that the radar system can correctly identify falls as critical events among the other activities.**

Keywords—radar micro-Doppler, human activity recognition, continuous activity streams, feature selection

I. Introduction

Fall events often come with serious consequences for older people [1], [2]. Together with physical injuries like head trauma and hip fractures, people affected usually lose the motivation for further exercise and rehabilitation, which may in turn lead to mental and physical illnesses and in general to the reduction of life expectancy. The UK government reports one in three over 65s will suffer from a fall each year [3], costing NHS estimated 4.6 million pounds a day [3]. Therefore, a fast and reliable fall detection system [4], [5] can significantly mitigate the risk for elderly people and reduce the cost of treatment. For the people who live alone, it would be even more desirable to integrate daily activity monitoring with fall detection, not only to avoid any false alarms in recognising falls, but also to evaluate their health conditions by monitoring essential activities such as food and water intake, personal hygiene, compliance to medical prescriptions.

Many sensing technologies, including wearable device-based sensors [6], [7] (e.g. smartphone or wristbands), depth or RGB video cameras [8] (e.g. Microsoft Kinect) and RF-based sensors [9] have been employed on the field of Ambient Assisted Living [10], for the purpose of monitoring daily activities and early-warning of the unintentional fall accidents. However, wearable devices require users to comply and carry them most of the day, and video camera-based systems are able to record images or videos that may raise the risk of privacy issues. For this reason, RF and radar have gained significant interest as a novel contactless technology in human activity recognition and fall detection. Radar sensing is not affected by indoor light conditions, does not record plain images of the environment or people under test, and can estimate simultaneously their trajectory and velocity with range-Doppler processing. Typically, radar signal processing of human activities relies on the extraction and analysis of micro-Doppler signatures, i.e. the complex patterns of small modulations on the received radar signal caused by small movements of head, torso, limbs [11].

In this paper, we start extending classification analysis to radar data recorded as continuous streams rather than individual snapshots activities. In this case the subjects were only told to perform a sequence of activities, without strict constraints in terms of the duration and transition from one to another. This helps towards working with more realistic data, more similar to natural behaviour although still in controlled laboratory environment. The paper presents an initial simple approach based on sliding windows to classify the continuous data which offers promising initial results and interesting ideas to further expand this work.

The remainder of this student paper is organised as follows. Section II introduces the experimental setup and describes the data collection at the Communication, Sensing and Imaging Laboratory of the University of Glasgow. Section III reports the data pre-processing and the preliminary results of the activity classification and fall detection. Finally, section IV summarizes conclusions and possible future work.

II. Experimental setup and data collection

The data utilized in this work were recorded in an indoor office environment at the University of Glasgow with two radar sensing systems operating at different bands. The measuring environment is depicted in Fig. 1. The radar systems used in this work were an FMCW radar (Ancortek 580-B) and a CW radar (RF-Beam), which operates at 5.8 GHz and 24 GHz respectively. The Ancortek radar transmits chirp signals with approximately 400 MHz bandwidth and 1 ms chirp duration. The transmitted power of the FMCW radar is in the order of 100 mW, with the receiver antenna gain of about 17dB, whereas the CW radar has an effective isotropic radiated power of 18 dBm. The radar sensors were placed on a plastic table at about 1m height and connected to a laptop to acquire the data. The distance between the two Yagi antennas used by the FMCW system approximately equates to 30 cm. Furthermore, the radar antennas were directly pointing to the center of the activity zone, with the red chair positioned at approximately 4m away from the radar.

In the data collection, 16 participants were asked to perform six different daily activities which includes walking, sitting on and standing up from the chair in front of the radar, bending to pick up a pen, drinking water from a glass for a couple of times and put the cup back on the chair, and simulating a frontal fall on a soft mattress. These activities are presented with sketch figures at the top of Fig. 2.

Two different recording methods were chosen to collect data of those activities. One method is the similar to the one used in [12], and denoted as 'snapshot', in which each activity is individually recorded in isolation. The second method, for the purpose of addressing a more realistic and challenging classification scenario, requires collection of 'continuous data streams', where the participants perform all the activities one after the other in the same recording, following three different ordered sequences. In the 'snapshot' mode, except for walking which was recorded for 10s, all the other activities have a duration length of 5s. In the continuous data stream mode, rather than determining a fixed time duration for each activity, the participants were asked to finish six activities within 35s, but they were not constrained in the duration of each single activity. For the snapshot collection, each activity was repeated three times for each subject to extend the numerosity of the database. For continuous activities, three long 35s recordings were collected per subject, but in each sequence the order of the six activities was changed as illustrated in Fig. 2. In the snapshot mode, the total observations are in total 288 (16 participants * 6 activities * 3 repetitions), whereas in the continuous mode the radar system collected 48 (16 participants * 3 sequences) long data frames.

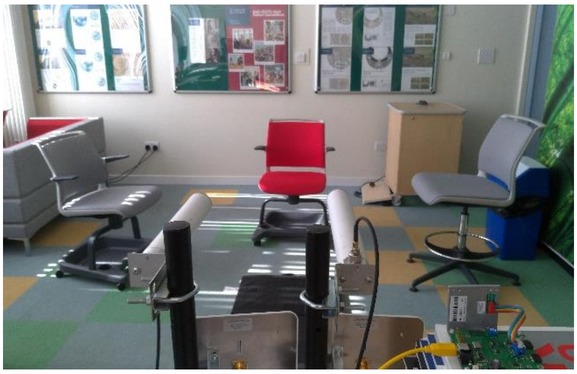

Fig. 1. View of the experimental setup for recording data: common room at the University of Glasgow, with furniture and clutter nearby

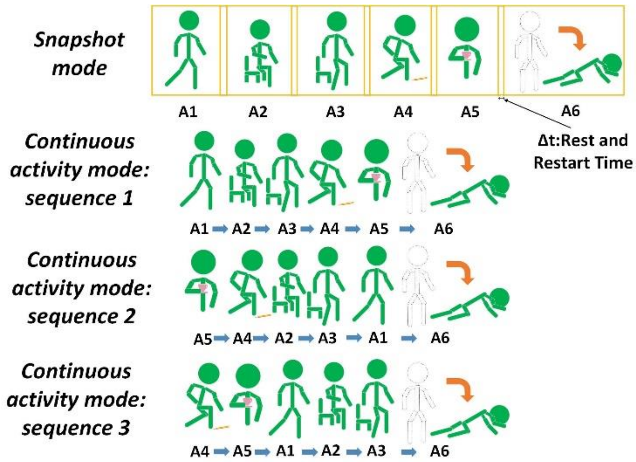

Fig. 2. Sketch of recorded activities for two different modes

Due to the limitation of CW radar, in particular its inability to provide range information, only the data from the FMCW radar is used for processing and classification for the preliminary results presented in this paper.

III. DATA PROCESSING AND DATA ANALYSIS RESULTS

Prior to the feature extraction, data from the radar sensor need to be pre-processed by a notch filter to remove the static clutter contribution, followed by a Short Time Fourier Transform (STFT) with a window size of 0.3s and 95% overlapping factor to generate the micro-Doppler signatures. After that, fine-grained information about moving speed relevant to different body parts (e.g. torso, arm, limbs) can be extracted through the analysis of those spectrograms. Numeric features [9], [13] are often utilized as more meaningful, compressive representation of the data in many works in the literature, including ours. In this case, only 20 simple features are considered, involving Doppler centroid and bandwidth, left and right singular vectors of the SVD (Singular Vector Decomposition) spectrogram matrix, and two-dimension mean & standard deviation of the spectrogram.

For the snapshots data, these features were extracted from each individual recording. This approach to feature extraction is not directly applicable to continuous data streams, which first need to be partitioned into different windows. In this case, three different durations of window, namely, 3s, 4s and 5s, were utilized to segment the continuous data into smaller data frames. The window is moving across the time axis with four different overlapping factors between the nearest two steps, notably, without overlapping (0%), 30%, 50% and 70%. Every single shorter frame is analysed to generate ground truth labels and the major, dominant activity is considered in case of two activities coexisting in the same frame at the transitions. For example, if a shorter frame contains the transition between walking and drinking water, the frame will be labelled as walking if walking is longer than drinking (or vice versa). It should be noted that the creation of ground-truth labels was done manually by looking at the spectrograms shortly after the data collection.

One robust classifier with relatively light computational burden, the Quadratic-kernel Support Vector Machine [14], was trained and evaluated by using a 'Leaving one person out' cross-validation approach, in which data frames from each participant are taken out for test and the rest of the data from all the other participants for training. An average across all the 16 subjects can then be evaluated to estimate the robustness of the approach. The purpose of partitioning data in this way is to simulate real-world situations, where the classifier deployed in a new environment will have no opportunity to see data from unknown testing subjects.

A. Results and discussion

Fig. 3 shows the classification results of data collected by snapshot mode. The diagonal elements of the confusion matrix show the events which were correctly classified, whereas the non-diagonal ones indicate incorrect or misclassifications. The row and column represent the output and target class, respectively, which means the summary of column elements are equal to 100%. The average validation accuracy of the 'Leaving one person out' data is about 80.56%, i.e. the average across the 16 subjects where each of them was used individually for testing the classifier. Activity 1 (walking) and 6 (falling) have high sensitivity, whereas the main misclassification takes place between activity 2 and 3 (sitting down and standing up) with 23-25% error rate. This may be due to the different sitting/standing habit of the different people, where some of them would lean forward when they are sitting down, hence causing positive Doppler shift similar to the standing up action.

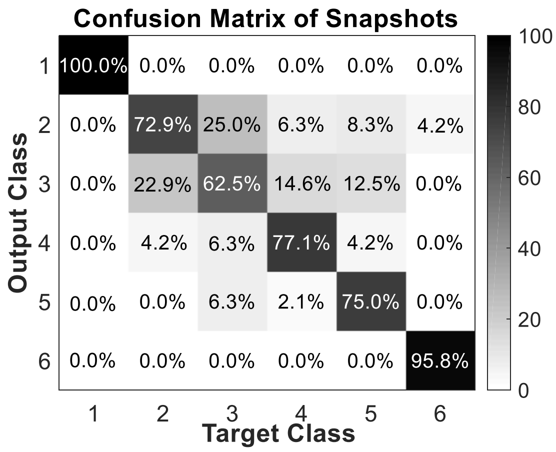

Fig. 3. Classification results of snapshots activities data (average of leave-one-person-out cross-validation)

Beyond snapshot activities, Fig. 4 summarises the classification results obtained for continuous streams of activities analysed by sliding windows, as a function of window size and overlapping factor. Overlapping appears to improve performance, with values between 50-70% providing the best results. The highest accuracy is obtained in the case of window size equal to 4s and using 70% overlapping, which provides approximately 84.7% classification accuracy. This is slightly higher than the value obtained for snapshots activities, showing that sliding window approach can provide classification capabilities for identification of continuous streams of data, even if it is dependent on the windows' parameters.

Subsequently, a wrapper feature selection method known as sequential forward selection (SFS) was applied on the feature set to search the optimal feature combination by using a SVM classifier. To generate a generalized feature set for all participants, six different participants were randomly selected, then SFS was performed individually, to find a personalised set of features that can improve performance for that individual. With this set, in Fig. 5 we show an improvement of about 4%-12% in the classification accuracy for each participant after applying SFS. The best window duration and overlap identified from the previous analysis were used to generate these results.

Common features from this set were then used to construct a generalised set. The strong features identified by SFS were the mean, standard deviation and skewness of Doppler centroid, the standard deviation of Doppler bandwidth, the mean of the first left singular vector, the standard deviation of the first right singular vector, plus two-dimensional mean of the micro-Doppler signature. These features were then used to build a new, more compact feature set and tested with 'Leave one person out' method again. The average validation accuracy by using this new feature set is shown in Fig.6 to improve accuracy approximately by 2.6% compared to the case without feature selection. Different from the snapshots, the classification results of continuous data with feature selection illustrates a high misclassification between picking up and drinking water. However, the classifier now can distinguish sitting down and standing up much better. Fig. 7 is a 'tracking' graph by using 'Leave one person out' test on a specific participant, No. 15, in the best-case scenario (i.e. parameters of the algorithms such as 4s window, 70% overlapping and using SFS). The classifier with sliding window and radar sensor can provide activity recognition with minor misclassifications between activity 2 and 3 (sitting and standing). For the fall detection capability, our system can identify falls from continuous activity streams without any missing detection and false alarm. It should be noted that in the figure all the three continuous activities streams for subject No. 15 have been concatenated and reported (i.e. 35 seconds of data for 3 times).

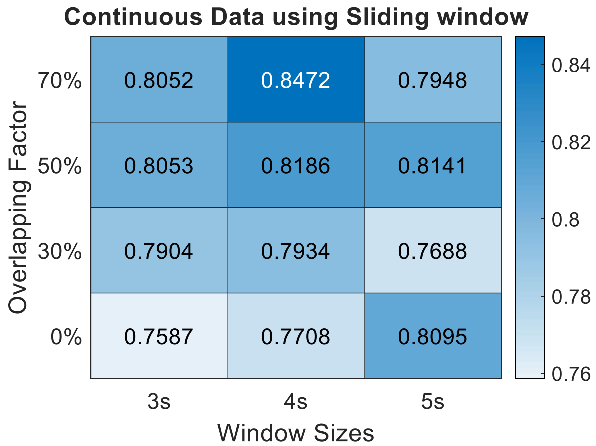

Fig. 4. Validation accuracy of the sliding window method on continuous data as a function of overlapping and window size

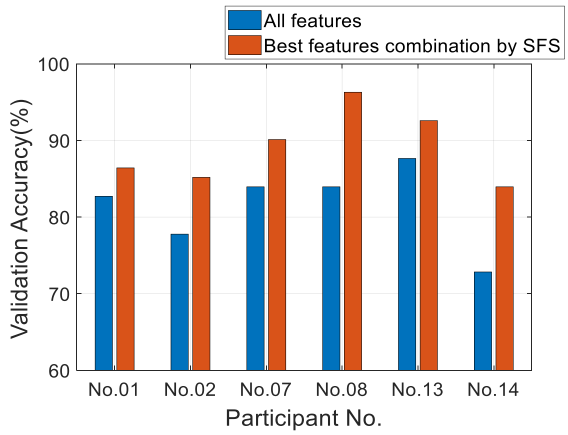

Fig. 5 Validation accuracy before and after SFS (continuous data analysed with sliding window with optimal parameters identified from figure 4).

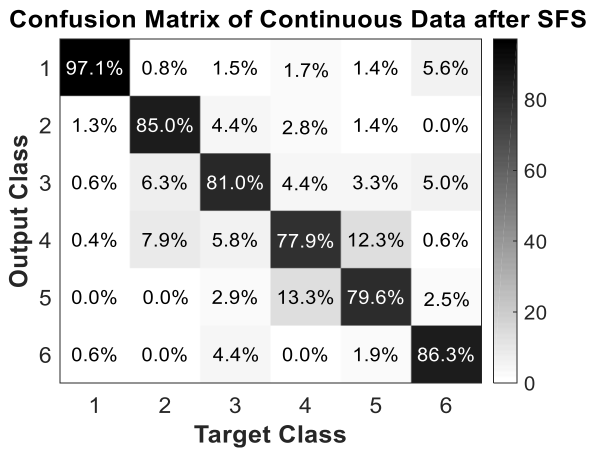

Fig. 6. Confusion matrix of continuous data using common features selected by SFS (average of leave-one-person-out cross-validation with sequences 1, 2 and 3)

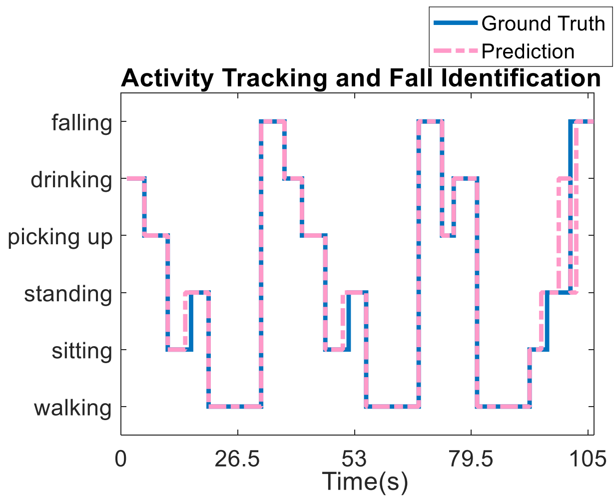

Fig. 7. Activity tracking of one participant with continuous data sequence 1, 2 and 3(window size =4s, overlapping =0.7, after SFS)

IV. Conclusions

In this paper, snapshots and continuous data from a FMCW radar sensor are utilized to train a SVM classifier and test it with a more challenging, realistic 'Leave one person out' method. The target classes are six human indoor activities, with data from 16 subjects analysed, including data with continuous activities performed one after the other in a single recording, without duration constraints for each activity. These data were processed with sliding windows, and three different window sizes and four overlapping factors were analysed to divide the continuous activity streams into small frames. SFS as feature selection tool was used as a robust approach to select optimal feature sets, with the potential of fine tuning the classification for each specific subject.

For the future work, more data, including older people with different high-resolution radar systems, will be collected in a more realistic and constraint-free (free walking route and different directions of fall) environment. In the context of classification algorithms, deep learning methods like Recurrent Neural Networks (RNN) and transfer learning will be used to boost the performance.

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V. References

[1] M. Terroso, N. Rosa, A. T. Marques, and R. Simoes, "Physical consequences of falls in the elderly: a literature review from 1995 to 2010," *Eur. Rev. Aging Phys. Act.*, vol. 11, no. 1, p. 51, 2014.

[2] M. Mubashir, L. Shao, and L. Seed, "A survey on fall detection: Principles and approaches," *Neurocomputing*, vol. 100, pp. 144–152, 2013.

[3] NIHR Dissemination Centre, "HELP AT HOME Use of assistive technology for older people," *Natl. Inst. Heal. Res.*, pp. 3–6, 2018.

[4] R. M. Gibson, A. Amira, N. Ramzan, P. Casaseca-de-la-Higuera, and Z. Pervez, "Multiple comparator classifier framework for accelerometer-based fall detection and diagnostic," *Appl. Soft Comput.*, vol. 39, pp. 94–103, 2016.

[5] K. Chaccour, R. Darazi, A. H. El Hassani, and E. Andrès, "From Fall Detection to Fall Prevention: A Generic Classification of Fall-Related Systems," *IEEE Sens. J.*, vol. 17, no. 3, pp. 812–822, 2017.

[6] J. Chen, K. Kwong, D. Chang, J. Luk, and R. Bajcsy, "Wearable sensors for reliable fall detection," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, 2006, pp. 3551–3554.

[7] R. C. King, E. Villeneuve, R. J. White, R. S. Sherratt, W. Holderbaum, and W. S. Harwin, "Application of data fusion techniques and technologies for wearable health monitoring," *Med. Eng. Phys.*, vol. 42, pp. 1–12, 2017.

[8] E. Cippitelli, F. Fioranelli, E. Gambi, and S. Spinsante, "Radar and RGB-depth sensors for fall detection: a review," *IEEE Sens. J.*, vol. 17, no. 12, pp. 3585–3604, 2017.

[9] A. Shrestha, J. Le Kernec, F. Fioranelli, E. Cippitelli, E. Gambi, and S. Spinsante, "Feature Diversity for Fall Detection and Human Indoor Activities Classification Using Radar Systems," *proceedings of IET Radar Conference*, 2017.

[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 Process. Mag.*, vol. 33, no. 2, pp. 36–44, 2016.

[11] V. C. Chen, W. J. Miceli, and D. Tahmoush, *Radar micro-Doppler signatures: processing and applications*. The Institution of Engineering and Technology, 2014.

[12] H. Li, A. Shrestha, H. Heidari, J. L. Kernec, and F. Fioranelli, "A Multisensory Approach for Remote Health Monitoring of Older People," *IEEE J. Electromagn. RF Microwaves Med. Biol.*, vol. 2, no. 2, pp. 102–108, 2018.

[13] F. Fioranelli, M. Ritchie, and H. Griffiths, "Centroid features for classification of armed/unarmed multiple personnel using multistatic human micro-Doppler," *IET Radar, Sonar Navig.*, vol. 10, no. 9, pp. 1702–1710, 2016.

[14] T. D. Bufler and R. M. Narayanan, "Radar classification of indoor targets using support vector machines," *IET Radar, Sonar Navig.*, vol. 10, no. 8, pp. 1468–1476, 2016.