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Bistatic human micro-Doppler signatures for classification of indoor activities

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***Abstract*—This paper presents the analysis of human micro-Doppler signatures collected by a bistatic radar system to classify different indoor activities. Tools for automatic classification of different activities will enable the implementation and deployment of systems for monitoring life patterns of people and identifying fall events or anomalies which may be related to early signs of deteriorating physical health or cognitive capabilities. The preliminary results presented here show that the information within the micro-Doppler signatures can be successfully exploited for automatic classification, with accuracy up to 98%, and that the multi-perspective view on the target provided by bistatic data can contribute to enhance the overall system performance.**

Keywords— bistatic radar, micro-Doppler, feature extraction and classification, machine learning

I. INTRODUCTION

Radar micro-Doppler signatures are defined as the additional frequency modulations on top of the main Doppler shift of moving targets, and these modulations are related to vibrating or rotating parts of vehicles and aircraft (e.g. the tracks of tanks or the blades of helicopters), as well as to swinging limbs and body parts for humans [1-2]. These signatures have been used in recent years as a source of information to perform the identification and classification of actions for a variety of applications in different contexts. These include discrimination of people vs animals and vehicles, recognition of different activities performed by humans, identification of specific individuals based on their walking or running gait [3-8].

The use of radar micro-Doppler signatures has been also reported in the context of ambient assisted living, fall detection, and general monitoring of the life patterns and conditions of people, especially elderly or vulnerable people affected by physical or cognitive impairments [9]. Radar systems can provide accurate persistent monitoring capabilities without the privacy concerns associated with camera systems, or requiring the patients to have to wear motion sensor devices or to modify their normal behavior. Different research articles in the literature have discussed aspects such as the study of time-frequency distributions in order to characterize walking with assistive devices like canes, various features to characterize common indoor movements, monitoring of patterns of life and vitality as well as detecting significant fall events when caring for the elderly [9-14]. One of the main issue in using radar micro-Doppler signatures for classification is their dependence on the cosine of the aspect angle between the target trajectory and the radar line-of-sight. For unfavorable angles close to 90° this can drastically reduce the classification accuracy [4,15]. Bistatic and multistatic radar systems have been proposed as an effective solution to this issue, as a collection of nodes can be deployed to provide favorable geometry with respect to the targets of interest, for at least a subset of nodes. However, experimental results involving actual bistatic or multistatic radar systems are rather limited, as their development and operations are more challenging than conventional monostatic systems. The issue of providing a unique phase reference to synchronize all the nodes is particularly challenging, especially if this has to be achieved over wireless channel with no direct connection between nodes, thus increasing the hardware complexity of the whole system [16].

This paper presents the preliminary analysis of radar micro-Doppler signatures for indoor human activities and investigates simple features and algorithms to perform automatic classification. The data were collected using a single channel radar (i.e. one transmitter and one receiver). First a series of measurements were taken using a co-located transmit/receive antenna monostatic setup, and then these were repeated with a spatially separated receiver for the bistatic equivalent results. It was unfortunately not possible to record both monostatic and bistatic results simultaneously with the available system. For the bistatic setup a bistatic angle of approximately 20° is obtained with respect to the target position. The same type of activities performed by the same subjects were recorded, although not simultaneously. The analysis shows that simple features extracted from the micro-Doppler signatures and simple classifiers can provide high classification accuracy, up to 98% in the most favorable cases. Furthermore, it is shown how different subsets of features at different nodes (monostatic and bistatic) are required to provide maximum accuracy. This opens up wide scope for further work in exploring this 'feature diversity' [17] in human indoor activities classification scenarios, aiming to characterize the effect on the overall accuracy of the many operational parameters. This includes parameters related to the radar (e.g. waveform, dwell time, Signal to Noise ratio), as well as parameters related to the deployment of the radar in the scene/environment (e.g. the bistatic angle and the aspect angle between the line-of-sight of the radar nodes and the trajectory/movement of the target). All these parameters can affect the suitability of the different

features for different classification problems, and dynamic or adaptive selection of features may be needed to achieve optimal classification performance. This is still a relatively unexplored research field. The remainder of this paper is organized as follows. Section II describes the radar system and the experimental setup. Section III presents the analysis of the data and the results. Section IV finally concludes the paper.

II. RADAR SYSTEM AND EXPERIMENTAL SETUP

The data were collected by an FMCW off-the-shelf radar sensor operating at 5.8 GHz (C-band). Parameters of interest were bandwidth and duration of the linear chirp 400 MHz and 1 ms respectively, the resulting PRF 1 kHz (sufficient to include the whole human micro-Doppler signature within the unambiguous Doppler region), and transmitted power of approximately +19 dBm. Two directional Yagi antennas were used to collect the data in vertical polarization, with 17 dBi gain and 24°×24° beam-width.

Figure 1 shows a sketch view of the experimental setup. These measurements were performed in a typical indoor environment, at the School of Engineering at the University of Glasgow. The room contained pieces of office furniture, namely a large meeting table, a couple of smaller tables, chairs, located around the subject performing the different movements, and a desktop computer near the radar system. Hence it represented a real-world cluttered environment, where such a sensor would be required to operate. The radar system was placed near a corner of the room, with the subjects performing the different movements positioned at approximately 4 m from the radar. In monostatic configuration (in color red in the figure) the transmitter and receiver antennas were co-located and separated by approximately 30 cm, whereas in bistatic configuration (in color green in the figure) the receiver antenna was moved at approximately 1.5 m from the transmitter and aimed at the target, originating a bistatic angle equal to approximately 20°. It should be noted that the collection of the monostatic and bistatic data was not simultaneous, as the radar sensor has only one receiver channel, but care was taken to perform the movements as consistently as possible for both cases.

Three subjects took part to this data collection, with the following key body parameters, namely 1.71 m, average body type for person A, 1.89 m, average body type for person B, and 1.84 m, slim body type for person C. Ten recordings of 10 s each were collected for each activity considered and for each subject, for a total number of datasets equal to 240 (4 movements, 3 subjects, 10 recordings, monostatic and bistatic data). The four activities considered were walking back and forth, sitting down and standing up on an office chair, bending down to pick up an object from the floor and coming up to stand, and waving with one hand left and right. Several repetitions of each activity were collected for each recording. Sitting and bending were chosen as they might be actions triggering false alarms for systems aimed at fall events detection because of their sudden acceleration component [9]. Repeated waving movements with one hand can be used as a key action to initiate the interaction with smart devices, to look them to a specific user to then detect additional commands (similarly to wave to another human being to ask for attention).

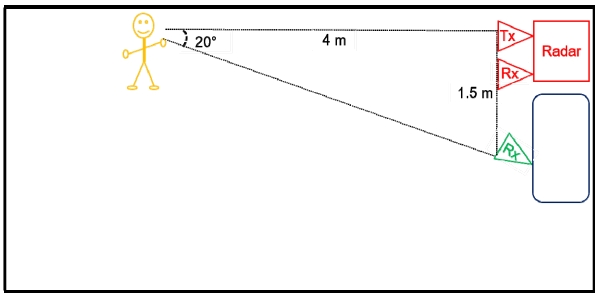

Fig. 1. Plan view of the experimental setup

III. DATA ANALYSIS AND RESULTS

The micro-Doppler signatures were extracted from the data by applying the Short Time Fourier Transform (STFT) to generate spectrograms. A Hamming window with 200 samples corresponding to 0.2 s was used, with 95% overlap. A notch IIR filter was applied to reduce the contribution of the static clutter around 0 Hz and highlight the actual signatures. Figure 2 shows examples of spectrograms for the four activities performed by subject A. The most evident difference is between the walking signature, which has a dominant positive and negative main Doppler shift caused by the overall motion of the whole body, and the other three signatures, which appear to be centred around 0 Hz as these were static motions, not involving complete movements of the body. Nevertheless, these static signatures present differences that can be empirically appreciated, suggesting that good automatic classification accuracy can be achieved, provided that relevant features can be developed to extract discriminating information. Figure 3 shows additional examples of spectrograms for the actions of walking and picking up an object performed by person B, for both monostatic and bistatic data. It is interesting to observe the differences in the signatures for the same type of movement, even at the limited bistatic angle of 20° of this setup. The bistatic signatures appear to have slightly lower Doppler values, e.g. the peaks for the picking up movement reach approximately 75 Hz for the monostatic case but only around 50 Hz for the bistatic case. This is compatible with the considered measurement setup, as the movements were performed facing the monostatic node, hence actions such as bending down towards the floor or standing up from the chair are expected to generate the highest Doppler shift in that direction.

Simple features based on the mean and standard deviation of the Doppler centroid and bandwidth of the micro-Doppler signatures were considered to analyze the data. These have been shown to be effective for different classification problems such as personnel recognition [18] and unarmed vs armed personnel classification [19], and have the advantage of not requiring any pre-processing or parameter tuning in the feature extraction algorithm. The Doppler centroid estimates the center of gravity of the micro-Doppler signature, and the Doppler bandwidth calculates the energy extent of the signature around the centroid [17]. These parameters were calculated as in equations (1) and (2), where $S(i,j)$ represents the value of the spectrogram at the ith Doppler bin and j^{th} time bin and $f(i)$ is the value of the Doppler frequency at the ith bin.

$$f_c(j) = \frac{\sum_t f(t) S(t,j)}{\sum_t F(t,j)} \quad (1)$$

$$B_c(j) = \sqrt{\frac{\sum_t (f(t) - f_c(j))^2 S(t,j)}{\sum_t S(t,j)}} \quad (2)$$

Each recorded 10 s dataset was divided into 3 s blocks and one feature sample extracted from each block, generating 360 samples for each feature for monostatic data and 360 for bistatic data. Figure 4 presents examples of feature space plots for the collected data. The features considered in the 2D plots are the mean and standard deviation of the signature bandwidth, with the addition of the mean value of the signature centroid as 3rd feature in the 3D plots. These features were selected out of the other different combinations as they empirically provided the best separation between samples belonging to different activities. It should be noted that different colors in figure 4 denote the different activities, whereas the different shapes of the marker (circle, square, and diamond) indicate the different subject. Good separation can be seen between samples of the three static activities in the 2D plots, and the additional feature considered in the 3D plots help separating the walking movement from the others. This appears to be true for both monostatic and bistatic data.

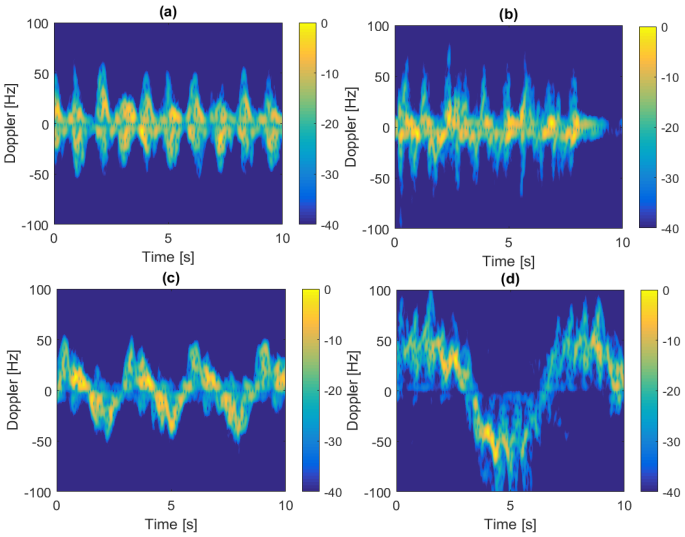

Fig. 2. Spectrograms for different movement performed by the same subject, radar in monostatic configuration: (a) bending and picking up an object from the floor, (b) waving with one hands, (c) sitting and standing up, and (d) walking back and forth

Three different classifiers were used to process the feature samples, namely Binary Tree (BT), Naïve Bayes (NB), and Nearest Neighbor with 3 neighbors (3NN). More details on the implementation of these classifiers can be found in [17, 20]. The classifiers were trained with 70% of the available data and tested with the remaining 30%. This process was repeated using 100 monte-carlo simulations that used different, randomly selected subset of samples for training and testing. The overall percentage accuracy is reported here as ratio of successful classifications over the total number of samples, averaged over the 100 different repetitions. Each classifier was tested using the two features and three features samples shown in figure 4, as well as with the whole four extracted features (standard deviation and mean value of both centroid and bandwidth parameter). As the collection of monostatic and bistatic data was not simultaneous for these preliminary data, the classifiers were implemented separately for these two cases and their accuracy is compared in this section.

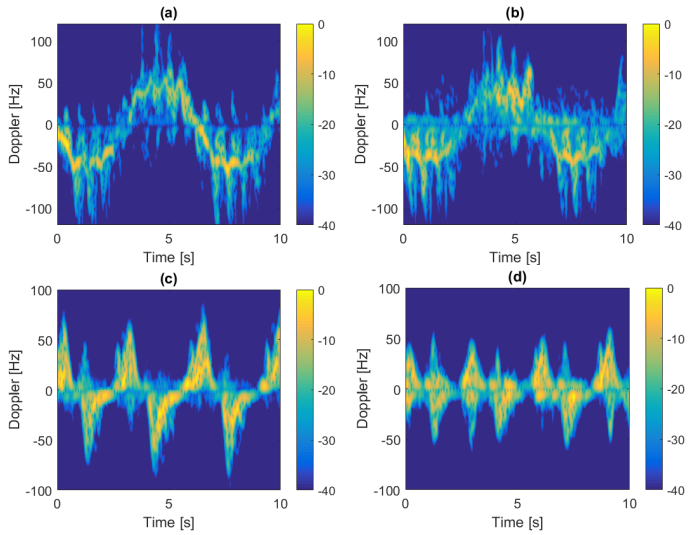

Fig. 3. Comparison of spectrograms in monostatic and bistatic configuration: walking movement monostatic (a) and bistatic (b), and picking up an object monostatic (c) and bistatic (d)

Table I and II show the accuracy obtained for monostatic and bistatic data, respectively. In both cases the 3NN classifier provides the best classification accuracy, up to approximately 97-98% in the most favorable cases, followed by the BT and then NB classifier. A common trend among the three classifiers for the monostatic case is that the accuracy is at its highest when using three features and is slightly reduced when adding the fourth feature. This does not appear to happen for bistatic data, where the accuracy increases proportionally to the number of features used. This phenomenon can be related to the feature diversity effect presented in [17], albeit for a different classification problem, i.e. the fact that different monostatic and bistatic nodes in a multistatic radar system can use different sets of features depending on situational parameters such as dwell time, signal-to-noise ratio, aspect angle to the target, and target trajectory, and that these sets of features can change dynamically in a cognitive radar paradigm. It is therefore interesting to observe this difference in these preliminary data even with a fairly limited bistatic angle (20°), and additional experimental work at other bistatic angles will be performed to further characterize this effect. Confusion matrices are also shown for the case of binary tree classifier with three features, in Table III and IV for monostatic and bistatic data respectively. It is interesting to observe that the majority of the misclassification events happen between activities 1 and 2, i.e. picking up and object and sitting and standing, whereas very few mistakes are reported for the classification of the walking movement. This seems to suggest that a hierarchical process could be more suitable for indoor activities classification, with a tree of different classifiers

acting on different features to discriminate different subsets of activities. A simple example of this approach was for instance presented in [21] where three Support Vector Machine classifiers were employed to discriminate between four different hand gestures.

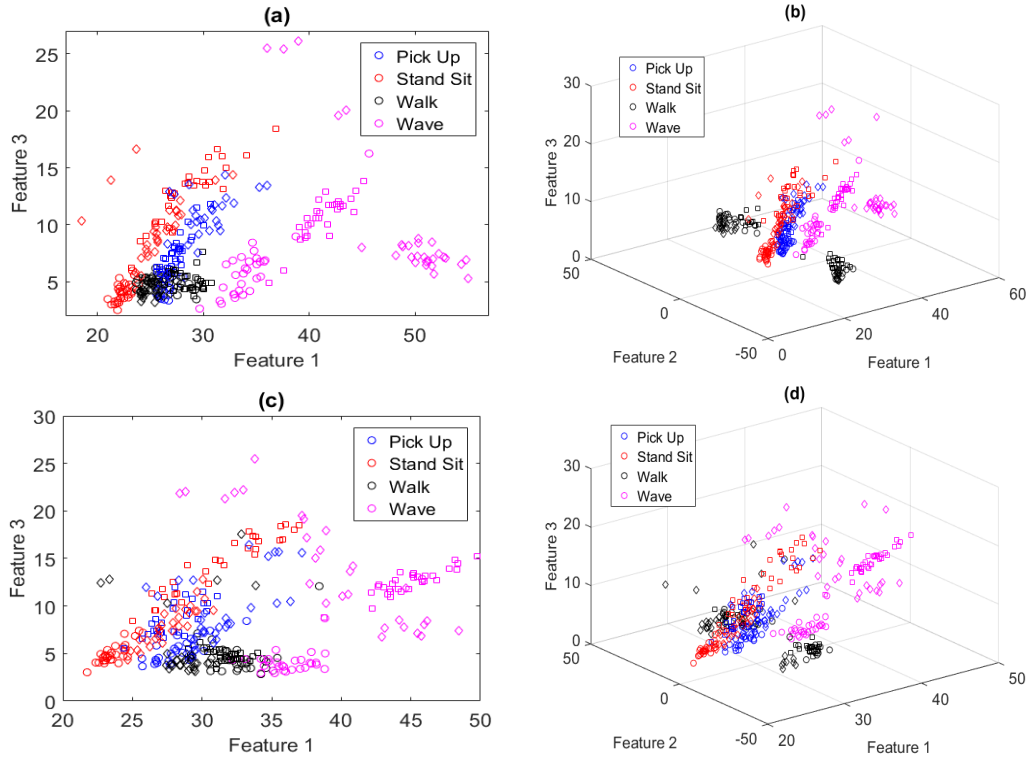

Fig. 4. Feature space plots with samples related to four actions: (a) monostatic data 2 features, (b) monostatic data 3 features, (c) bistatic data 2 features, and (d) bistatic data 3 features

TABLE I. CLASSIFICATION ACCURACY RESULTS FOR MONOSTATIC DATA

Accuracy [%]	2 features	3 features	4 features
BT	79.5	90.4	87.3
NB	71.5	87.7	86.7
3NN	89.5	98.3	97.2

TABLE II. CLASSIFICATION ACCURACY RESULTS FOR BISTATIC DATA

Accuracy [%]	2 features	3 features	4 features
BT	74.8	83.3	87.2
NB	69.3	83.8	86.7
3NN	82.9	92.0	97.2

TABLE III. CONFUSION MATRIX FOR MONOSTATIC DATA – BINARY TREE CLASSIFIER WITH 3 FEATURES

Accuracy [%]	A1	A2	A3	A4
A1	75.7	21	0	3.3
A2	8	90.7	0	1.3
A3	0	0	100	0
A4	4.8	0	0	95.2

TABLE IV. CONFUSION MATRIX FOR BISTATIC DATA – BINARY TREE CLASSIFIER WITH 3 FEATURES

Accuracy [%]	A1	A2	A3	A4
A1	72	22.3	0	5.7
A2	19.8	75.7	0.5	4
A3	0	1.4	96.8	1.8
A4	4.6	6.7	0	88.7

IV. CONCLUSIONS

This paper has presented the preliminary analysis of bistatic human micro-Doppler signatures to classify indoor activities. The development of robust automatic classification approaches will benefit the deployment of systems for monitoring daily life patterns of people, especially elderly or vulnerable individuals with some form of physical or cognitive impairment, and for detecting fall events. This simple analysis considered actions that may be mistaken for actual fall events, namely sitting down and bending to pick up objects, together with walking and waving. There may be several variations in terms of bending and crouching actions that may generate false alarms for fall detection. Figure 5 shows examples of spectrograms collected in a different laboratory environment for the following actions performed by the same subject, namely sitting on a chair, standing from a chair, bending to pick up a

chair and coming back up, bending and stay bent to tie shoelaces, frontal fall towards the radar, and crouching down to check below a piece of furniture and then standing back up. Sitting and standing (Figure 5a and 5b) appears to be different enough from the fall event (Figure 5e), but this is rather similar to the bending action (Figure 5d) and the initial part of the signatures of Figure 5c and 5f. This shows the importance of considering also the observation time to extract features in order to develop a classification scheme robust to false alarms, as well as highlighting the challenge posed by similar activities to fall, taking also into account the large variability of micro-movements for different subjects and for different environments.

Accuracy up 98% can be achieved with simple features based on the centroid and bandwidth of the micro-Doppler signatures and Nearest Neighbor classifier. It was found that the bistatic classifier performance continued to increase with added features, whereas the monostatic generally peaked at 3 feature inputs. The bistatic channel did have an overall reduction in classification performance, but this has only been shown for one bistatic angle. Further results over a series of angles will be analyzed through additional data collection in order to understand this phenomenon further.

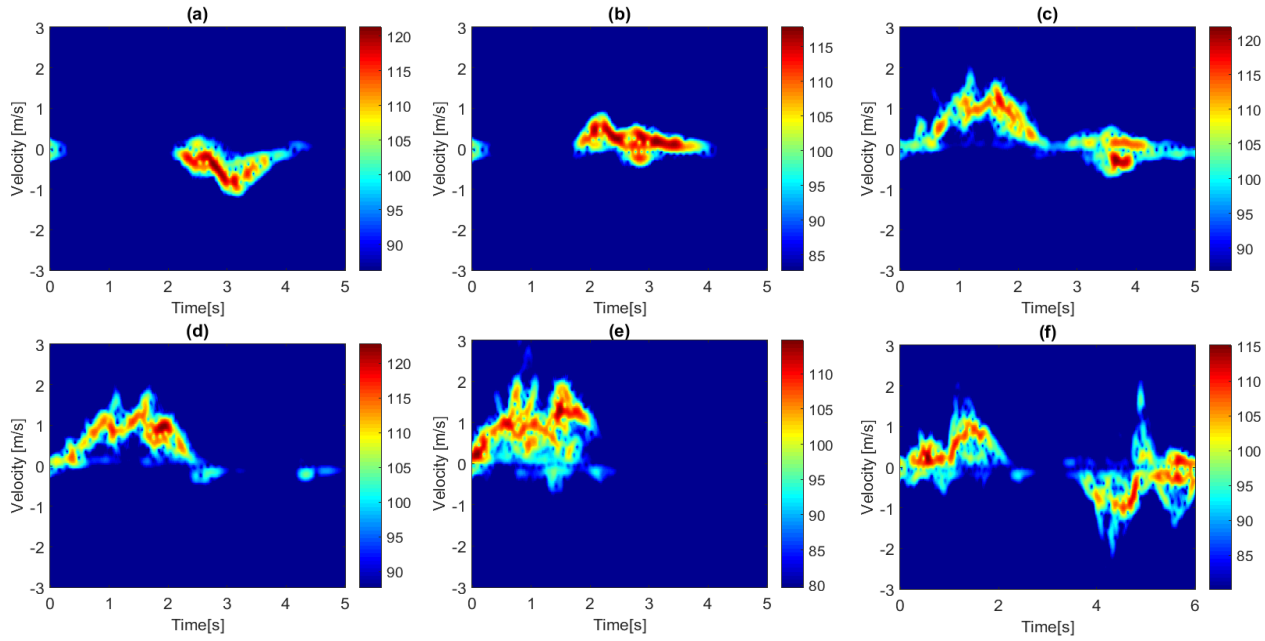

Fig. 5. Spectrograms for 6 activities performed by the same subject: (a) sitting on a chair, (b) standing up from a chair, (c) bending and picking up a pen, (d) bending and staying low to tie shoelaces, (e) frontal fall, and (f) crouching to look below a piece of furniture and standing back up

Further work will aim at collecting a larger database of activities with more actions and more subjects, and investigating the effect of the many operational parameters such as frequency, dwell time, signal-to-noise ratio, aspect angles, number of radar sensors and bistatic angles. The differences in the optimal selection of features between monostatic and bistatic data has already been highlighted in this simple analysis, and further work is needed to fully characterize and exploit this 'feature diversity'. Enhanced approaches to select subsets of features at each radar node will also be explored, for example using wrapper and filters methods proposed in the literature [5, 17], as well as hierarchical classifiers to separate different actions at different levels of the classification process.

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