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Classification of Unarmed/Armed Personnel Using the NetRAD Multistatic Radar for Micro-Doppler and Singular Value Decomposition Features

Francesco Fioranelli, Matthew Ritchie, and Hugh Griffiths, *Fellow, IEEE*

Abstract— In this letter we present the use of experimental human micro-Doppler signature data gathered by a multistatic radar system to discriminate between unarmed and potentially armed personnel walking along different trajectories. Different ways of extracting suitable features from the spectrograms of the micro-Doppler signatures are discussed, in particular empirical features such as Doppler bandwidth, periodicity and others, and features extracted from Singular Value Decomposition (SVD) vectors. High classification accuracy of armed vs unarmed personnel (between 90-97% depending on the walking trajectory of the people) can be achieved with a single SVD-based feature, in comparison with using four empirical features. The impact on classification performance of different aspect angles and the benefit of combining multistatic information is also evaluated in this work.

Index Terms— Micro-Doppler, multistatic radar, human detection, target classification, feature extractions, SVD.

I. INTRODUCTION

MOVING targets with rotating or vibrating parts are characterized by additional modulations on top of their main Doppler shift known as micro-Doppler [1]. Humans performing different activities have also characteristic micro-Doppler signatures because of the motion of limbs and body, and these signatures can be used to perform target detection and classification of such activities in a variety of applications (security, warfare, search and rescue operations among others) [2]. It has been shown that micro-Doppler signatures from a monostatic radar can be used to distinguish between humans and animals such as dogs [3] or horses [4], potentially even between men and women [5], and to discriminate between different activities such as walking, running, or crawling by extracting features and using them as inputs to a classifier [6].

The classification accuracy can be compromised when the aspect angle (i.e. the angle between the target velocity vector and the line-of-sight of the radar) is close to 90° and therefore

the micro-Doppler signature is strongly attenuated [7], whereas only a minor performance degradation is expected for angles around 30° or smaller [6]. Bistatic or multistatic radar systems have been suggested as possible solutions to solve this problem, as different radar nodes could be deployed to achieve favorable aspect angles to the targets so that feature extraction from micro-Doppler signatures and classification is still achievable [8, 9].

In [10] the same radar system used in this work provided multistatic micro-Doppler signatures of people running and walking in different directions, and these were compared with simulated data. It was predicted that multistatic micro-Doppler would achieve better performance for automatic target recognition than conventional monostatic systems, as multistatic data contain more information. Our previous work in [11] built on the results in [10] discussing the classification of unarmed and potentially armed personnel using features extracted from multistatic micro-Doppler signatures of different subjects. All of this data was generated from an individual walking on the spot. The work presented in this letter provides significant extensions compared with reference [11]. One of the limitations of that work is when walking on the spot the motion of the legs and arms may not be natural and perfectly realistic. In this work we expand the analysis with human multistatic micro-Doppler signatures of people actually walking in a realistic manner. A new approach of extracting suitable features for classification purposes is also proposed using Singular Value Decomposition (SVD), and compared with the previous method of extraction of empirical features from the spectrograms (such as periodicity, bandwidth, Doppler offset) used in [11]. The extraction of features using SVD does not require an estimation or pre-analysis of the spectrograms to evaluate at which Doppler bins the micro-Doppler signature and the contributions of the different body parts are located. The SVD decomposition is simply applied to the spectrogram and features are extracted from the resulting left and right SVD vectors. Good classification accuracy (90% and higher) is demonstrated using even a single feature. The impact of aspect angle on classification performance is also analyzed with data referring to aspect angles equal to 0° , 30° , and 60° from the line-of-sight of the monostatic radar node. Two different approaches

F. Fioranelli, M. Ritchie, and H. Griffiths are with the Department of Electronic and Electrical Engineering, University College London, Torrington Place, WC1E 7JE, London, UK (e-mail: f.fioranelli@ucl.ac.uk, m.ritchie@ucl.ac.uk, h.griffiths@ucl.ac.uk).

of combining multistatic data are also tested, the former being processing the whole set of data from all radar nodes at a single classifier, and the latter using separate classifiers at each node and then combining their partial decisions to reach the final decision.

The rest of the paper is organized as follows. Section II describes the radar system and the experimental setup to collect the data. Section III presents the analysis of the micro-Doppler signatures, describes different ways of extracting features from the spectrograms, and compares classification performance of using different features and different ways of combining information from multistatic data. Section IV concludes the paper.

II. RADAR SYSTEM AND DATA COLLECTION

The radar system used to collect the data presented in this paper is the three-node multistatic system NetRAD, which has been developed over the past years at University College London. The system is a coherent pulsed radar and operates at 2.4 GHz. The data shown in this work were collected using the following RF parameters: 0.6 μ s pulse duration, 45 MHz bandwidth, linear up-chirp modulation, and 5 kHz pulse repetition frequency (PRF) to include the whole human micro-Doppler signature within the unambiguous Doppler region. Five seconds of data were recorded for each measurement in order to collect a multiple periods of the average human walking gait, which is on average approximately 0.6 seconds. The transmitted power of the radar is approximately 200 mW. The antennas have 24 dBi gain and are operated with vertical polarization to effectively interact with human subjects, as the human body shape is such that the vertical dimension is more significant than the horizontal dimension. This is expected to increase the signal-to-noise of the return from the targets in comparison with horizontal polarization.

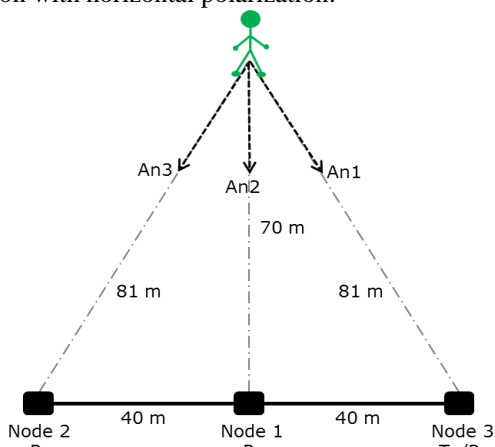


Fig. 1 Sketch model of the experimental setup

The data presented in this work were collected in a series of experiments performed in early December 2014 in an open field at the UCL sports ground. Fig. 1 shows the experimental setup with the three NetRAD nodes deployed with 40 m spacing between them, and the human subject at approximately 70 m from the linear baseline. Node 1 and node 2 were used as multistatic receiver-only nodes, whereas node

3 was the monostatic transceiver, generating data with two bistatic angles, 30° and 60° respectively. During the experiment the different subjects walked from approximately 70 m from the baseline towards the NetRAD nodes. Three different subjects took part in these experiments and each of them walked towards each node, hence data with three different aspect angles were recorded as shown in Fig. 1.

The main objective of this work is to investigate the possibility of using micro-Doppler signatures to discriminate between unarmed and armed walking personnel, that are walking forward not on the spot. In the first case the subject was walking empty-handed allowing the arms to move freely, in the second case the subject was carrying a metallic pole with both hands in the manner a rifle would be held. The pole had length comparable to that of a real rifle and was therefore expected to affect the individual's motion in the same way a real rifle would. Each walking movement was repeated five times for each subject and for each aspect angle, for both the unarmed and armed case. Hence 270 dataset of actual walking data were recorded, considering 3 subjects, 3 aspect angles, 5 repetitions, 2 classes (unarmed vs armed), and 3 nodes.

III. MICRO-DOPPLER DATA ANALYSIS

Spectrograms were generated from the recorded data applying Short Time Fourier Transform (STFT) to analyze the micro-Doppler signatures [6]. The STFTs were calculated using a time window length equal to 0.3 s. Each resulting micro-Doppler spectrogram was normalized to 40 dB dynamic range from its 0 dB peak, which suppresses undesired noise and clutter artefacts and keeps the details of the human micro-Doppler signatures.

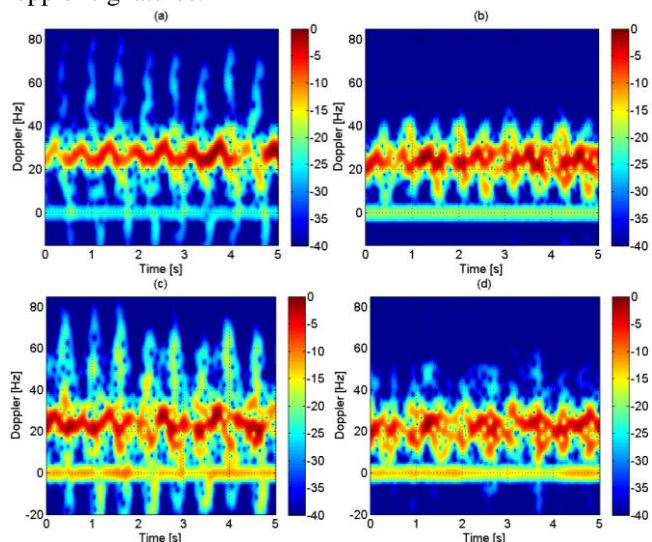


Fig. 2 Spectrograms for subjects walking towards node 3 (aspect angle 1): (a) monostatic data unarmed, (b) monostatic data armed, (c) bistatic data unarmed, and (d) bistatic data armed

Fig. 2 shows examples of monostatic and bistatic spectrograms for one of the subjects walking towards node 3 (monostatic) for the armed and unarmed case. The bistatic data, shown in Fig. 2c and Fig. 2d, were recorded at node 1. The differences between the armed and unarmed case is easily noticeable by eye for both monostatic and bistatic data, in

particular the fact that in the armed case the micro-Doppler signature is more compressed around the main torso contribution at around 20 Hz, without the peaks associated to the free swinging movements of the limbs. This is valuable information, as it has been shown that limited and confined limbs movement may be linked to people carrying potentially hostile objects, or to the presence of injured people or hostages [12, 13]. These differences between spectrograms in the armed and unarmed cases will be numerically quantified and converted into features to use as input to a classifier.

A. Empirical features

Four empirical features related to the kinematics of the movements have been extracted from the spectrograms of actual walking data presented in this work. These features are bandwidth, mean period, Doppler offset, and Radar Cross Section (RCS) ratio of limbs and body. They aim at quantifying the speed and the degree of arm swinging, possible asymmetries in the movement, and variations in RCS because of items potentially carried by the person. Two samples for each feature are estimated from the spectrogram of each dataset, i.e. each feature sample is estimated from 2.5 seconds of micro-Doppler signature. This leads to 540 samples per feature as a whole, considering the 270 available datasets, as indicated in section II. More details on these features and their extraction can be found in our previous work in [11]. However in that previous work the features were extracted from spectrograms related to subjects walking on the spot where the micro-Doppler signatures were therefore centered at 0 Hz. This simplified the feature extraction procedure in comparison with actual walking data analyzed in this paper, where different spectrograms may be centered at different Doppler frequencies and the main Doppler shift may change frequency with time even in the same spectrogram. This is due to the fact that the average walking speed may change in different repetitions of the movements, and the subject can accelerate or decelerate within the same measurement. This makes the feature extraction procedure more complex and difficult to automate, requiring further analysis or pre-processing steps on the spectrograms prior to feature extraction.

B. SVD based features

SVD has been proposed as a way to extract relevant features to characterize small unmanned aerial vehicles (UAVs) and to discriminate them from birds [14], but has not to the best of our knowledge been applied to analyze human multistatic micro-Doppler data. SVD allows the reduction of the feature space dimensionality and it is shown that parameters with physical meaning such as target velocity, spectrum periodicity, and spectrum width can be inferred from the SVD vectors. The SVD of a given matrix \mathbf{M} is simply expressed as $\mathbf{M} = \mathbf{U}\mathbf{S}\mathbf{V}^T$, where \mathbf{U} is the matrix containing the left singular vectors, \mathbf{S} is the diagonal matrix with the singular values of \mathbf{M} , and \mathbf{V} is the matrix of the right singular vectors.

When a spectrogram \mathbf{M} is decomposed using SVD, the

singular values in \mathbf{S} are only scaling factors and do not represent information on the spectrogram, whereas both left and right singular vectors in \mathbf{U} and \mathbf{V} contain information on the time and Doppler dimensions of the spectrogram. The first three right and left singular vectors have been analyzed looking at significant differences between the armed and unarmed case. Only the first three vectors have been considered as they contain most of the relevant information, as it can be seen looking at the values of the singular values. The aforementioned vectors have not been used directly as inputs to the classifier, but different parameters such as average, standard deviation, periodicity, variance, bandwidth of non-zero values, and difference between maximum and minimum values have been extracted from them to be used as possible features. Multiple tests have been conducted using these feature samples as input to a classifier to identify those providing the best classification accuracy.

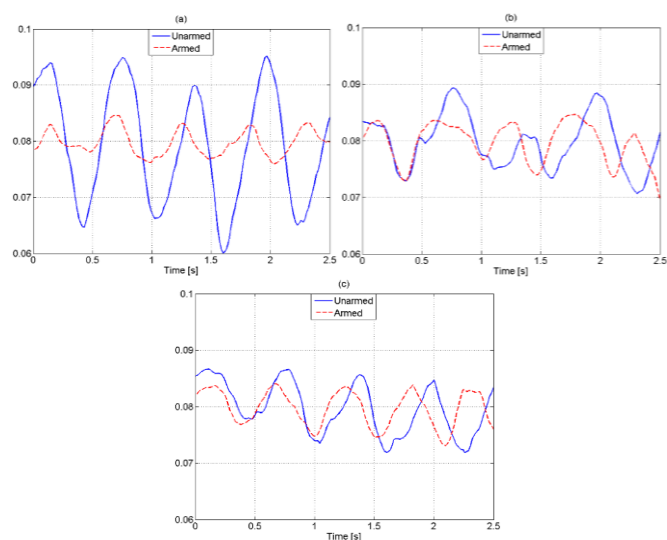


Fig. 3 First right singular vector from the spectrogram of a person walking towards node 3 for both armed and unarmed cases. (a) Data from node 1, (b) Node 2, and (c) Node 3

Fig. 3 shows the absolute value of first right singular vectors, from \mathbf{V} , for spectrograms of one subject walking towards the monostatic node 3 in both armed and unarmed case, with data from all the three radar nodes. It appears that the pattern of the vector for the armed case is more confined around the mean value and has smaller amplitude variations in comparison with the unarmed case. The standard deviation of these vectors appears therefore to be a suitable feature to discriminate between the armed and unarmed case. Fig. 4 shows samples of this potential feature for data from three subjects walking towards node 3 (aspect angle 1 as in Fig. 1). The color distinguishes between armed vs unarmed cases, the marker shape between data from different radar nodes. There is a good separation of the samples along the vertical axes, with the values of the samples for the armed case which is lower than the unarmed case. It should be noted that SVD was applied on spectrograms 2.5 seconds long, so that 540 feature samples were collected as a whole as in the case of empirical features.

C. Classification and results

The feature samples extracted with the two different methods described in section II-A and II-B are used as input to a classifier. The classifier is trained with 25 % of the samples, whereas the remaining samples are used to test the classifier and calculate the classification error. This calculation is repeated 30 times with a randomly chosen set of samples for training in order to evaluate the consistency of the classifier behavior. The resulting mean classification error is reported in this work. The classification error is defined as the ratio of all misclassification events over the total number of samples, without distinguishing between false positives (unarmed case mistaken for armed) and false negatives (armed case mistaken for unarmed).

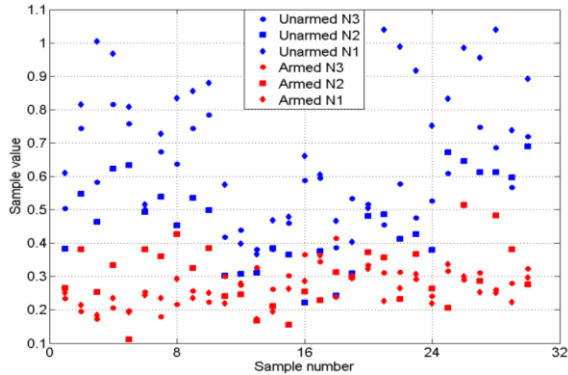


Fig. 4 SVD-based feature samples for armed vs unarmed case. Data gathered at all three radar nodes from three subjects walking towards the monostatic node 3

The classifier used in this paper is a Naïve Bayes classifier, based on the assumption that the elements of the feature vectors are Gaussian distributed and statistically independent, and that the mean and variance of these Gaussian distributions can be estimated at the training phase [15]. Data related to different aspect angles are analyzed separately to see the impact of this variable on the classification accuracy. Two different approaches of combining multistatic data have been tested to see the impact on the classification performance, in comparison with using only monostatic data as in a conventional radar. In the first approach a single, centralized classifier is given feature samples from all the multistatic nodes as input (hence feature vectors have 180 samples) and this provides a final decision. In the second approach three separate classifiers process the feature samples extracted at each node (hence feature vectors have 60 samples each) and produce a partial decision; the final decision armed vs unarmed is then reached through binary voting with a majority of at least two classifiers out of three. Table I shows the classification error for all considered aspect angles and different approaches of using the available data when the SVD-based feature samples are used. Table II shows correspondent results when the four empirical features mentioned in section II-A are used. Tables III and IV report for further information the confusion matrix for classification with the SVD-based feature and with the four empirical features, respectively.

TABLE I

CLASSIFICATION ERROR PERCENTAGE AS A FUNCTION OF ASPECT ANGLES AND APPROACHES IN COMBINING MULTISTATIC DATA. SVD-BASED FEATURE IS USED

Classification Error [%]	Mono data only	All multi data	Binary voting
Aspect Angle 1	4.22	11.20	2.78
Aspect Angle 2	17.50	13.98	9.50
Aspect Angle 3	18.94	18.07	8.44

TABLE II.

CLASSIFICATION ERROR PERCENTAGE AS A FUNCTION OF ASPECT ANGLES AND APPROACHES IN COMBINING MULTISTATIC DATA. FOUR EMPIRICAL FEATURES ARE USED

Classification Error [%]	Mono data only	All multi data	Binary voting
Aspect Angle 1	14.50	16.20	9.11
Aspect Angle 2	14.11	25.24	9.94
Aspect Angle 3	18.61	33.87	13.00

TABLE III

CONFUSION MATRIX FOR CLASSIFICATION USING THE SVD-BASED FEATURE

Confusion Matrix		Mono data only		All multi data		Binary voting	
		Unarm	Arm	Unarm	Arm	Unarm	Arm
Angle 1	Unarm	95.1	4.9	82.4	17.6	94.4	5.6
	Arm	3.6	96.4	4.9	95.1	0.0	100.0
Angle 2	Unarm	74.1	25.9	79.7	20.3	85.8	14.2
	Arm	9.1	90.9	7.7	92.3	4.8	95.2
Angle 3	Unarm	80.8	19.2	77.3	22.7	89.6	10.4
	Arm	18.7	81.3	13.5	86.5	6.4	93.6

TABLE IV

CONFUSION MATRIX FOR CLASSIFICATION USING THE 4 EMPIRICAL FEATURES

Confusion Matrix		Mono data only		All multi data		Binary voting	
		Unarm	Arm	Unarm	Arm	Unarm	Arm
Angle 1	Unarm	81.9	18.1	79.9	20.1	84.9	15.1
	Arm	10.9	89.1	12.3	87.7	3.1	96.9
Angle 2	Unarm	81.6	18.4	75.7	24.3	87.2	12.8
	Arm	9.8	90.2	26.2	73.8	7.1	92.9
Angle 3	Unarm	74.4	25.6	62.7	37.3	80.4	19.6
	Arm	11.7	88.3	30.5	69.5	6.4	93.6

The proposed SVD-based feature achieves good classification performance, with error around 9.5% and below when the separate classification and binary voting approach is used. The classification error with this single feature (data in table I) is consistently lower than the error obtained when all four empirical features are used (data in table II), even if the error obtained with these features is still not too significant (between 9.1% and 13% when binary voting approach is used). The results show that the correct processing of multistatic data has a great impact on the classification performance. The separate classification plus binary voting provides classification error consistently lower in comparison with a single classifier processing all the data or with the conventional monostatic case, and this effect can be seen for all aspect angles and for both SVD-based and empirical features. The separate classification allows the exploitation of the differences in micro-Doppler signatures due to different aspect angles to each node for a given target trajectory. On the contrary, if all the data are processed in a single classifier, this information is not properly exploited and the result is an increased classification error, as the classifier can get confused

between changes in the micro-Doppler signatures due to the presence of the carried rifle and changes simply related to the aspect angle. The results show also that the error is lower for aspect angle 1 (facing the monostatic node), and this may be useful when deploying a multistatic system so that the monostatic node is facing the direction which potential targets are most likely to come from.

IV. CONCLUSIONS

In this work we have analyzed experimental human micro-Doppler data gathered using the UCL multistatic radar system NetRAD. The analysis aimed at identifying people walking empty-handed and people walking while carrying a metallic pole simulating a rifle. Data from three different subjects and three different walking trajectories were considered in this analysis. Two different approaches of extracting features from the spectrograms were discussed. One approach estimates empirical features such as spectrogram bandwidth and periodicity directly related to the kinetics of the movement, but this may require some pre-processing steps of the spectrograms of actual walking data because of changes in walking speed within a measurement or in different measurements. The other approach we proposed uses SVD directly on the spectrograms and estimates feature samples from the standard deviation of the first right singular vector, without preliminary processing steps on the spectrograms.

Feature samples extracted with both approaches were used as input to a Naïve Bayes classifier to evaluate the classification accuracy in distinguishing armed/unarmed personnel. The results showed that good classification accuracy, up to 97.22 %, can be achieved using the single SVD-based feature and that this accuracy is higher in comparison with results obtained using all four empirical features, up to 90.99 %. This was obtained with a database of 540 samples, 135 samples (25%) to train the classifier and 30 repetitions to validate the classification, with error variance below 10^{-3} . The impact on the classification performance of different aspect angles and different ways of combining information from multistatic radar nodes was also evaluated. The results showed that better armed vs unarmed classification can be achieved by separate classification and partial decision at each radar node, followed by a binary voting to reach the final decision. This approach would be also more efficient to implement in actual systems, as only partial decisions would be exchanged between the radar nodes and not raw data or feature vectors. The computational time for calculating a spectrogram from raw data, performing the SVD-based feature extraction, and running the classification algorithm is below one second on an average PC. Dedicated hardware and optimized algorithm implementation are expected to be required for a realistic and efficient in-field application of the proposed method.

Future work will aim at validating these results with a larger set of data involving more subjects and different aspect angles, as well as different configurations of the nodes rather than a simple linear baseline. The proposed SVD-based feature will be also tested with different classifiers (linear discriminant

analysis, nearest neighbors, support vector machine). A further step in this analysis will also be taking into account the level of confidence of the decisions at each classifier. This could lead to a more effective way of combining data from multistatic nodes, for instance using weights to reduce/increase the impact of each radar node on the final decision. The classification performance is influenced by the duration of the data set used to calculate STFT and SVD. For instance the classification error for the binary voting approach increases from between 2.98% and 9.5% up to between 5.6% and 14.6%, depending on the aspect angle, when only 1.25 s of data are used for feature extractions rather than 2.5 s. This aspect will be also investigated in further work.

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