Aspect Angle Dependence and Multistatic Data Fusion for Micro-Doppler Classification of Armed/Unarmed Personnel

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Abstract

This paper discusses the analysis of multistatic micro-Doppler signatures and related features to distinguish and classify unarmed and potentially armed personnel. The application of radar systems to distinguish different motion types has been previously proposed and this work aims to further investigate the applicability of this in more scenarios. Real data have been collected using a multistatic radar system in a series of experiments involving several individuals performing different movements. Changes in classification accuracy as a function of different aspect angle between the direction in which the target faces and the line-of-sight of the radar nodes are analysed. Multiple data fusion methodologies are proposed, showing that significant improvement of the classification accuracy can be achieved when using separate classification at each node followed by a voting procedure to reach the final decision. This is beneficial especially at those aspect angles for which micro-Doppler detection is less favourable.

1. Introduction

Radar micro-Doppler is an additional frequency modulation on a radar echo on top of the main Doppler shift caused by moving targets with rotating or vibrating parts, such as vehicle wheels or helicopter blades. These signatures contain information that can be used to classify a target, which may not be possible with only range profile information. Humans have particular characteristic micro-Doppler signatures as a result of the motion of their body and limbs [1, 2]. This has been investigated over a number of years in the context of security, warfare, and search and rescue applications to perform target recognition and classification in cluttered environments [3]. Micro-Doppler signatures collected with a monostatic radar have been analysed using Short Time Fourier Transform (STFT) and suitable features extracted from the spectrograms, achieving successful classification of different human activities [4, 5]. Human micro-Doppler signatures from a monostatic radar can be used to distinguish between humans and animals such as horses [6] and dogs [7], between armed and unarmed personnel exploiting polarimetric information [8], and even to potentially distinguish between men and women [9]. Micro-Doppler signatures have been also analysed with alternative approaches, such as the Hilbert-Huang transform [10], empirical mode decomposition [11], the Pseudo Wigner-Ville Distribution and B-Distribution [12].

One of the main issues of classification techniques based on human micro-Doppler is the dependence on the aspect angle between the radar line-of-sight and the target trajectory. When this angle approaches 90° the micro-Doppler signature is strongly attenuated as it depends on the cosine of the aspect angle, hence the classification performance can be severely hindered. In one example it is reported that the performance can drop approximately to below 40% for target trajectories with aspect angles close to 90° [13]. For smaller aspect angles, around 30°, it is expected that the classification performance will degrade only slightly as the micro-Doppler signatures will be only scaled and not completely attenuated, hence it is still possible to perform STFT and feature extraction on the data [5].

Bistatic and multistatic radar systems could potentially overcome this problem by deploying the radar nodes so that the target is visible with an acute aspect angle to at least one of the nodes. Little research has been presented on experimental bistatic/multistatic radar system for human micro-Doppler classification. Simulated data using the Boulic kinematic model have been used to show how a single spectrogram can be obtained by fusing spectrogram data from each node of a radar network, and how this spectrogram is suitable to perform subsequent feature extraction and classification [14, 15]. Other approaches of combining multistatic data are only briefly mentioned, such as classification and decision based only on data from the most accurate node, or a weighted combination of data from different nodes ranked on the base of the mutual information parameter. A bistatic radar system with two receivers, one co-located with the transmitter and one physically separated, has been reported in [16]. This system is capable of inferring the orientation of oscillating mechanical targets such as a pendulum, as well as the facing direction of human beings performing different activities such as swinging arms and picking up objects. In [17] preliminary results fusing experimental data from a monostatic radar system, co-located monostatic acoustic system and bistatic acoustic receiver are presented. It is shown that the classification accuracy using standard feature extraction methods (Cepstrum coefficients and PCA) and classifiers (K-NN and Naïve Bayes) improves when radar and acoustic systems are used jointly, and even more when information from the bistatic receiver is used.

Directly related to experimental results within this paper are both [18, 19]. In [18] multistatic micro-Doppler signatures of human walking and running towards different directions are presented, showing both simulated data and experimental data obtained with a 3-node radar system (NetRAD). It is demonstrated that multistatic micro-Doppler contains more target information than the monostatic case, and therefore it is predicted that multistatic automatic target recognition would have better accuracy compared to conventional monostatic solutions. The analysis within [19] built on the results in [18] by presenting the classification of different kinds of movements using features extracted from the spectrograms of human micro-Doppler signatures. The particular focus was on the discrimination between unarmed and potentially armed personnel.

This paper presents significant new elements in comparison with the previous work in [19]. New data with targets facing eight different aspect angles have been generated and a detailed investigation of the effect of these aspect angles on the classification performance is presented, with a quantitative analysis of the classification error and accuracy. On the contrary the data analysed in [19] were collected with the targets facing only a single aspect angle. The quantitative analysis of multistatic micro-Doppler classification as a function of aspect angle is to the best of our knowledge novel, as limited experimental bistatic/multistatic human micro-Doppler data have been published, and the analysis has been often restricted only to a few favourable aspect angles, even for the case of published monostatic data such as in [5]. Another element of novelty is the investigation of effective methods to exploit information available across the different nodes of a multistatic radar system. In [19] the data from all multistatic nodes were only processed altogether in a single centralized classifier, whereas in this work another approach is investigated and compared with the centralized classifier, i.e. the separate classification at each node followed by the combination of partial results to reach the final decision. This can be done either by simple binary voting when fusing partial decisions, or taking into account the level of confidence of each separate classifier before fusing. The separate classification is shown to increase the classification accuracy for all the aspect angles. Another type of classifier (Naïve Bayes) has also been applied to the data in section 4.1, showing that the trends of the classification error as a function of aspect angles or multistatic data processing are similar to those reported with the discriminant analysis classifier.

The paper is organized as follows. Section 2 presents a short recap of the theory of micro-Doppler, in particular its dependence on aspect angle, and the theory of the Discriminant Analysis Classifier. Section 3 describes the experimental setup and the multistatic radar system used for data collection. Section 4 presents the analysis of the micro-Doppler data using features extracted from the spectrograms obtained via STFT and a linear discriminant classifier. Changes in the classification accuracy as a function of the aspect angles and number of features are investigated, as well as quantifying how the classification performance changes for different multistatic data fusion techniques. Section 5 concludes the research and discusses future work.

2. Theory

2.1 Micro-Doppler

The Doppler frequency shift for a simple point target moving with velocity v as measured by a conventional monostatic radar is shown in Equation 1, where f_c is the carrier frequency of the radar and θ is the angle between the velocity vector of the target and the line-of-sight of the radar.

$$f_d = \frac{2f_c v}{c}\cos\theta \tag{1}$$

For the bistatic radar case the expression for the Doppler shift needs to be modified to that in Equation 2, where β is the bistatic angle between the line-of-sight of the transmitter and receiver nodes, and δ is the angle between the velocity vector of the target and the bisector of the bistatic angle β.

$$f_d = \frac{2f_c v}{c}\cos(\beta/2)\cos\delta \tag{2}$$

These equations show the relevance of target aspect angles to achieve significant Doppler shifts and micro-Doppler signatures. Bistatic angles close to 180° (forward scatter geometry) or target aspect angle approaching 90° are not favourable for micro-Doppler detection, as shown in Equation 2. It is expected that multistatic radar systems can help resolve this issue by suitable deployment of the nodes such that targets are visible with a favourable angle to at least one node.

2.2 Classifier

The classifier used in this work is based on the discriminant analysis method, in particular its diagonal-linear variant which is described in details in [19-21]. The assumption of this method is that the samples of each class are represented by a multivariate Gaussian distribution, and the parameters of this distribution (mean and covariance matrix) are estimated during the initial training phase of the classifier. Equation 3 shows the density function of the Gaussian distribution, where μ_k is the mean for class k, Σ_k the covariance matrix, and $|\Sigma_k|$ is the determinant of the matrix.

$$P_{(x|k)} = \frac{1}{\sqrt{2\pi|\Sigma_k|}} \exp\left(-\frac{1}{2}(x-\mu_k)^T \Sigma_k^{-1}(x-\mu_k)\right) \tag{3}$$

At the training phase the diagonal-linear variant of the classifier estimates a single covariance matrix for all the classes, with the assumption that only the mean values change between different classes. The sample space is divided into different regions where an expected classification cost is related to each predicted classification with the aim of minimizing this cost as in Equation 4:

$$\hat{y} = \underset{y=1,\dots,K}{\operatorname{argmin}} \sum_{k=1}^{K} \hat{P}(k|x)C(y|k) \tag{4}$$

Only this simple type of classifier is considered in this work, as it is has been shown in [19] that factors such as the number and type of features will have a more significant impact on the classification performance than the type of classifier.

3. Data Collection and Experimental Setup

The data analysed in this paper were collected using the three-node multistatic netted radar system NetRAD. This system has been developed over a number of years at University College London and has provided key novel results in the area of bistatic sea clutter characterisation [22-24]. NetRAD is a coherent pulsed radar operating at 2.4 GHz with variable linear FM chirp parameters. For the experiments presented in this work the RF parameters were set at 45 MHz bandwidth, 0.6 μs pulse duration, and 5 kHz PRF, which is sufficiently high to contain the whole human micro-Doppler signature within the unambiguous Doppler region. Each recorded data set consisted of 25000 pulses, equal to 5 seconds of data, which is sufficient to include several periods of the average walking gait of a person, which is approximately 0.6 seconds.

The experiments were performed in early December 2014 at the UCL sports ground in a large open football field to the North of London. The experimental setup is shown in Figure 1. The three nodes were deployed along a linear baseline with 40 m spacing between them. Node 3 was used as the monostatic transceiver, whereas node 1 and node 2 as multistatic receiver-only nodes. This configuration allows to record simultaneous data with two bistatic angles, approximately 60° for the node 3 to node2 combination and approximately 30° for the node 3 to node 1 combination. The transmitted power of the radar was 23 dBm and the antenna gain approximately 24 dBi, with 10° beamwidth in both elevation and azimuth.

Building on the previous work in [19], the aim of these experiments was the collection of micro-Doppler data from different armed and unarmed people walking on the spot. In the former case the person was carrying with both hands a metallic pole with size comparable to that of a realistic rifle and holding the pole as a real rifle would be held. In the latter case the person had both arms free to swing as in natural walking. The use of micro-Doppler to distinguish between free and confined arms swinging may be of interest, as confined arms and reduced limbs movement could be related to people carrying potentially hostile objects, or to the presence of hostages or injured people [25-27]. Walking on the spot removes the main Doppler shift contribution from the micro-Doppler signatures, and ensures that targets remain within the main beam of the transmitting and receiving antennas during the recording. One limitation of this kind of movement is that the motion of the legs is not completely natural. The individual is raising and lowering their legs and knees during the recording, hence these body parts are contributing to the micro-Doppler signature but it may be slightly different from a natural forward walking motion. Despite this it is expected that feature extraction and the trends in classification accuracy presented in this work will be valid for realistic forward walking movement. Unlike in [19], we collected and analysed data from individuals facing eight different aspect angles whilst walking on the spot. Data from three different people were recorded, and there was no predefined speed at which the subjects were walking, i.e. everyone was walking at his own normal walking speed. The key body parameters of the three subjects were as follows. Subject A male, 1.87 m, 90 kg, average body type, subject B male, 1.8 m, 68 kg, slim body type, and subject C male, 1.69 m, 68 kg, average body type. Figure 1 shows these angles and Table 1 presents a verbal description of them, as well as the value of the angle between the facing direction and the line-of-sight of the monostatic transceiver (assuming that 0° is the aspect angle facing the monostatic node 3).

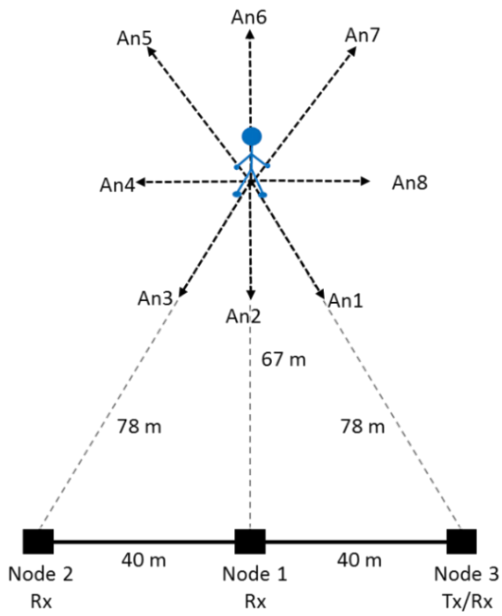

Figure 1 Representation of the experimental setup

Table 1 Description of the different aspect angles considered

An1 – Facing Node 3	0°
An2 – Facing Node 1	30°
An3 – Facing Node 2	60°
An4 – Left Side facing Node 1	120°
An5 – Giving Back to Node 3	180°
An6 – Giving Back to Node 1	210°
An7 – Giving Back to Node 2	240°
An8 – Right Side facing Node 1	300°

4. Micro-Doppler data Analysis

Following a common approach in the literature, micro-Doppler signatures were analysed through the STFT to generate spectrograms, and then numerical features were extracted for classification purposes [4, 28]. The STFTs were calculated using a 300 ms Hamming window. Each micro-Doppler spectrogram was normalized to a peak of 0 dB and a dynamic range of 40 dB, which was found empirically to preserve the details of the human micro-Doppler signatures and remove undesired clutter and noise artefacts.

Figures 2 and 3 show monostatic and bistatic examples of spectrograms respectively, the spectrograms were obtained for the same person walking empty-handed and then walking with rifle. These data refer to the same person and compare two different aspect angles, namely angle 1 and angle 4. Angle 1 corresponds to the facing direction in line-of-sight with the monostatic transceiver and with a small aspect angle of approximately 30° to the bistatic node 1, hence a favourable scenario to get good micro-Doppler data. While angle 4 corresponds to a facing direction which is perpendicular to the line-of-sight of the bistatic node and with a large aspect angle of approximately 120° to the line-of-sight of the monostatic node 3, hence a consistent reduction of the micro-Doppler signature is expected. This is verified by the data in Figures 2 and 3, where the micro-Doppler signatures related to aspect angle 4 present a much smaller overall bandwidth. In both monostatic and bistatic data there is a noticeable difference between the micro-Doppler signature of the empty-handed walking and walking with rifle, in particular the signature appears more compact and concentrated around the main component at 0 Hz, without the positive and negative peaks which are related to the free swinging movement of the limbs. This empirically visible difference can be quantified in numerical parameters or features which will be used as input to a classifier.

Figure 4 shows the spectrograms for a person walking towards node 3 with and without carrying the metallic pole simulating the rifle, hence walking towards aspect angle 1 as indicated in Figure 1. Comparing these spectrograms with those in Figures 2a-2b and 3a-3b, it can be seen that there are some differences between spectrograms for actual walking and walking on the spot, especially the shift of the main Doppler component due to the overall forward motion of the subjects while walking as opposed to walking on the spot. These differences are not significant in terms of the actual feature extraction technique presented in this work. The positive and negative peaks due to the limbs movement are still observed when the person is walking on the spot, as well as the different intensity for limbs and main torso reflection.

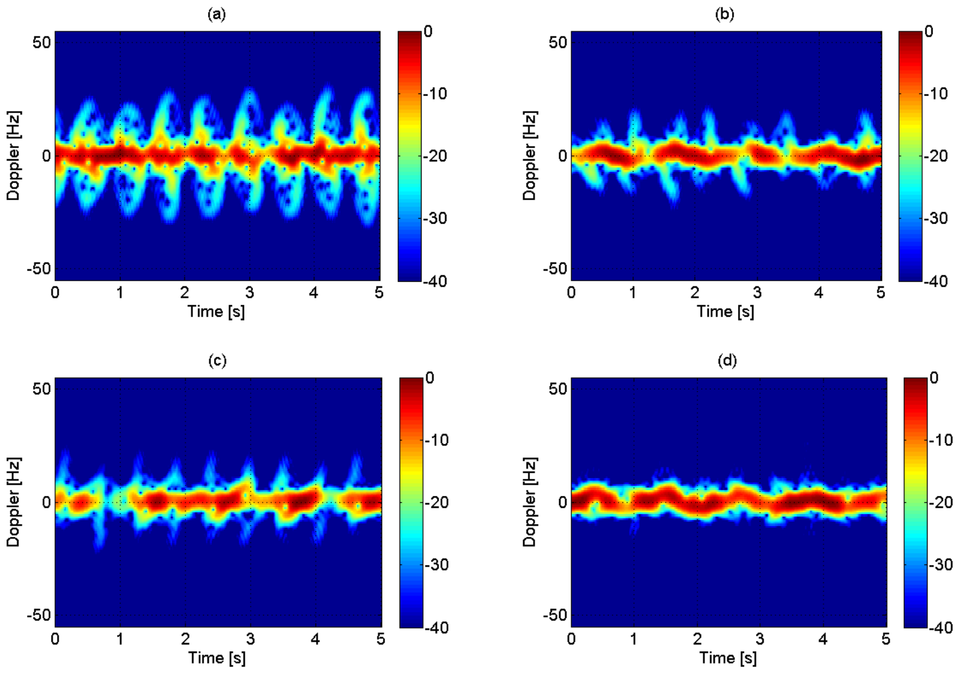

Figure 2 Spectrograms of data recorded at monostatic node 3: normal walking angle 1 (a), normal walking angle 4 (b), walking with rifle angle 1 (c), and walking with rifle angle 4 (d)

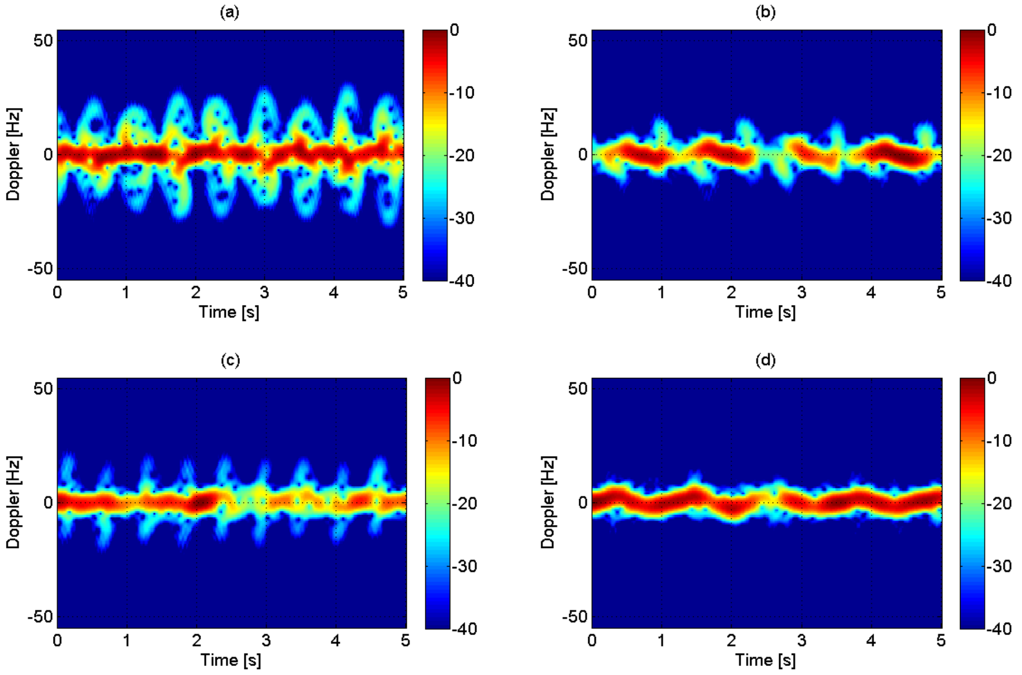

Figure 3 Spectrograms of data recorded at bistatic node 1: normal walking angle 1 (a), normal walking angle 4 (b), walking with rifle angle 1 (c), and walking with rifle angle 4 (d)

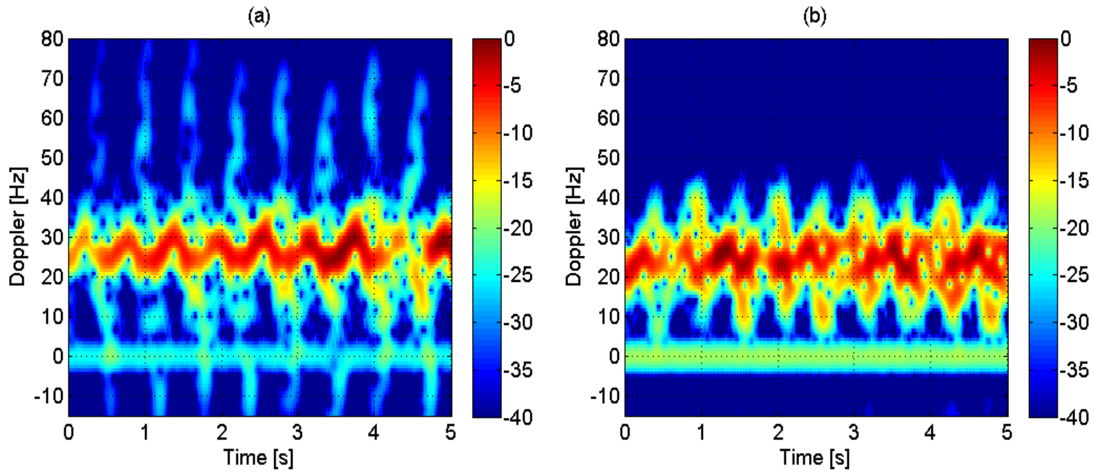

Figure 4 Spectrograms of data recorded at the monostatic node 3: actual walking towards node 3 (aspect angle 1) without (a) and with rifle (b)

The features considered in this work are the same as in [19], namely bandwidth, mean period, Doppler offset, and RCS Ratio of limbs and body. They are related to the kinetics of the movements and take into account the amount of swinging of the arms, the speed at which the limbs move, the possible asymmetry of the movement and the change in RCS due to the presence of objects carried by the person. The micro-Doppler bandwidth is defined as the overall frequency range between the lowest and the highest Doppler bins containing the micro-Doppler signature in the spectrogram, i.e. the negative and positive peaks related to the swinging motion of the limbs.

In the experiments presented in this work we collected data from three different people, with five repetitions of empty-handed walking and walking with rifle for each aspect angle. Each recording has a duration of 5 seconds and contributes to 2 samples for each feature extracted, as each sample is extracted from 2.5 seconds of spectrogram data. This produced a total database of 1440 individual datasets from all three radar nodes for features to be extracted from.

In the following part of the analysis the samples belonging to different aspect angles are kept separate in order to quantify how the classification accuracy changes with aspect angle. Therefore a single feature vector for a given aspect angle consists of 180 samples (3 people × 5 repetitions × 3 radar nodes × 2 classes (unarmed vs armed) × 2 samples extracted from each recording). More features can be used together as inputs to the classifier, generating a feature matrix with sizes of 180×2 (pairs of features), 180×3 (triplets of features), and 180×4 (all features together). Figure 5 shows feature samples referring to the empty-handed walk class (blue circle markers) and to the walking with rifle class (red square markers) for the pair of features bandwidth and mean period. Data from both aspect angles 1 and 4 are shown in Figure 5(a) and (b) respectively. A good spatial separation between samples of the two classes can be seen for both angles, but the actual numerical values of the bandwidth are quite different for the two angles as expected (higher bandwidth up to 90 Hz for aspect angle 1, and lower bandwidth below 60 Hz for aspect angle 4). On the contrary, the feature mean period has numerical values which do not seem to depend on the aspect angle. Figure 6 shows feature samples in a 3D space when triplets of features are considered, namely bandwidth, mean period, and RCS ratio. The separation between empty-handed and walking with rifle class is still evident even in this case.

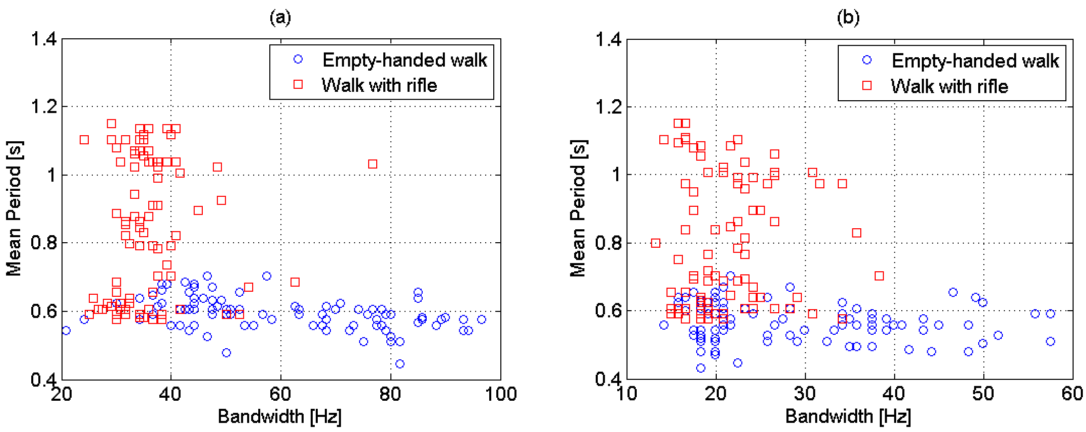

Figure 5 2D plots of samples extracted for bandwidth and mean period features: aspect angle 1 data (a), and aspect angle 4 data (b)

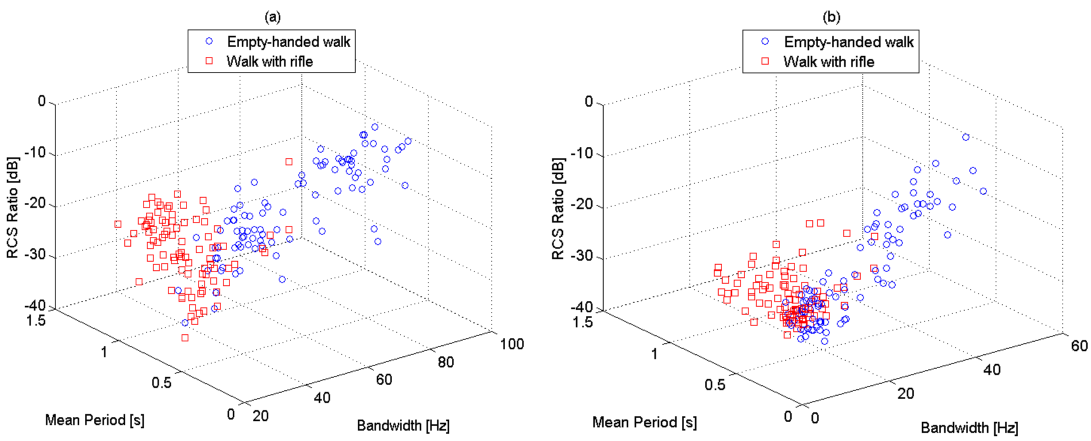

Figure 6 3D plots of samples extracted for bandwidth, mean period, and RCS Ratio features: aspect angle 1 data (a), and aspect angle 4 data (b)

As discussed in section 2, the classifier used in this work is based on the diagonal-linear variant of the discriminant analysis method, described in [19-21]. The classifier is trained using 10% of the available samples, and the remaining 90% of samples is used to test its behaviour and calculate the classification error, which is the ratio of total misclassification events (sum of walking with rifle mistaken for empty-handed samples and vice versa) over the total number of samples. This process is repeated 30 times with different, randomly chosen training data, and the mean of the classification error obtained in these repetitions is reported in this work.

Developing further from previous work in [19], we can assume that using only a pair of suitable features provides good classification performance. Table 2 shows the classification error in percentage for all the six possible pairs of features as a function of the aspect angle. In this table data from all the three nodes have been used as input to the classifier. We can see that the pairs of features providing the lowest classification error are bandwidth vs mean period and mean period vs RCS ratio, on average across all the eight aspect angles considered. This may be related to what already observed in the comments to Figure 5, i.e. that features such as mean period are aspect angle independent and can still be useful for classification purposes at aspect angles which are not favourable for micro-Doppler analysis.

Table 2 Classification error percentage for six pairs of features as a function of aspect angle. All three multistatic node data used as input. (Bandwidth – Ban, Offset – Off, Period - Per, RCS ratio – RCS)

	Ban-Per	Ban-Off	Ban-RCS	Per-Off	Per-RCS	Off-RCS
An1	14.89	19.24	18.41	17.52	15.48	25.76
An2	11.20	13.74	8.93	28.39	10.74	15.26
An3	16.41	35.20	33.06	16.00	15.78	36.50
An4	20.09	33.59	31.33	22.35	19.94	35.44
An5	9.11	22.52	21.59	19.28	10.39	27.59
An6	10.35	17.78	19.91	24.31	12.28	21.93
An7	12.41	25.56	16.80	16.54	9.11	20.87
An8	14.31	34.89	33.69	19.44	13.70	36.81
AVG	**13.60**	**25.31**	**22.96**	**20.48**	**13.43**	**27.52**

In the second half of this papers analysis one of the key questions that is addressed is the investigation of different ways of combining/fusing data from different nodes of a multistatic system. For each aspect angle the analysis of the data has been performed in four different ways in order to quantify the advantage of having multistatic system. These four ways are as it follows.

1. The input to the classifier consists only of data recorded at the monostatic node 3, as in a conventional radar. In this case the size of the feature vector (or matrix) is scaled

by three as samples from data recorded at node 1 and node 2 are not considered, hence each feature vector is made of 60 elements.

2. The input to the classifier consists of data from all three nodes, i.e. 180 samples. In this case the assumption is that data/samples from all the nodes are sent to a single classifier which makes a decision between empty-handed and walking with rifle classes.
3. The data/samples recorded at each node are used as inputs to three separate independent classifiers, one per node. A final decision is reached through a binary voting procedure out of three separate partial decisions, i.e. the final decision (empty-handed walking or walking with rifle) that one reached by a majority of at least two nodes out of three.
4. Three independent classifiers are used as in method 3. In this case the binary decision from the previous point takes into account the level of confidence of each independent decision reached at the separate classifiers. In this case when two nodes have agreed on a decision, their confidence is compared to a threshold. If their confidence is above such threshold, their decision will be the final decision. If their confidence is below such threshold and at the same time the confidence of the third node is higher than the confidence of both other nodes, then the final decision will be that one from the third node. This approach addresses the issue of having two nodes reaching an incorrect decision because they are both at aspect angles which are not favourable for good detection of the micro-Doppler target. Different values of this threshold within the interval 55-75% have been tested with the available data, and the threshold has been fixed at 65% as the value providing the best classification accuracy. The choice of this value is linked to the available data, and therefore can updated should additional data become available.

Table 3 shows the classification error for each aspect angle when the four defined methods are used to process multistatic data. In this case a pair of features has been used as input to the classifier (mean period and RCS Ratio) as this provided the lowest error as from the analysis reported in Table 2.

Table 3 Classification error percentage as a function of aspect angle for four different approaches in using multistatic data. The pair of features used are mean period and RCS ratio.

	Mono data only	**All multi data**	**Binary voting**	**Voting with threshold**
An1	14.61	15.48	12.00	11.78
An2	9.50	10.74	9.28	9.06
An3	20.56	15.78	9.78	9.78
An4	26.17	19.94	17.72	14.56
An5	18.17	10.39	10.83	9.39
An6	20.17	12.28	11.06	9.89
An7	9.33	9.11	2.50	2.56
An8	13.00	13.70	10.39	8.61
AVG	**16.44**	**13.43**	**10.44**	**9.45**

There is a strong dependence of the error on the aspect angles as expected. The classification error tends to be higher at aspect angles which are less favourable for micro-Doppler detection, such as angle 4 for which the person is facing the direction perpendicular to the line-of-sight of node 1 and at 60° with respect to the line-of-sight of node 2 and node 3. On average there is an improvement in classification error when using multistatic data rather than monostatic, but this is not consistent across all aspect angles. For some angles are significant improvement (angles 3 to 6), for others there is a similar performance (angle 7) or even a slight worsening (angles 1, 2, and 8). This seems to suggest that the use of data from different multistatic nodes in the same single classifier may be not very effective, as the micro-Doppler signatures recorded at different nodes may be quite different even for the same target because of the effect of different aspect angles. On the contrary it is observed that the approach of separate classification and decision at each node plus voting provides a significant improvement in terms of classification error, and this is consistent across all the eight considered aspect angles. A further reduction of the classification error is achieved when using the voting with threshold approach rather than simple binary voting.

A comprehensive analysis of the classification performance for all the possible combinations of one single feature, pairs of features, triplets of features, and all four features together has been performed. This identified the best performing single feature (mean period), the best pair as reported in Table 2 (mean period and RCS), and the best triplet (mean period, bandwidth, and RCS ratio). Figure 7 shows the classification accuracy for the eight considered aspect angles as a function of the number of features when the best single, pair, and triplet of features are used. The voting with threshold approach has been applied to combine multistatic data, as it provided the lowest classification error as from Table 3. The best classification accuracy is achieved when the best pair or the best triplet are used, depending on the aspect angle, and there is a more or less significant reduction of the accuracy when all the four features are used together. This is in line with what already observed in [19] for data referring to aspect angle 2 only, i.e. that it is not always true that the use of more features improve the performance. The limiting case is aspect angle 4 for which the best classification accuracy is achieved using only one feature rather than any combination.

Table 3 and Figure 7 have shown that the classification accuracy for all aspect angles is improved when combining effectively multistatic data with separate classification at each node and voting, and when using a combination of only two or three suitable features. Figure 8a shows the classification error as a function of aspect angles and number of features in a “spider plot”, which provides an easy way to check visually the dependence on the aspect angle. Multistatic data were combined with the separate classification and voting with threshold approach. The pair of features used were mean period and RCS ratio, the triplet were mean period, RCS ratio, and bandwidth. This figure highlights the dependence of the classification performance on the aspect angle, with the error decreasing when using more feautes for some aspect angles (angles 1,2, and 5) and increasing for others (angles 3,4, and 8). Figure 8b shows a similar “spider plot” with the classification error as a function of aspect angles and different data fusion methods. The advantage of using the indipendent classification at each node plus voting can be clearly seen in terms of reduction of the classification error across all the considered aspect angles.

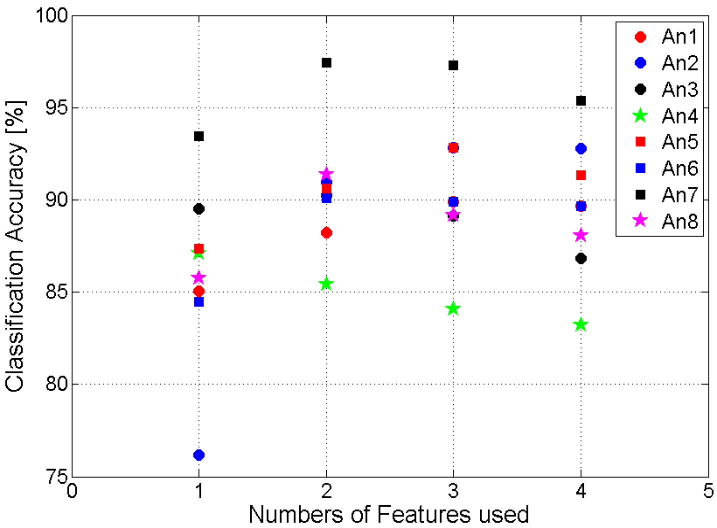

Figure 7 Classification accuracy for each considered aspect angle as a function of the number of features

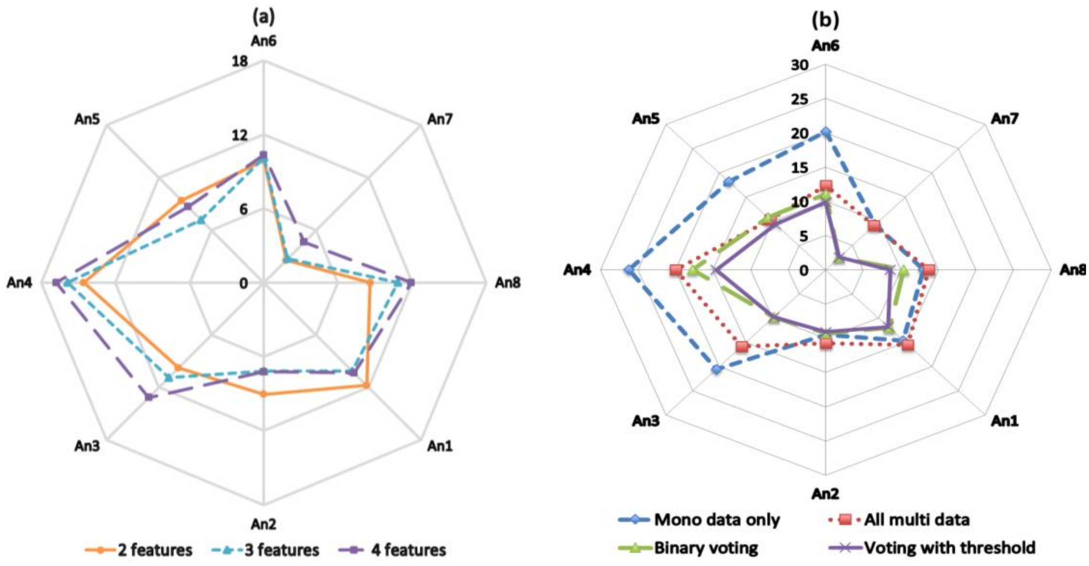

Figure 8 Spider plot of the classification error as a function of aspect angles and number of features used (a), and as a function of aspect angles and data fusion method used (b)

4.1 Data analysis extension

In this section results from further analysis work on the data are presented. A first extension of the analysis involves the use of another classifier, namely the Naïve Bayes [28]. Table 4 shows the classification error as a function of different aspect angles and different ways of exploiting multistatic information. The features used are the RCS ratio and the mean period, as in the results presented in table 3 using the discriminant analysis classifier. The observable trends in the classification error are consistent, with a strong dependence of the classification error on the aspect angle and the benefit of using data from multiple nodes, even if the error is on average approximately 3-4% higher than when using the discriminant analysis classifier.

Table 4 Classification error percentage as a function of aspect angle for four different approaches in using multistatic data. The pair of features used are mean period and RCS ratio. The classifier is the Naïve Bayes.

	Mono data only	**All multi data**	**Binary voting**	**Voting with threshold**
An1	19.10	17.13	15.53	15.27
An2	17.37	12.60	13.63	13.70
An3	27.97	19.21	17.17	17.03
An4	27.03	22.61	20.23	19.03
An5	12.60	10.51	9.73	9.77
An6	21.87	15.64	16.07	15.60
An7	13.87	9.31	6.43	5.93
An8	18.20	12.39	11.60	11.33
AVG	**19.75**	**14.93**	**13.80**	**13.46**

Additional feature samples from other three different subjects have then been added to the analysis in order to increase its statistical significance. These samples refer to aspect angle 2 only. The body parameters of the additional subjects were subject C, female, 170 cm, 58 kg, slim body type, subject D, male, 174 cm, 65 kg, toned body type, and subject E, male, 170 cm, 67 kg, toned body type. The same analysis as for the results in tables 3-4 has been repeated, evaluating the classification error when RCS ratio and mean period are used as pair of features, for both linear discriminant and Naïve Bayes classifier. In the former case the error is equal to 8.61% (mono data only), 8.52% (all multi data), 7.62% (binary voting), and 7.18% (voting with threshold); in the latter case the error is 11.43% (mono data only), 9.93% (all multi data), 8.81% (binary voting), and 8.77% (voting with threshold). Good performance with accuracy around 90% and better is achieved even with extra subjects.

The proposed classification approach is finally tested by training the classifier with feature samples from five out of six subjects and then performing the classification on samples from the remaining subject. This would be closer to the realistic situation where the classifier would be trained in a controlled environment and then tested on unknown subjects in the field. The usual pair of features (RCS ratio and mean period) have been used. The classifier is the Naïve Bayes and the effect of changing the amount of available data used for training has been investigated. When 10% of data are used to train the classifier, the error is 18.33%, 8.06%, 9.17%, and 10% (respectively for monostatic data only, all multistatic data, binary voting, and voting with threshold), when 20% of data are used for training the error decreases to 16.67%, 5.28%, 4.17%, and 4.17%, and again a further decrease to 10.83%, 3.89%, 2.5%, and 3.33% when 40% of the data are used for training. The results appear to show the robustness of the proposed classification approach even when dealing with a subject "unknown" to the classifier. Further work with more samples and subjects for different aspect angles will be performed to get a deeper understanding.

5. Conclusions

In this paper the analysis of experimental human micro-Doppler data collected by the UCL three nodes NetRAD radar system has been presented, with focus on the distinction and classification of unarmed and potentially armed personnel. The analysis has used four features extracted by the spectrograms of the micro-Doppler signatures, namely bandwidth, mean period, Doppler offset, and RCS ratio between limbs and body. These features have been used as inputs to a classifier based on the discriminant analysis method.

The issues this research has explored are how the classification performance depends on the aspect angle, and how multistatic data can be effectively combined to improve the classification accuracy. It is shown that there is a strong dependence of the classification error on the aspect angle, and that such error increases at aspect angles for which the target is facing directions close to approximately 90° with respect to the line-of-sight of the radar node. Significant improvement of the classification accuracy can be obtained using multistatic rather than conventional monostatic systems, as they provide the opportunity of looking at targets so that at least one node is at a favourable aspect angle for micro-Doppler detection. The analysis in this paper has shown that better classification results can be achieved for all considered aspect angles when separate classifications are performed at each node, and the final decision is reached by fusing the partial decisions at each node through a voting procedure which takes into account the level of confidence of the classification. This distributed approach has been shown to be more effective than simply processing all the multistatic data from different nodes at a single centralized classifier, as this is expected to take into account that feature samples estimated at different nodes may be rather different because of the different aspect angles, even if referring to the same recording. The separated classification approach would be also more efficient to implement in an actual system, as only the partial decisions at each node (and in case confidence level) will be transferred over the network interconnecting the multistatic radar nodes, and not all the multistatic raw data or feature matrices which would be required for a centralized approach. However, such improved performance of distributed decision in comparison with centralized decision may be linked to the non-optimal extraction of the features chosen in this work and their dependence on the aspect angle, and is not a general result valid for every classification algorithm.

Future work will be aimed at validating the results presented in this work through a larger database of samples with more subjects involved in the experiments, as well as with data of subjects actually walking forward naturally rather than walking on the spot. The empirical difference between the spectrograms in the armed and unarmed cases for actual walking as presented in Figure 4 suggests that it is possible to select suitable features for successful classification.

Alternative ways of extracting suitable features from the micro-Doppler signatures can be also tested, for instance selecting features that do not rely too much on the limbs motion as a “proxy” for the detection of possible carried objects, but are more directly related to the presence of objects themselves (for instance through RCS and polarimetric analysis). Features extracted through PCA or Singular Value Decomposition (SVD) will be also considered to provide a more automatic way of extracting features, less dependent on the empirical characteristics of the spectrograms. It is believed that the results presented tend to be valid also for different types of classifiers, but this will be verified applying alternative classification methods (naïve Bayes, nearest neighbours, support vector machine, and so on).

The use of different variants of the Discriminant Analysis classifier in [19] has shown that features providing good separation of the samples of different classes allows successful classification for all the four variants considered in that work. Hence it should be more important to focus on the extraction and selection of the best features (i.e. those which maximize the separation of the samples of different classes), rather than on the type of classifier considered.

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