Multistatic Human Micro-Doppler Classification of Armed/Unarmed Personnel

Francesco Fioranelli, Matthew Ritchie, Hugh Griffiths

Electronic & Electrical Engineering, University College London

Abstract

Classification of different human activities using multistatic micro-Doppler data and features is considered in this paper, focusing on the distinction between unarmed and potentially armed personnel. A database of real radar data with more than 550 recordings from 7 different human subjects has been collected in a series of experiments in the field with a multistatic radar system. Four key features were extracted from the micro-Doppler signature after Short Time Fourier Transform analysis. The resulting feature vectors were then used as individual, pairs, triplets, and all together before inputting to different types of classifiers based on the discriminant analysis method. The performance of different classifiers and different feature combinations is discussed aiming at identifying the most appropriate features for the unarmed vs armed personnel classification, as well as the benefit of combining multistatic data rather than using monostatic data only.

1- Introduction

This paper presents the analysis of radar micro-Doppler signatures from a multistatic radar system. The data was generated using NetRAD [1] which is a three-node multistatic radar system that has been developed over the last decade at University College London. The system has been adapted since 2007 to a higher power wireless configuration to increase the flexibility of the measurement possibilities [2], and has provided interesting and novel results in the field of bistatic sea clutter characterisation and analysis [3].

Radar Micro-Doppler is the phenomenon of the observed micro-motions on top of the bulk main Doppler component of a target's motion. It has been the subject of research over a number of years focusing on the additional information that can be extracted from this signal. Such information can then be exploited in a variety of applications for security, law enforcement, urban warfare, and search and rescue, where the detection, tracking, and classification of many human targets moving in a cluttered environment is of paramount importance.

1.1 – Prior Literature

Chen has authored some key publications in the field of human micro-Doppler analysis [4-6]. These studied simulated and real data results from human movement as measured by a radar system. The conclusions of this work state that micro-Doppler signals provide useful information about objects and their motion, and suggest that this information can be exploited for classification purposes. Micro-Doppler signatures have been previously studied using Short Time Fourier Transform (STFT) followed by feature extraction in [7], showing successful classification of different types of movements with data from a monostatic radar. Tahmoush has shown how micro-Doppler signatures can be used to analyse human gait movements along different trajectories [8], and the use of polarimetric information to distinguish between armed and unarmed personnel [9], as well as the different signatures that humans and animals such as horses can generate [10], all completed with monostatic radar systems.

The analysis of micro-Doppler signatures in case of free and confined arm swinging was the core contributions seen within [11-13], where limited arm swinging or no arm swinging at all can be an indication of a person carrying objects or in hostile situations (hostages). This analysis exploited positive and negative micro-Doppler caused by the arms and the periodicity of their motion for successful classification based on different techniques (for instance hierarchical image classification architecture for visual pattern recognition), also considering different aspect angles between 0°-30°. The importance of the micro-Doppler contribution of the arms for classification purposes suggested by these papers has been taken into consideration in this work when extracting suitable features, but further analysis has been performed to exploit Radar Cross Section (RCS) related features and above all the use of multistatic operation to improve classification performance. The use of two bistatic sensors with reference to human activity classification has been reported in [14], with one receiver co-located with the transmitter and another physically separated. The successful identification of the motion direction for a series of human movements such as swinging arms or picking up an object is achieved with this system. In our work we investigate and try to quantify how the information collected using a multistatic radar with 3 receivers can improve classification performance. As pointed out in [14], it is expected that a bistatic/multistatic system allows the problem of micro-Doppler signature not visible to a monostatic sensor at particular aspect angles to be overcome. Other approaches to analyse micro-Doppler signatures use alternative time-frequency techniques such as Pseudo Wigner-Ville Distribution and B-Distribution [15], principal component and independent component analysis [16], empirical mode decomposition [17] and the Hilbert-Huang transform [18], which may be more suitable to process non stationary signals. Research into the micro-Doppler domain has also been completed with an acoustic radar by Balleri [19]. This work not only qualitatively demonstrated the differences in the micro-Doppler signatures from different types of motion, but also quantified the motion using feature extraction techniques. These features were then used in classifiers algorithms in order to identify individuals from their unique micro-Doppler signatures. Prior research performed with the NetRAD system investigating micro-Doppler signatures was published by Smith [20]. This work showed both simulated and real micro-Doppler data of moving human targets, in particular for running movements along one direction, and then walking movement towards different directions. The research presented within this paper aims to build on these results and expand to the classification of different motion types using multiple features extracted by the micro-Doppler signatures from a multistatic radar, focusing on distinguishing between unarmed and potentially armed personnel.

This paper is organized as follows. Section 2 briefly describes the NetRAD radar system and the experimental setup where the data were collected. Section 3 presents the data analysis, focusing on the selection and extraction of suitable features from the micro-Doppler signatures, and on the subsequent classification based on the discriminant analysis method. The performance of different classifier types for different feature combinations and the benefits of fusing multistatic data rather than using just monostatic data are discussed. Section 4 finally concludes the paper.

2- Radar system and experimental setup

The radar used for the experiments is a 2.4 GHz pulsed coherent three node netted radar system. It is capable of transmitting and receiving from all nodes, although for this work a single master node (node 3) was used to both transmit and receive, with the additional nodes (nodes 1 and 2) used only as receivers.

The experimental geometry used was a straight line configuration for the 3 nodes with a separation of 40 m between the nodes, as shown in Figure 1. The transmitter node was located at the end of this line to enable measurements with two simultaneous bistatic angles, rather than two identical bistatic angles if located in the centre. The bistatic angles are approximately 30° for the node 3 and node 1 combination, and approximately 60° for the node 3 and node 2 combination. The experiments were conducted in a large open football field at the University College London sports ground, to the north of London.

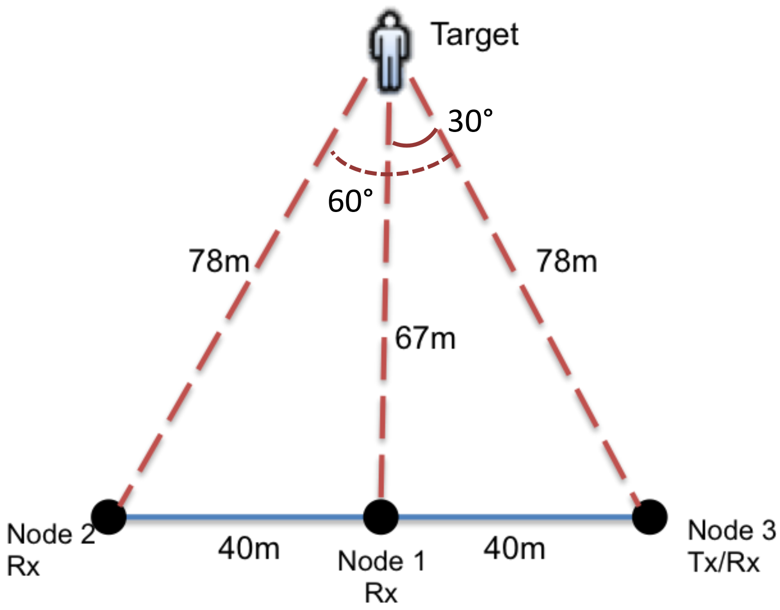

Figure 1 Model of the experimental geometry

The radar parameters that were selected for these experiments were a linear FM chirp pulse length of 0.6 µs, bandwidth of 45 MHz, PRF 5 kHz and each recording generated 25,000 pulses covering 5 seconds in duration. The transmitted power was 200 mW and the gain of the antennas approximately 24 dBi, with 10° beamwidth in both azimuth and elevation angles. These parameters allow for the system to produce a sufficiently high PRF such that all human micro Doppler is contained within the unambiguous Doppler region. The length of the recording was set to capture a number of periods of the average walking gait for a human. As seen in [6], this is shown to be approximately 0.6 seconds, hence with a 5 seconds capture the data should include approximately 8 periods of motion.

3- Data analysis

Figure 2 shows Range Time Intensity (RTI) plots for one of the recordings, with data taken from all the three nodes. The target signature is located at the expected range as from the geometry in Fig. 1, namely at approximately 156 m for nodes 3 and 2, and at 145 m for node 1. The average SNR for the human target over the 5 second recording was 32 dB, 33.3 dB and 33.4 dB for nodes 1, 2 and 3 respectively. This high SNR meant that the contribution of human appendages, such as arms and legs, were clearly visible, making the micro-Doppler signatures from them easier to extract from the data. The direct interference from the transmitter node is present within the received signal at a range of 40 m for node 1 and at 80 m for node 2, but it not shown in Figure 2.

In this work we focus on walking movements performed on the spot, i.e. the person is facing node 1 and moving as if walking, swinging arms and raising and lowering legs and knees, but remaining in the same spatial location, without moving towards any direction. This removes the main Doppler shift contribution from the micro-Doppler signatures. This also ensures the target remains in the same range bin for the whole duration of the recording, as seen in Figure 2, thus avoiding a decrease of signal-to-noise ratio due to the motion of the target outside the main beams of the receiving and transmitting antennas.

The main aim of the experiment was to collect micro-Doppler data of separate persons performing different movements, focusing in particular on people walking empty-handed and people walking while carrying with both hands a metallic pole which represents a simulated rifle. The metallic pole was approximate 1 m in length and the manner in which it was held during the experiments was similar to the manner in which a rifle would be held. Data from 7 separate subjects and more than 650 recordings were gathered by the three nodes. The data were then analysed to extract features to try and differentiate the case of unarmed and armed personnel through the use of a classifier. There is indeed interest in using micro-Doppler data to identify people carrying objects with their hands, which could be an indication of a potentially hostile activity, or people with reduced movements of their limbs, which could indicate the presence of hostages or injured people [13].

In this work the micro-Doppler data were examined via time-frequency analysis using STFT, followed by the extraction of numerical parameters or features for classification purposes. This is a common approach in the literature for micro-Doppler analysis [7, 19, 21]. The STFTs were calculated using a 0.3 s Hamming window, with the duration of the window empirically chosen to obtain a clean contribution of the limbs in the micro-Doppler signatures. Each micro-Doppler signature was normalized to a peak of 0 dB with a dynamic range of 40 dB, in order to remove possible noise and clutter artefacts but still preserve the details of the contribution due to the movement of the person. The theory of human micro-Doppler signatures is well known [22-23], hence it is not further discussed here for conciseness.

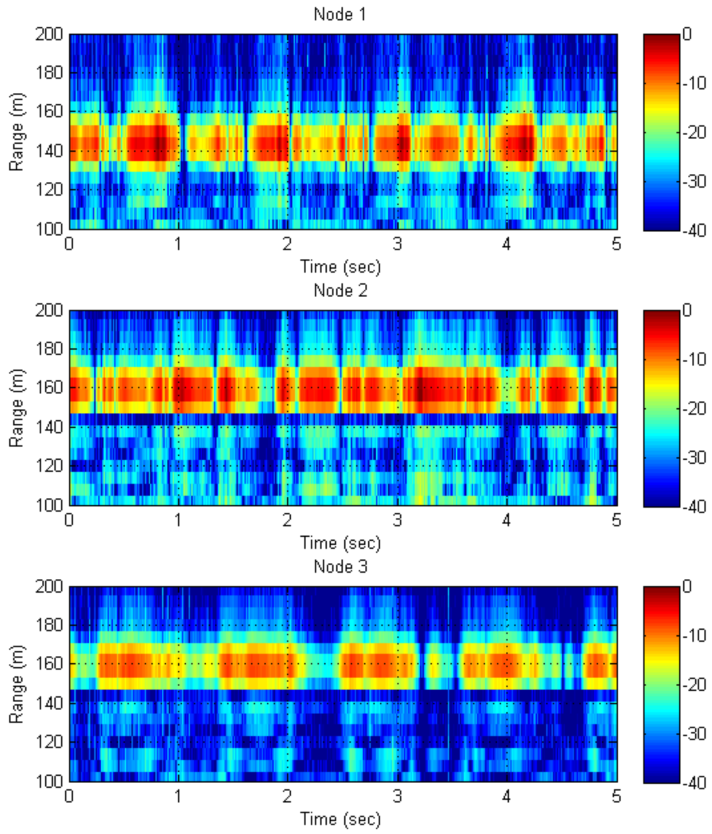

Figure 2 Range Time Interval (RTI) plots of human walking on the spot from Nodes 1, 2 and 3

It can intuitively be assumed that the main difference between walking empty-handed and walking while carrying objects is the degree of swinging of the arms, which is reduced in the latter case because of the weight and size of the object. The impact of the swinging of arms can be empirically seen in Figure 3, which compares the micro-Doppler signatures of a person walking on the spot normally and when keeping arms stationary beside the torso. When the person tries to keep the arms stationary and does not swing them, the micro-Doppler signature appears more compact and close to the main component at 0 Hz, without the peaks at about ±30 Hz which can be seen for normal walking. Such peaks are therefore related to the free swinging movements of the arms.

A similar result can be seen in Figure 4, where the micro-Doppler signatures for normal walk and walking while holding the metallic pole are compared, showing data from all the three radar nodes used in these two experiments. As expected, when the person is carrying the metallic pole the micro-Doppler signature is more compact and regular as the movement is more regimented and the arms are less free to swing around.

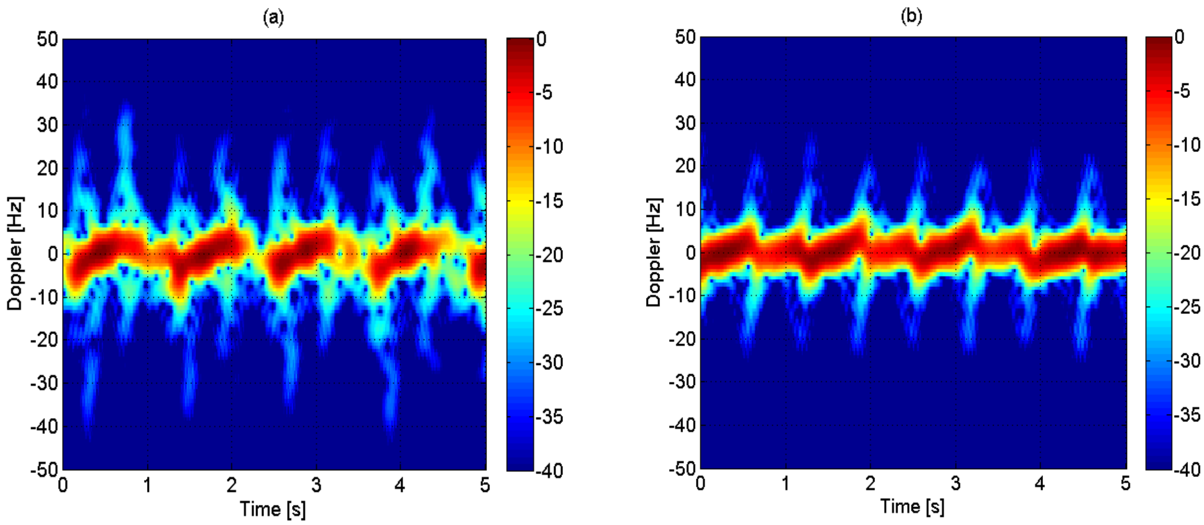

Figure 3 Micro-Doppler signature of a person walking on the spot (a), and walking on the spot without moving arms (b) – Data received at node 3

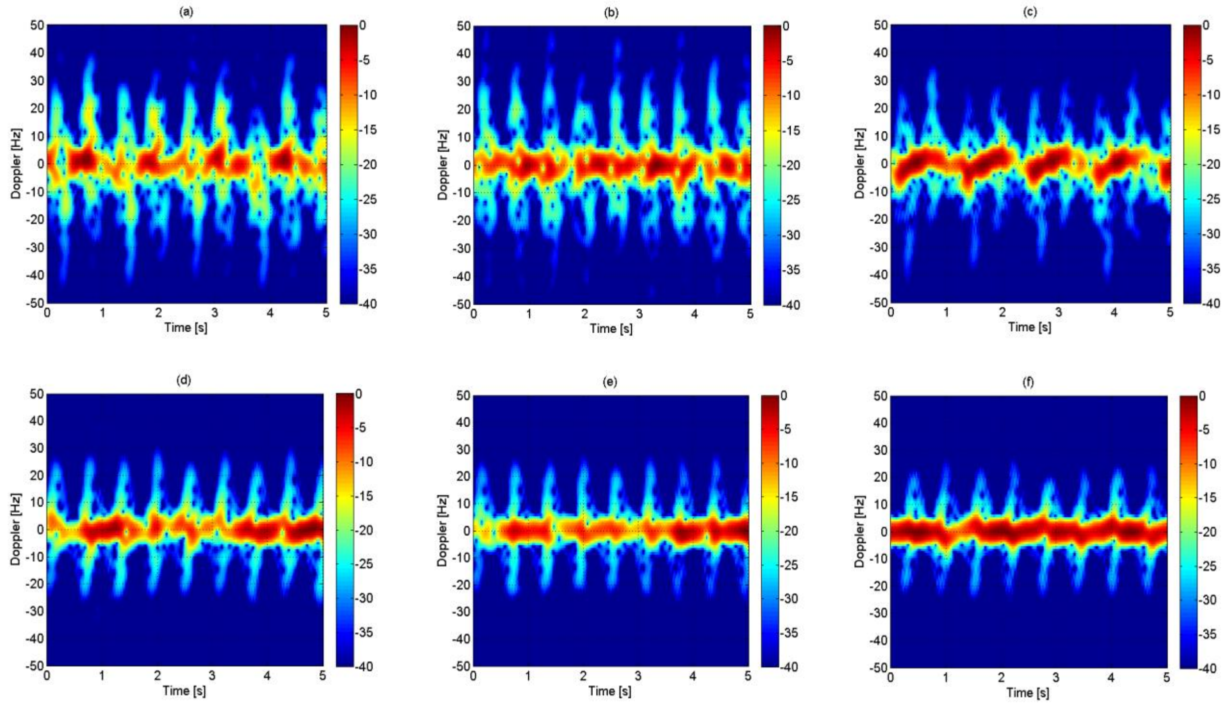

Figure 4 Micro-Doppler signature of a person walking on the spot with data received at node 1 (a), node 2 (b), and node 3 (c), and signature of a person walking on the spot while carrying a metal pole with both hands with data received at node 1 (d), node 2 (e), and node 3 (f)

Figure 5 shows a further example where the person is walking empty-handed for the first few seconds and then picks up the metallic pole and walks holding it. In this particular case the recording was longer (10 seconds) and data from the monostatic and one of the bistatic nodes are shown. The difference between the two movements can be clearly seen in the micro-Doppler signatures, with a more pronounced swinging of the limbs in the first seconds corresponding to the empty-handed walk, followed the absence of swinging at 4-5 seconds when the person bends and picks up the pole, and finally a limited swinging of the arms corresponding to the walk carrying the pole with both hands. This result clearly captures these changes in one continual recording, to show these qualitative differences as clearly as possible.

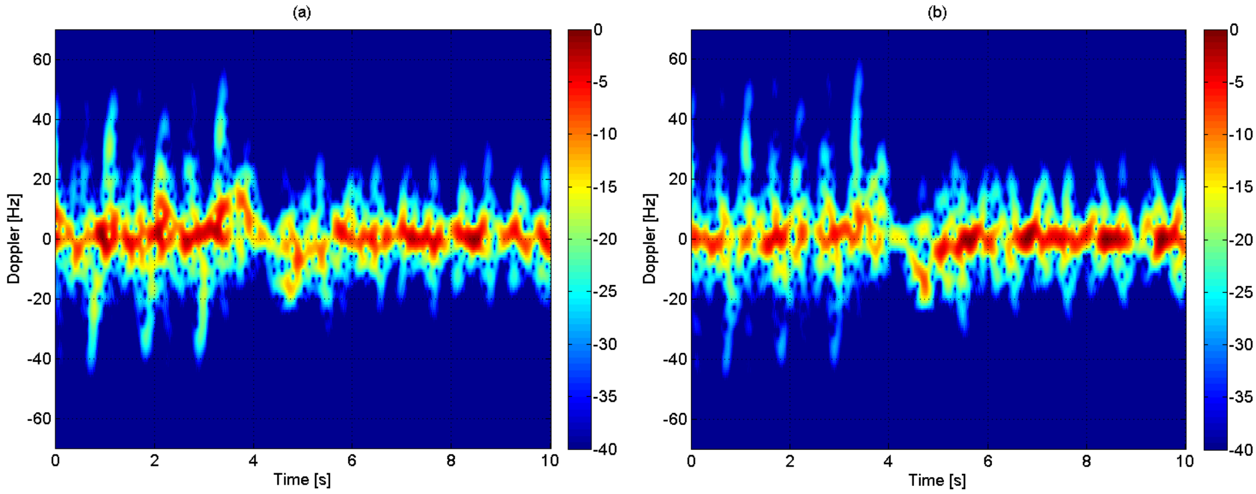

Figure 5 Micro-Doppler signature of a person walking on the spot empty-handed, picking up a metallic pole, and walking with the pole in both hands. Data from the monostatic (a) and one of the bistatic nodes (b)

The following section of the research consisted of quantitative extraction of numerical parameters or features which can be used to differential between the differences in the motions observed by eye in the micro-Doppler signatures shown within Figure 4. From the empirical observation of the spectrograms, four features of interest have been selected as the most appropriate to identify different types of motion, as they are related to the kinetics of the movements and to the presence of objects carried by the subject under observation. They were extracted as follows.

- **Bandwidth:** Defined as the total range of frequencies between the highest and the lowest Doppler frequency recorded in the micro-Doppler signature, i.e. at the positive and negative peaks due to the swinging of limbs. This parameter indicates the overall frequency width of the micro-Doppler signature and can give an indication on how free to swing the limbs are. This can be related to the presence of objects carried by the person, as these will limit the swinging movements of the limbs as observed empirically in Figures 4-5.
- **Mean Period:** Defined as the average of the difference in time between each positive peak in the micro-Doppler signature due to the periodicity of the swinging of the limbs. This parameter is related to the speed at which the limbs move during the

walking gait, and may provide information on possible objects carried by the person, as these will slow down the movement of the limbs.

- **Doppler Offset:** Defined as the difference between the highest and the lowest Doppler frequency recorded in the micro-Doppler signature. This parameter would be exactly 0 if the forward and backward movement of the limbs is perfectly symmetric, hence it can give an indication on the asymmetry of such movement, which may be due to the presence of an object carried by the person.
- **Radar Cross Section (RCS) Ratio between limbs and body**: Defined as the ratio in dB between the magnitude of the micro-Doppler signature at the peaks related to the swinging arms and at the main Doppler line related to the body. Changes of this ratio can provide an indication of an object carried by the person, as the RCS of the limbs plus object would be different from the RCS of limbs only.

A sample of each feature has been extracted from 2.5 seconds of data which correspond to half a recording, hence each 5 second recording contributes to 2 samples for each feature extracted. This has generated a database of 594 samples as whole, considering data collected from all the three radar nodes and for both empty-handed walking and walking with rifle classes. Each feature vector is therefore made of 594 samples extracted from data measured at all the three nodes, or only 198 if considering only data gathered at the monostatic node 3. These features vectors can be input as individual, pairs (2 vectors of 594 or 198 samples each), triplets (3 vectors) or 4 vectors altogether to a classifier, where each row represents a sample belonging to the unarmed or armed class. The dimensionality of the problem is therefore how many features are necessary to provide good classification performance for the example armed vs unarmed scenario, which features and which combinations are the most suitable, what classifier provides best results, as well as investigating the impact of using only monostatic data or the whole dataset of multistatic data. The focus of this work is on which features are most suitable and on the comparison of monostatic vs. multistatic classifier performance.

Initially the extracted features were used in pairs, assuming that an individual feature did not provide good enough classification performance and combinations of more features increased the complexity of the classifier without a significant improvement of the performance. In addition by evaluating the classifier performance using pairs of features it was possible to identify which features provide the best performance.

Using the four features described above in pairs, six combinations of features are possible, namely bandwidth vs mean period, bandwidth vs offset, bandwidth vs RCS ratio, mean period vs offset, mean period vs RCS ratio, and offset vs RCS ratio. An empirical representation of the separation between the elements of the two classes can be given by 2D scatter plots as shown in Figure 6, where the samples in red refer to the walking with rifle classes and those in blue to the empty-handed walk classes. This includes data generated from all the radar nodes, not just monostatic results. The different shapes of the markers used in these sub-figures refer to the different subjects taking part to the experiment. This allows you to see how the features change for different people even when they are performing the same movement, although the focus of this work is not distinguishing between different subjects, rather distinguishing the rifle from the empty-handed case. Figure 6 demonstrates that some combinations provide a greater separation in the feature space of the two selected classes, for instance subfigures Figure 6a and Figure 6e have a greater separation than Figure 6f, and therefore they are expected to improve the performance of classifier when input. Analysing further Figure 6a and Figure 6b, the feature bandwidth is consistently lower for most of the elements of the "rifle" class, approximately not above 60 Hz, and this may relate to the smaller swinging movements of the limbs when the person is carrying the metallic pole. Also, the period appears to be higher for the "rifle" class, probably because the movement of the limbs is slower because of the weight of the carried object, and the offset appears to be more concentrated around 0 Hz for the "rifle" cases, as the movement of the limbs is more regimented and controlled compared with the empty-handed walk situation.

After the visual inspection of the 2D scatter plots, a numerical evaluation of the classification performance for different types of classifiers is given in the following part of this work. The classifier used in this work is based on the discriminant analysis method, for which a rigorous mathematical description is provided in the literature [24-25]. Linear Discriminant Analysis (LDA) provides an optimal solution for linearly separable problem [26]. The method assumes that each different class generates samples represented by a different multivariate Gaussian distribution, and the parameters of these distributions, namely mean and covariance matrix, can be estimated by the classifier during the initial training phase. Equations 1-3 show respectively the density function of the Gaussian distribution and the aforementioned parameters:

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

$$\mu_k = \frac{1}{N_k} \sum_{n=1}^{N} x_n \tag{2}$$

$$\Sigma_k = \frac{1}{N_k - K} \sum_{n=1}^{N} (x_n - \mu_k)(x_n - \mu_k)^T \tag{3}$$

where μ_k is the mean for class k, Σ_k the covariance matrix, and $|\Sigma_k|$ is the determinant of the matrix. Different types of classifiers perform different estimations of these parameters, for instance a linear classifier estimates one covariance matrix for all the classes assuming that only the mean values change between different classes, whereas a quadratic classifier estimates one covariance matrix for each class. These methods have both a diagonal variant where the diagonal of the covariance matrices is used. After the training phase the classifier divides the samples space into regions where an expected classification cost is associated to each predicted classification, and the aim is minimizing such cost as in equation (4):

$$\hat{y} = \text{argmin}_{y=1,\ldots,K} \sum_{k=1}^{K} \hat{P}(k|x) C(y|k) \tag{4}$$

where $\hat{y}$ is the predicted classification, K is the total number of classes (2 in this work), $\hat{P}(k|x)$ is the posterior probability and $C(y|k)$is the cost of mis-classifying a sample as y when it is actually k.

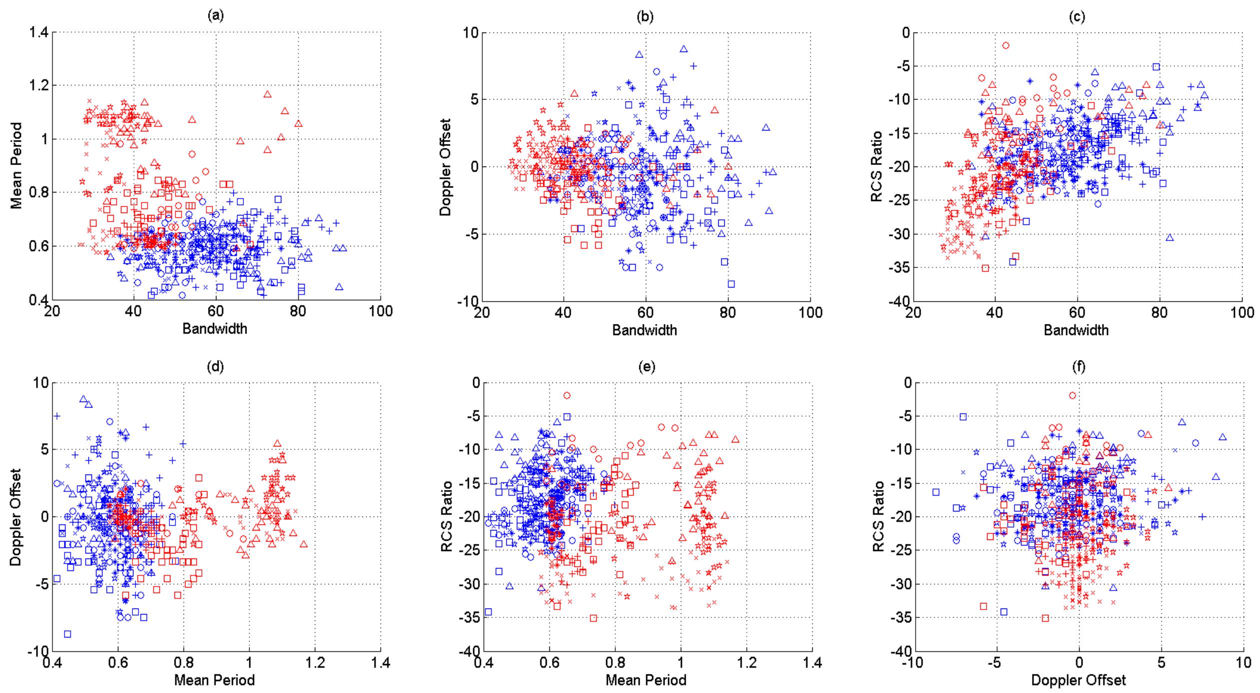

Figure 6 2D plots of samples extracted from walking and walking with rifle data for different combinations of features: (a) Bandwidth vs period, (b) Bandwidth vs Doppler offset (c) Bandwidth vs RCS Ratio (d) Period vs Doppler offset (e) Period vs RCS Ratio (f) Doppler offset vs RCS Ratio

In the following work we have used four variants of discriminant analysis, namely linear, diagonal-linear, quadratic, and diagonal-quadratic, focusing on identifying the combinations of features providing the best classification performance for each variant, and possibly those which provide good performance regardless of the classifier type. Figure ***6***7 shows examples of outputs from a linear and quadratic classifier for two combinations of features, namely bandwidth vs period and bandwidth vs offset. All three nodes data were used as an input to these different classifiers. The elements of the two classes can be distinguished by colours (red for rifle, blue for empty-handed walk), as well as the two areas separated by the magenta line estimated by the classifier. Any further samples analysed by the classifier will be assigned to one of the two areas and labelled as “rifle” or “normal walk”. The quadratic classifier offers further degrees of freedom in the estimation of the separating line, but its effectiveness in comparison with the linear classifier will depend on how the samples of the two classes are separated in the feature space.

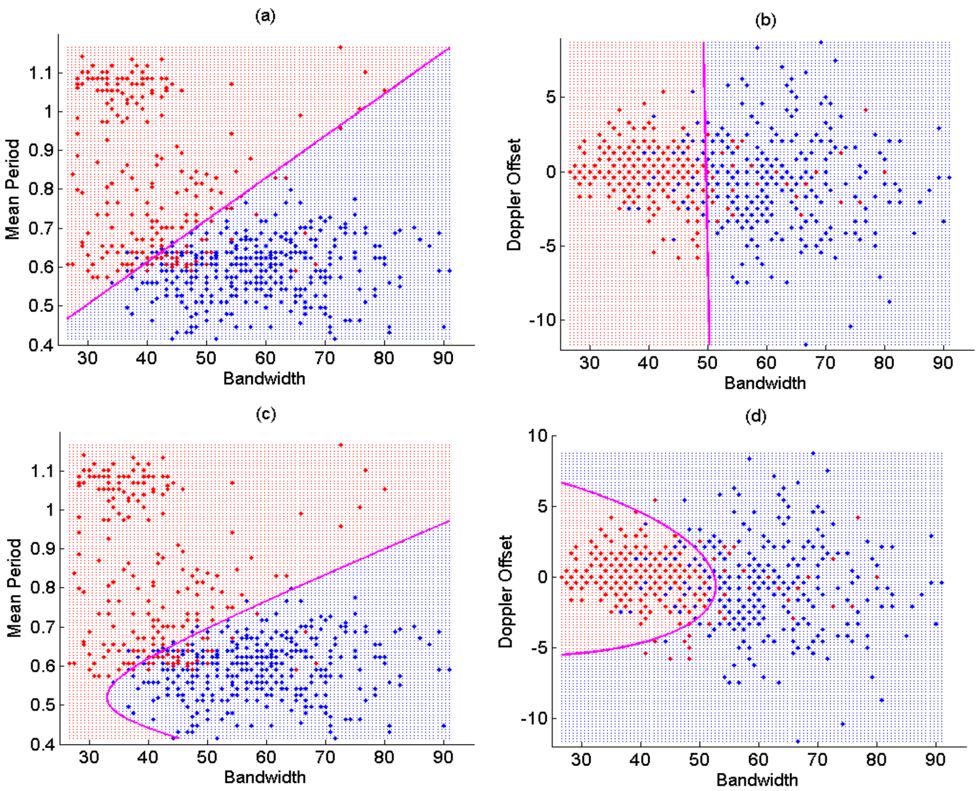

Figure 7 Examples of classifier plots for walking and walking with rifle data: (a) Linear classifier using bandwidth vs period (b) Bandwidth vs Doppler offset (c) Quadratic classifier using bandwidth vs period (d) Bandwidth vs Doppler offset

Depending on how the samples are distributed in the feature space, a false positive consisting of a normal walk mistaken for a rifle walk event could be more or less likely to happen than a false negative when a rifle walk event is mistaken for a normal walk event, and one could argue as to which case is more detrimental to the overall performance. In the following analysis of the classification performance there is no distinction between the two types of misclassification errors as both are considered equally important to avoid. The overall error for a given classifier and combination of features is calculated as the percentage of total misclassification events (sum of “empty-handed” mistaken for “rifle” events and “rifle” mistaken for “empty-handed” events) over the total number of samples.

Table 1 summarizes the classification results showing this error for different types of classifiers based on discriminant analysis and different combinations of features. The data used to generate Table 1 was taken from all three nodes and therefore includes monostatic and passive bistatic results. The classifier types are in order (1) Linear, (2) Diagonal-linear, (3) Quadratic, and (4) Diagonal-quadratic. The types (2) and (4), use a diagonal covariance matrix estimate as used in classic Naïve Bayesian classifiers. The combinations of features are I) bandwidth vs mean period, II) bandwidth vs offset, III) bandwidth vs RCS ratio, IV) mean period vs offset, V) mean period vs RCS ratio, and VI) offset vs RCS ratio. The training set for the classifiers presented in the following tables amounts to a randomly selected 10% subset of the recorded data samples and includes at least one sample from each different individual. The remaining 90% is used to assess the classification performance. This assessment is repeated 15 times with different training data to generalize the performance of the classifier, and the average of the classification error obtained in these repetitions is reported in the following tables.

The first and fifth combinations present the lowest classification error for all types of classifier analysed, with the percentage of successful classification around 90%, using only 10% training data. The performance is still good for feature combinations II to IV, with the classification error not higher than 24%, whereas the performance degrades for combination number VI (Offset vs. RCS ratio). This might have been expected looking at the 2D scatter plots in Figure 6f, where the samples of the two classes are almost completely overlapped for the feature combination number VI.

Table 1 – Classification error percentage for four types of classifier and six pairs of features when distinguishing empty-handed walk and walk with rifle. All three multistatic node data input.

	I	II	III	IV	V	VI
Classifier 1	10.15	21.05	20.38	17.42	11.68	34.51
Classifier 2	9.85	22.64	20.81	18.00	12.10	33.31
Classifier 3	10.39	24.00	19.79	18.81	10.97	29.64
Classifier 4	10.16	23.37	19.91	18.66	11.01	30.79

Another aspect to investigate is the benefit of collecting micro-Doppler signatures with the multistatic system NetRAD used in this work, in comparison with a conventional monostatic radar. A multistatic radar allows to gather the target micro-Doppler data from different aspect angles and this may therefore improve the classification performance, as in some circumstances the target may be not completely visible or the features not easy to extract for a particular node, whereas the other nodes can still provide information. The analysis of classification performance is repeated using only data from the monostatic node, rather than all nodes data used in Table 1. In this case the classifier is provided with one third of the whole dataset (hence feature vectors made of 198 samples rather than 594 samples), with samples extracted only from data recorded at node 3 (monostatic). The results are summarized in Table 2 with overall classification error.

For the feature combinations I to III, the use of only monostatic data increases the overall error and shows the advantage of using a multistatic geometry. This happens only partially for combination number V, for which the error does not increase for the linear classifier, whereas for combination number IV the error seems to decrease consistently when using only monostatic data. An actual system could therefore exploit those feature combinations providing reduced classification error when multistatic data are available (for instance feature combination I), and at the same time be robust towards failures of one or more multistatic passive nodes by using those feature combinations which provides good classification performance even with monostatic data only, such as feature combination V.

Table 2 - Classification error percentage for four types of classifier and six pairs of features when distinguishing empty-handed walk and walk with rifle, using only monostatic data.

	I	**II**	**III**	**IV**	**V**	**VI**
Classifier 1	12.38	24.15	26.47	16.47	11.26	39.05
Classifier 2	11.12	29.44	24.15	15.99	13.70	35.24
Classifier 3	13.05	32.16	27.59	17.39	11.96	36.81
Classifier 4	12.89	29.19	22.77	16.47	13.84	33.22

The following step of the analysis was checking the classification performance with triplets of feature vectors rather than pairs as input to the classifier. The possibility of combining information from more features may indeed improve the classification, but the actual performance depends on how the samples belonging to the different classes are spread in the 3D space generated by three features. Given the four features considered in this work, there are four combinations of three features which can be examined, namely I) bandwidth, period and offset, II) bandwidth, period and RCS ratio, III) bandwidth, offset and RCS ratio, and IV) period, offset and RCS ratio. Table 3 shows the overall error for the different triplets of features and the different types of discriminant analysis classifier. Combination number II provides the lowest classification error, with percentage of success higher than 90%, but very good results and low error (below 13%) are also provided by combinations I and IV. The classification error tends to decrease in comparison with the results shown in Table 1 where pairs of features were combined, so there is an advantage in combining more features to perform the classification, but this needs to be assessed with the increased complexity and computational burden of the classifier. Again it is interesting to test how the classification results differ if only data from the monostatic node are used, as if in a conventional radar system. Table 4 shows the results for this test. In most cases the classification error slightly increases when using only monostatic data, but the performance remains fairly good with percentage of success higher than 87% for combinations number I, II, and IV for linear and diagonal-linear classifiers. Feature combination II still provides the best performance. The difference in classification error between monostatic only data vs multistatic data from three nodes has been evaluated for the four triplets of features and averaged across the four types of classifier. This average difference is 2.5%, 1.7%, 5.8% and 0.6% for combinations I to IV respectively. The greatest improvements were found in feature combination III but despite this it still has the highest error rate when using monostatic or multistatic data. These results confirm the robustness of the proposed feature-based classification approach for a multistatic radar system even in case of failure of one or more passive nodes, as well as the advantage in exploiting data from different nodes if available.

Table 3 - *C*lassification error percentage for four types of classifier and four triplets of features when distinguishing empty-handed walk and walk with rifle. All three multistatic node data input.

	I	II	III	IV
Classifier 1	10.57	9.75	21.40	11.94
Classifier 2	9.42	9.46	22.11	13.74
Classifier 3	11.36	9.17	22.14	11.57
Classifier 4	11.16	9.08	21.74	11.47

Table 4 - Classification error percentage for four types of classifier and four triplets of features when distinguishing empty-handed walk and walk with rifle, using only monostatic data

	I	II	III	IV
Classifier 1	12.18	11.32	27.59	11.79
Classifier 2	12.52	9.41	24.62	13.00
Classifier 3	15.38	11.82	29.92	14.43
Classifier 4	12.49	11.54	28.57	11.93

Finally the classification error when all four feature vectors are used as inputs to the classifier have been calculated when using both multistatic data and monostatic data only. The error for the multistatic data is 9.47%, 9.60%, 10.71%, and 9.72%, respectively for classifier type 1 to 4. The error for the monostatic data only is 10.53%, 12.18%, 13.05%, and 12.16%. The use of multistatic data consistently improve the classification error for all types of classifier considered.

Using 4 feature vectors, the classification error has not significantly decreased in comparison with using the best triplet of feature vectors in tables 3-4 (namely triplet II), and even in comparison with the best pair of feature vectors in tables 1-2 (namely pair I). Figure 8 shows the classification accuracy for all the possible combinations of feature vectors when used as individual (4 combinations), pairs (6 combinations), triplets (3 combinations), or altogether (1 combination). In this case classifier 2 (diagonal-linear) has been used as it has provided the best results in the previous analysis. This shows that the classification accuracy can be very similar when using pairs of feature vectors in comparison with triplets or all feature vectors, provided that the most suitable features are extracted and exploited, in this case bandwidth and mean period (pair I). Hence good classification can be achieved using only two feature vectors reducing the complexity of the classifier and the computational time to extract feature vectors which may be not necessary.

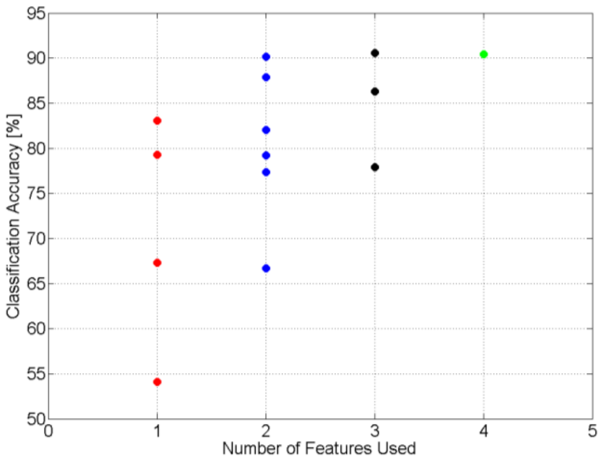

Figure 8 Classification accuracy for all possible combinations of feature vectors as input to the diagonal-linear classifier

One of the main challenges in classification based on micro-Doppler is the dependence on the aspect angle, as the torso may shield the arm movements and reduce their contribution to the overall micro-Doppler signature. Additional data have been collected for a preliminary investigation of the proposed features and classification performance for different aspect angles. In this case the subject was walking on the spot and facing different directions for each recording, namely facing node 3, then node 1, then node 2, and then facing opposite direction to node 1 (see Figure 1). This allows an evaluation of micro-Doppler signatures with differences of aspect angles up to 60° (for instance when the person is facing node 3 and data recorded at node 2) and with the person showing his back to node 1.

Samples of the previously described features have been extracted, with an equal number of samples for each facing direction, and these samples have been used as inputs to a separate classifier for each aspect angle. In particular 20 samples for each direction have been generated at each of the three nodes, so that each feature vector input to the classifier is made of 60 samples. The single classifier used is the diagonal-linear, as in Figure 8, and all four feature vectors have been used as inputs. The error percentages obtained are as follows: 4.7% for direction 1 (facing node 3), 3.8% for direction 2 (facing node 1), 6.3% for direction 3 (facing node 2), and 9.3% for direction 4 (facing opposite to node 1). Better classification performances are obtained when the person is facing at least one of the nodes, with the error slightly increasing when the person is facing the bistatic node (node 2) that is furthest away from the transmitter. The maximum error occurs when the person is facing the opposite direction to node 1, but the performance of the classifier using the proposed features is still reasonably robust. These preliminary results show that there is classification dependence on the aspect angle, as expected, with error rates increasing when the person is facing away from the radar nodes. Further work will be carried out to investigate in detail such dependence and identify the most suitable deployment strategy for a multistatic radar system to achieve best classification performance.

4- Conclusions

In this paper we have presented the analysis of human micro-Doppler data generated by the multistatic radar system NetRAD, focusing on the classification of unarmed and potentially armed personnel. The analysis shows that suitable features can be extracted from the micro-Doppler signatures after time-frequency processing through STFT, and that these features can be fed to classifiers based on discriminant analysis. Classification performances with percentage of success up to approximately 90%, using a training set of only 10%, have been achieved for classifiers combining pairs of features. Feature vectors have been used as input to classifiers as individual, pairs, triplets, or altogether. The impact on the classification performance has been evaluated, showing that good performance can be achieved even with pairs of feature vectors, provided that the most suitable features are exploited (in this case bandwidth and mean period). The effect of using only data from the monostatic node compared with the full multistatic database has been investigated. Quantifiable increases in classification performance have been demonstrated when using a 3 node multistatic system in comparison to a single monostatic radar. It has been shown that some feature combinations can provide reduced classification errors when combining data from multistatic aspect angles, on the other side other combinations are robust in providing low errors even with just monostatic data. This would allow a classifier to perform well in actual in-field applications for both monostatic and multistatic systems.

It is believed that the suitability of the features and hence the multistatic vs. monostatic classifier performance will be very geometry specific and dependent on the aspect angle of the motion. Although the proposed feature provided good performance for a preliminary test using data collected with different aspect angles, further experimentation are needed to quantify performance based on different geometries of the multistatic sensor, different bistatic angles, and different motion directions. In addition to this, future analysis will be performed to investigate the effectiveness of the proposed classification method using data where the subject is actually walking, producing a net Doppler motion and more realistic leg micro-Doppler signature compared with walking on the spot. A better knowledge of these parameters would further the practical recommendations when deploying multistatic systems for micro-Doppler classification. The work can be also extended by applying different classification methods (naïve-Bayes, nearest neighbour, support vector machine) to the data already available and comparing the results. The database could be also extended including further measurements with more subjects taking part.

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