Micro-Doppler based target classification using multi-feature integration

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Abstract

Three novel micro-Doppler feature extraction algorithms are presented and applied to a dataset containing real X-band radar data of moving ground targets. In each case data dimensional reduction was carried out using principal component analysis (PCA) and incorporated into the feature extraction process. Extracted features are classified using a support vector machine (SVM) classifier. It was found that all three algorithms were able to produce classification accuracies in excess of 90%. The performance of the different algorithms are shown to depend on the method used and the degree of dimensionality reduction imposed at the PCA stage.

1 Introduction

The presence of internal motions on moving radar targets introduce signal modulations known as micro-Doppler (m-D) [1] [2]. These phenomena can be exploited to characterize the target time-frequency radar response in order to classify and identify the target [3] [4] [5]. Specifically, the classification of moving ground targets, including humans and animals, has potential applications relating to tasks such as surveillance and border control [3] [6]. The motion of human bodies is an articulated locomotion where the motion of limbs can be characterized by a repeated periodic movement. Walking is a typical human articulated motion and can be decomposed into a periodic motion in the gait cycle [1] [7].

Various human movements, such as walking, running, or jumping, have different body movement patterns. Compared with visual image sequences, radar micro-Doppler signatures are not sensitive to distance, light conditions and background complexity, which is advantageous for the purposes of estimating gait characteristics [8] [9].

This paper describes three algorithms that were developed to perform feature extraction from m-D signals. The Spectrogram Frequency Profile (SFP) algorithm generates features based on the projection of a spectrogram, gained through Time Frequency Analysis (TFA) of the m-D signal, onto its frequency axis. The Cadence Velocity Diagram Frequency Profile (CVDFP) algorithm generates features which benefit from the localisation in time of TFA by projecting a Cadence Velocity Diagram (CVD), which is formed from the spectrogram, onto its cadence frequency axis. A third novel algorithm combines SFP and CVDFP features, using Principal Component Analysis (PCA) to remove redundancy between the two.

Features produced by each of these algorithms were used for classification of real X-band radar data containing micro-Doppler of six classes of human and animal motions. These data were collected in an outdoor scenario with the influence of clutter and noise providing a realistic test-bench for the algorithms.

In addition to the three novel feature extraction algorithms, an additional algorithm was used to extract features from the X-band dataset. This was the time frequency distribution-direction features (TFD-DF) algorithm which was introduced by Molchanov et al in [3]. This algorithm was used as a benchmark by which to assess the performance of the novel feature extraction algorithms when classifying the X-band dataset. The use of a benchmark algorithm was considered important since this dataset had not previously been used as a test-bench for micro-Doppler classification and thus the complexity of the classification problem that it presents had not been established.

In conjunction with each feature extraction algorithm, a feature dimensionality reduction stage was applied as part of the feature extraction process. This stage exploits the minimum covariance determinant method [10] to robustly reduce the feature vector dimensions using a Robust PCA (RPCA) algorithm. The use of RPCA increases the separability of the classes due to its outlier rejection capability.

Classification was performed using a Support Vector Machine (SVM) classifier. It was found that all three algorithms performed favourably when compared to the TFD-DF benchmark algorithm, and were able to produce classification accuracies greater than 90%. A maximum value of 94.9% was achieved using the SFP-CVDFP-PCA algorithm, but the performance of each algorithm was found to be dependent on the method used and the degree of dimensionality reduction imposed at the feature reduction stage.

2 Feature extraction

Many approaches to micro-Doppler feature extraction have been documented where the aim has been to generate feature sets which are useful for a subsequent classification stage to identify the type of motion present in the original micro-Doppler observation. In many cases the first stage of feature extraction is to perform time-frequency analysis (TFA) of the Doppler signal [3] [4] [5] although other methods which bypass TFA, relying instead on signal properties such as DCT coefficients [11], cepstrum coefficients [6] and autoregressive models [12] also exist.

The effects of a target's micro motions are manifested as the time variant modulations of the frequency content of the received Doppler signal [1]. Representing the Doppler signal in the joint time-frequency domain can therefore be useful when analysing micro-Doppler signatures. Each of the algorithms which will be described in this section rely on time-frequency analysis, and specifically the short time Fourier transform (STFT), as a first step in extracting features from micro-Doppler signatures. Figure 1 gives an example spectrogram showing micro-Doppler of a walking human with could be used as the basis for the algorithms which will be described in this section. The modulated micro-Doppler component can be seen at around 150Hz (the strong signal at zero Doppler is static ground clutter).

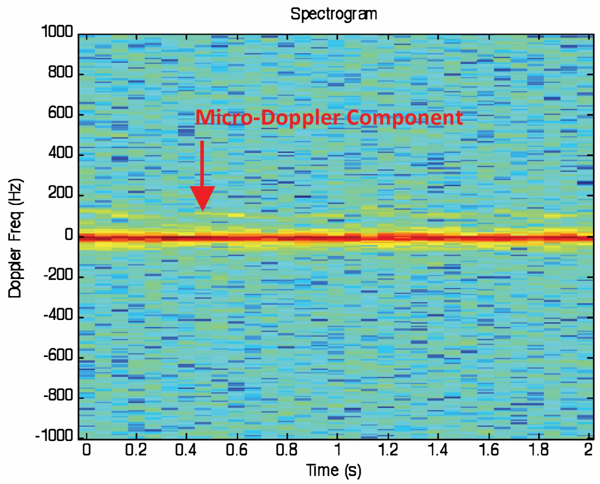

Figure 1: Spectrogram of walking human m-D signature

2.1 The SPF algorithm

The spectrogram frequency profile (SFP) algorithm generates a feature vector from the spectrogram of a micro-Doppler signal (gained via the STFT) simply by summing over time for each of the frequency bins. The resultant feature vector is the average over time of the spectrum of the Doppler signal.

2.2 The CVDFP algorithm

One shortcoming of the SFP algorithm is that it does not exploit the time varying information about the instantaneous frequency contained in the time-frequency distribution. The cadence velocity diagram frequency profile (CVDFP) algorithm was therefore developed in an attempt to create an algorithm that would generate features which benefit from the localisation in time property of the STFT.

A signal's cadence velocity diagram (CVD) is formed from its spectrogram, as described in [4], taking the Fourier transform along the time dimension for each frequency bin. The result is a matrix whose rows represent Doppler frequency (or target velocity since the two are directly proportional) and whose columns represent cadence frequency, which is a measure of how often different frequencies occur over time within the signal. Figure 2 shows the CVD obtained from the spectrogram of Figure 1. From the CVD can be seen two peaks in ±2Hz, a characteristic feature which is brought out in the CVD representing the cadence of the steps.

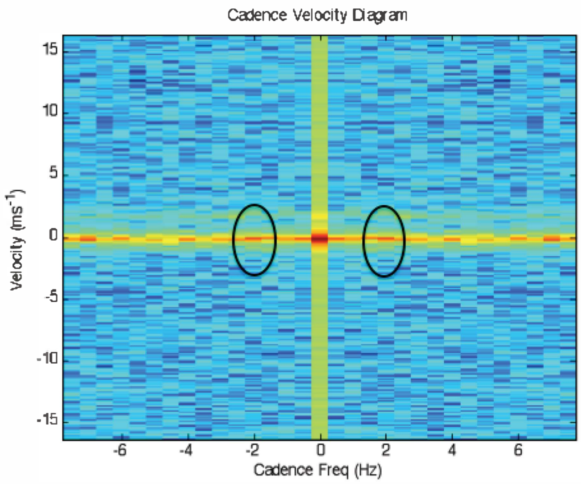

Figure 2: CVD of walking human m-D signature

Just as the SFP algorithm creates a feature vector by summing over time for each Doppler frequency bin of the spectrogram, the CVDFP algorithm creates a feature vector by summing over cadence frequency for each Doppler frequency (or velocity) bin of the CVD.

2.3 The SFP-CVDFP-PCA algorithm

Preliminary investigations demonstrated that both the SFP and CVDFP algorithms were capable of generating features which led to good classification performance when using a support vector machine (SVM) classifier to classify micro-Doppler of humans and animals. These preliminary tests also indicated that the feature vectors generated by the two algorithms were significantly correlated. The SFP-CVDFP-PCA algorithm uses principal component analysis to remove redundancy between the correlated SFP and CVDFP feature vectors, and to generate a new feature vector which contains information from each of these which is useful for classification.

The first step of the SFP-CVDFP-PCA algorithm is to take the logarithm of the SFP and CVDFP feature values. Figure **3** shows an example of a scatter plot of CVDFP feature values against SFP feature values gained from an observation of micro-Doppler of a walking human, subsequent to this step. The correlation between the two feature vectors can clearly be seen.

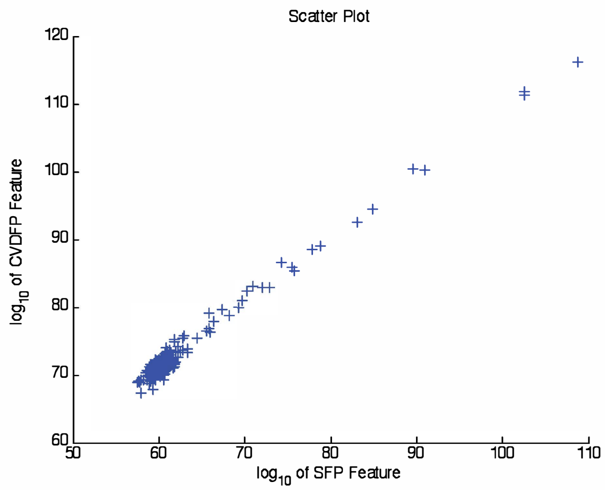

Figure 3: Scatter plot of SFP and CVDFP features

The second step of the algorithm is to perform PCA on the SFP and CVDFP features. Figure 4 shows the resultant score plot, where the data are plotted relative to the newly calculated principal components. Here we can see that the features are no longer correlated.

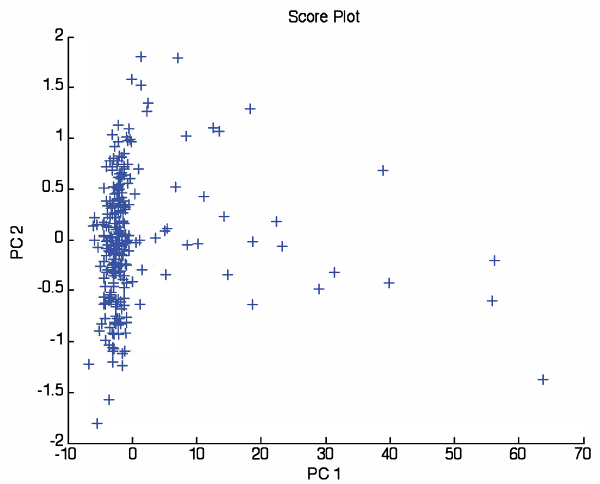

Figure 4: Score plot after PCA of SFP and CVDFP features

The final step of the SFP-CVDFP-PCA algorithm is to perform dimensionality reduction of the data, by discarding principal component 2, so as to form a feature vector. This is tantamount to projecting the scatter plot of Figure 4 onto the PC1 axis.

3 Feature dimensionality reduction

Regardless of the algorithm used to generate feature vectors from each observation of micro-Doppler data, the following stage in the feature extraction process is the application of PCA for dimensionality reduction of features. Dimensionality reduction is a common application for PCA and this approach has been used previously in the context of micro-Doppler [13].

Dimensionality reduction with PCA can be viewed as a sort of lossy compression: the number of dimensions, or principal components, used to represent the data is reduced and so information that would have been represented by higher ordered principal components is lost. However, the majority of variation in the data is explained by few low ordered components. The higher order components account for little variation in the data and can in fact identify near–constant linear relationships between the original features [14]. The data-reduced feature set can therefore be seen as a more efficient representation of the original data in which the underlying structure is retained despite the loss of some information. Presenting the data in this feature-reduced representation can increase the separability of classes, leading to improved performance at the classification stage.

One issue with PCA when using experimental data is that a small number of outliers can skew the results of PCA [14]. Robust PCA addresses this problem by using the minimum covariant determinant (MCD) estimator method [10] to gain a robust estimate of the covariance matrix of the data, excluding outliers, which can then be used to gain robust estimates of the principal components of the dataset. Work carried out in [15] has shown that RPCA is effective for dimensionality reduction and that the computational costs of the fast MCD algorithm are sufficiently low that it can be implemented on an embedded device.

Three methods of dimensionality reduction were evaluated. The first method uses standard PCA to reduce the number of features, without making any attempt to reduce the effects of outliers. The second method uses replaces PCA with RPCA. In the third method, standard PCA is performed to reduce the dimensionality of the data, and then RPCA is performed on the resulting data to remove the effects of outliers without performing any further dimensionality reduction.

4 Experiments with Real Radar data

The feature extraction methods described here were applied to X-band radar data of moving humans and animals. The dataset used was generated during a single test using a Selex ES PicoSAR system operating in GMTI mode (using a carrier frequency of 9.2 GHz and PRF of 2kHz) [16]. The radar was used to target a fixed scene from a ground-based platform. Humans and/or horses were then introduced to the scene to act as targets. Data were collected for targets performing each of the following classes of motion:

- Class 1: Human Walking (slow)
- Class 2: Human Walking (medium)
- Class 3: Human Walking (fast)
- Class 4: Horse With Rider Walking (medium)
- Class 5: Horse With Rider Walking (fast)
- Class 6: Horse and Human Both Present

The dataset consists of 28 observations for each class of motion where the duration of each observation is 0.5s. The exception to this is class 6 for which there are 112 observations. Figure 5 shows a high resolution spectrogram of the m-D signature of a walking human (class 3) from this dataset. The micro-Doppler can clearly be seen at around 150 Hz, and the effects of static clutter, manifested as a strong signal at 0 Hz, and background noise are also apparent. These features of the data help to provide a rigorous test scenario for feature extraction methods.

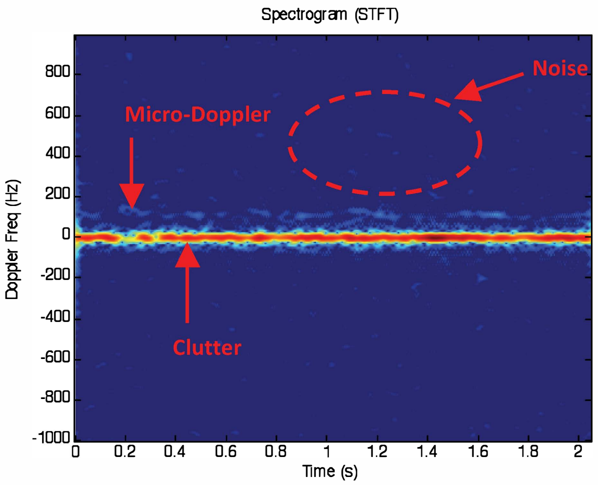

Figure 5: Spectrogram of class 3 m-D signature

5 Classification

Classification of extracted feature vectors was performed using an SVM classifier with a radial basis function (RBF) kernel, employing a cross-validation grid search for selection of cost function and kernel parameters [17] [18]. The "one-against-all" approach was used to perform multi-class classification between the six classes described in section 4 [19].

When classifying the test dataset, a system of Monte Carlo testing was applied whereby classification was performed repeatedly using randomly generated permutations of training and test for each repetition. For each test 50 repetitions were carried out, and a ratio of roughly 70% training data to 30% test data was maintained throughout testing.

Each of the feature extraction algorithms described in section 2 as well as the TFD-DF algorithm were tested and compared using standard PCA for feature reduction. The number of principal components retained when generating features was varied from 5 to 30. Figure 6 shows the average classification accuracy (percentage of test observations whose classes were correctly predicted by the SVM) achieved when each of the algorithms was used for feature extraction.

The dotted lines represent the classification accuracies achieved by each of the algorithms when no feature reduction was performed. In these cases, 128 features were included in each uncompressed feature vector. The results of Figure 6 indicate that PCA can give improvements both in the number of features needed for each observation, and in classification accuracy.

Each of the novel algorithms achieved significantly better classification results than the TFD-DF algorithm. This comparison helps to contextualise the results of this test by relating them to the results of tests carried out in [3].

Furthermore the results of Figure 6 show that the SFP-CVDFP-PCA algorithm is capable of outperforming both the SFP and CVDFP algorithms when low numbers of PCs are retained at the feature reduction stage. A maximum classification accuracy of 94.9% was achieved, using this algorithm, when 15 PCs were retained. This validates the method of using PCA to combine the similar SFP and CVDFP feature vectors, benefiting from useful information from each.

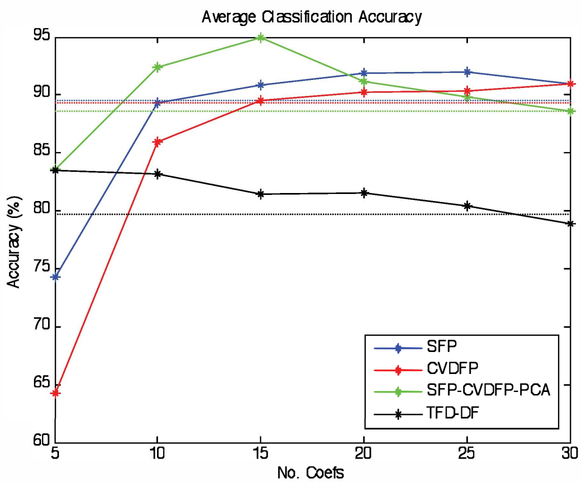

Figure 6: Comparison of extraction algorithm performance

Figure 7 shows results gained from a comparison of the three methods of dimensionality reduction described in section 3. These results are for an example case where the SFP was used for feature extraction in conjunction with each of the feature dimensionality reduction methods.

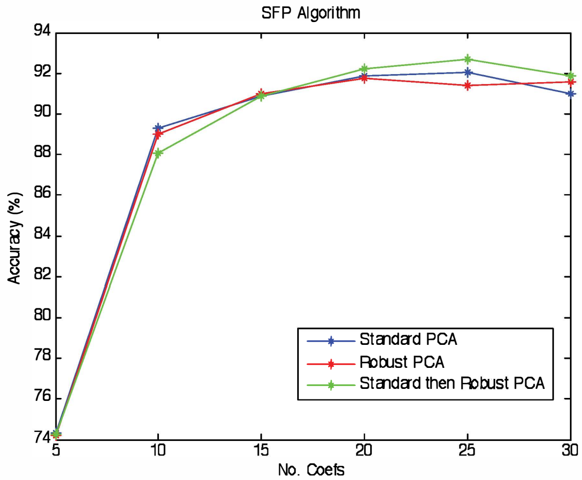

Figure 7: Comparison of PCA methods

The best result was achieved when using standard PCA followed by robust PCA when 25 PCs were retained, leading to a maximum classification accuracy of 92.7%. This result is an improvement over any value gained using standard PCA.

6 Conclusion

Three novel micro-Doppler feature extraction algorithms, the SFP algorithm, the CVDFP algorithm and the SFP-CVDFP-PCA algorithm have been described along with three methods of using PCA for feature dimensionality reduction. These methods of feature extraction were tested through their application to an X-band radar dataset and the use of an SVM classifier to classify observations of this dataset according to the type of motion described by the micro-Doppler.

High classification accuracies were achieved particularly when the SFP-CVDFP-PCA was used. Feature reduction using PCA was shown to be effective in reducing the number of features needed for each observation of micro-Doppler with the dimensionality reduced feature sets leading to better classification performance in some cases. In addition it was demonstrated that the use of robust PCA improves the classification accuracy per number of components used.

Further development of this work will include the evaluation of performance with other data sets and with the inclusion of an ‘unknown’ class as a possible output from the classifier. This will be more representative of what would be needed in a real operational system, and will provide a better understanding of how well these classification techniques can perform in a range of scenarios.

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