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Operational assessment and adaptive selection of micro-Doppler features

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Abstract: A key challenge for radar surveillance systems is the discrimination of ground-based targets, especially humans from animals, as well as different types of human activities. For this purpose, target micro-Doppler signatures have been shown to yield high automatic target classification rates; however, performance is typically only given for near-optimal operating conditions using a fixed set of features. Over the past few decades dozens of micro-Doppler features have been proposed, when in fact utilisation of all possible features does not guarantee the maximum classification performance and the selection of an optimal subset of features is scenario dependent. In this work, a comprehensive survey of micro-Doppler features and their dependence upon system parameters and operational conditions – such as transmit frequency, range and Doppler resolution, antenna–target geometry, signal-to-noise ratio, and dwell time – is given. Algorithms for optimising classification performance for a reduced number of features are presented. Performance gains achievable using adaptive feature selection are assessed for a case study of interest.

1 Introduction

Ascertaining whether a detected target comprises a threat is a key challenge for radar surveillance systems, especially in the area of discriminating animals from humans, as well as different types of human motion. Radar can be used to recognise targets and their activities by analysis of the target's micro-Doppler signature. The micro-Doppler effect refers to the frequency modulations that are incurred about the main Doppler shift due to vibrational or rotational motion in addition to the target's gross translational motion [1, 2]. Thus, the periodic rotational motion of the wheels of a vehicle [3], treads of a tank [4], or blades of a helicopter [5] all result in micro-Doppler modulations that possess a specific pattern based upon the type of the target. Human motion, too, results in a unique micro-Doppler signature that can be used to discriminate not just humans from animals and vehicles, but also varying human activities. Walking with one arm swinging, two arms swinging, or no arm motion, as well as jogging, running, jumping, boxing, creeping, and crawling are all examples of various activities that have unique micro-Doppler signatures. Indeed, the change in gait due to the carrying of a bomb, as would be done by a suicide bomber, has even been shown to result in a difference in micro-Doppler that can be used to detect such a threat [6].

The automatic detection of a specific pattern in micro-Doppler signatures is typically accomplished using a variety of machine learning techniques, in which first a set of features thought to be characteristic of the signature are extracted and subsequently used as an input to one of a number of classifiers, such as support vector machines, *k*-nearest neighbours (kNN), artificial neural networks, Gaussian mixture models, or naïve Bayesian classifiers. Over the past few decades a plethora of features have been proposed for use in micro-Doppler classification. These features may be divided into four basic types: (i) physical features [7–9], which aim at deriving quantities relating to the physical characteristics of targets and their motion; (ii) transform-based features [10–12], which utilise the coefficients of transforms, such as the discrete cosine transform (DCT), as features; (iv) component analysis features [13–15], where the basis computed from algorithms such as principle component analysis (PCA) are defined as features; and (iv) speech features [16–18], which have typically been designed for and used to process speech signals, but have yielded good results in micro-Doppler classification as well. Combined, hundreds of features may potentially be extracted from micro-Doppler signatures.

However, utilisation of all possible features generally does not give optimal classification performance. Just a handful of features are typically sufficient to yield good performance. In many works on micro-Doppler classification published to-date, a small number of features, presumably chosen based on the experiments and experiences of the investigator, have been seen to give good performance under nearly-ideal conditions. Indeed, there is a wide variety in the feature sets utilised. Interestingly, although most papers do not use the exact same feature set, all attain adequate performance for the specific classification problem under consideration. This triggers the question, then, of not just what number of features is ideal for a given classification problem, but also which features truly yield – not just sufficient – but optimal performance and how they may be systematically chosen by the radar processor.

The capability of a given feature to discriminate between classes is dependent on two primary issues: (i) the relevance of the feature to the classification problem and (ii) the ability to accurately estimate or extract the feature from the micro-Doppler signature. A strongly relevant feature is defined as a feature that is always necessary for optimal performance, whereas an irrelevant feature is one that is never necessary under any condition. If the feature cannot be accurately estimated from the data, however, what may normally be a highly relevant feature due to underlying phenomena may become entirely irrelevant and even detrimental to the classification process. Feature selection algorithms aim at finding an optimal subset comprised of a minimal set of features that maximise classification performance. This is typically accomplished by trying to discard redundant (highly correlated) features while choosing accurately estimable, relevant features. An alternative approach that has been proposed in several works pertaining to micro-Doppler analysis is to use dimension reduction algorithms, such as PCA, to reduce the feature set size. Dimension reduction fundamentally differs from feature selection, however, in that the number of features is decreased by in fact forming a new, smaller set of features that are optimally uncorrelated as opposed to selecting from an existing set. Although dimension reduction minimises redundancy, there is no explicit optimisation of relevance and hence the resulting features do not necessarily imply optimal class separability.

In this work, a comprehensive assessment of micro-Doppler features and their use for human activity classification is accomplished. There are three main contributions: first, the robustness of micro-Doppler features is analysed under varying operational conditions, thereby filling a key void in the literature, where most results are given for only nearly-ideal conditions. Second, a detailed discussion of key feature selection algorithms is given to show the necessity and advantages of a feature selection stage (also often omitted in many micro-Doppler studies published to-date) prior to applying a classifier. Third, adaptive feature selection is proposed to optimise classification performance under varying operational conditions.

Towards these aims, in Section 2, first a description of the micro-Doppler dataset used in this work is presented, followed by a survey and evaluation of micro-Doppler features under varying operational conditions in Section 3. A discussion of feature selection is given in Section 4. In Section 5, the performance of these methods is compared for several classification case studies and the relevance of different features is discussed. The potential performance gains of adaptive feature selection are demonstrated. Conclusions and future work are summarised in Section 6.

2 Micro-Doppler signature database

Micro-Doppler signatures may be obtained over a wide range of sensors, including linear frequency-modulated continuous wave, pulse Doppler, and ultra-wide band radar as well as sonar. Frequencies at which micro-Doppler signatures are typically extracted vary from as low as 2 GHz to as high as 77 GHz in automotive applications. To enable evaluation of micro-Doppler features for a variety of system parameters, target activities and antenna–target geometries, simulated micro-Doppler signatures generated from motion capture data acquired by the Kinect sensor were utilised in this study. The use of video motion capture data to simulate human micro-Doppler was first proposed in 2006 [19], further developed in 2008 [20], and has since been used in many studies on micro-Doppler classification [21–23]. Motion-capture-based simulations possess several advantages over kinematic-model-based simulations, such as those generable from the Boulic walking model [24, 25]. Advantages include the ability to simulate a wide variety of activities beyond just walking and to capture the nuances of individual gait characteristics in the resulting micro-Doppler database. For example, the Boulic model primarily depends on two parameters, the average speed and height of thigh. Thus, signatures for people of different height and speed may be generated for walking. Motion capture, on the other hand, involves actually recording the activity of a specific individual; thus, the signatures generated for different people of the same stature and speed are also different. This enables the generation of a signature database that is statistically more variable and better representative of the range of signatures a radar operating in the field would measure.

In this work, the Kinect sensor is used as a source of motion capture data. To simulate the radar return from a human, the body is first divided into K parts, each represented as a point target. The radar return from each point target is then summed to find the overall return from a human

$$s_h(n, t) = \sum_{i=1}^{K} a_{t,i} \mathrm{rect}\left(\frac{\hat{t} - t_{d,i}}{\tau}\right) \exp\left\{ \mathrm{j}[-2\pi f_c t_{d,i} + \pi\gamma(\hat{t} - t_{d,i})^2] \right\} \tag{1}$$

Here, n is the pulse number; $\hat{t}$ is the time relative to the start of each pulse repetition interval (PRI); $t = \mathrm{PRI}(n-1) + \hat{t}$; τ is the pulse width; c is the speed of light; γ is the chirp slope; and f_c is the transmitter frequency. The amplitude $a_{t,i}$ is computed from the range equation, which among other factors, depends on radar cross-section (RCS). In this work, the RCS of the head and limbs are computed from the scattering of a sphere and ellipsoid, respectively.

The round-trip time delay between the radar and each point target, $t_{d,i}$, is related to range as $t_{d,i} = 2R_i/c$. The Kinect sensor, equipped with both video and an infrared sensor capable of depth measurements, is used to track a skeleton superimposed upon the image of the test subject. The Kinect measurements provide a time-varying estimate of the range, R_i, which is used to complete the computation of (1). Next, the received signal is pulse compressed across fast time, and the peak value for each pulse recorded to form the slow-time signal $x[n]$.

The squared amplitude of the short-time Fourier transform (STFT) is utilised to represent the time–frequency signature. The discrete-time STFT of a signal $x(n)$ is defined as

$$\mathrm{STFT}(n, \omega) = \sum_{m=-\infty}^{\infty} x(n+m) w(m)\, \mathrm{e}^{-\mathrm{j}\omega m} \tag{2}$$

The function $w(m)$ is a window function, whose length affects the time and frequency resolution of the resulting representation. In this work, spectrograms were generated using 1024 frequency samples, a Hanning window of length 256 and an overlap of 16 samples. Example spectrograms for each activity collected for a subject directly walking towards a 15 GHz radar with a pulse repetition frequency (PRF) of 2.4 kHz are shown in Fig. 1. Detailed information about the Kinect-based micro-Doppler simulator and its validation may be found in [26].

3 Micro-Doppler feature robustness

The first key stage in micro-Doppler signal classification is feature extraction. Ideally, it is desired that the value of the feature as estimated from the micro-Doppler data is dependent only upon the target characteristics to be classified, e.g. underlying human motion. However, in practice, the signature itself is affected by a number of external factors, some of which are under operator control, such as the transmitted signal parameters of the radar system employed, while some are entirely dependent on operational conditions, such as the environment in which the radar is situated, direction from which the target approaches, and duration of data collection.

Features may be computed both from the raw I/Q radar data or spectrogram. Four main types of features may be defined: physical, transform-based, component analysis, and speech features. Physical features refer to those derived from measuring characteristics of the spectrogram and are related to physical traits of the target or its motion. Examples include average torso Doppler frequency; total Doppler bandwidth (BW); frequency of torso response or stride rate; envelope characteristics; stride rate; and features extracted from the Cadence Velocity Diagram (CVD), which is computed as the fast Fourier transform (FFT) of the spectrogram across time. Features extractable from the CVD include torso power, harmonic frequencies, harmonic power, and appendage-to-torso ratio, which are defined as the ratio of the power of the harmonics over the torso power.

In addition to physical features, which were the earliest features to be proposed for use in micro-Doppler classification, more recently transform-based and speech processing inspired features have been employed. Commonly used transform-based features include FFT and DCT coefficients and are generally computed from the spectrogram, as are cepstrum and bi-cepstrum coefficients, while speech-based features such as mel-frequency cepstrum coefficients (MFCC) and linear predictive coding (LPC) coefficients are computed from the raw I/Q data. The DCT for a discrete signal x_n

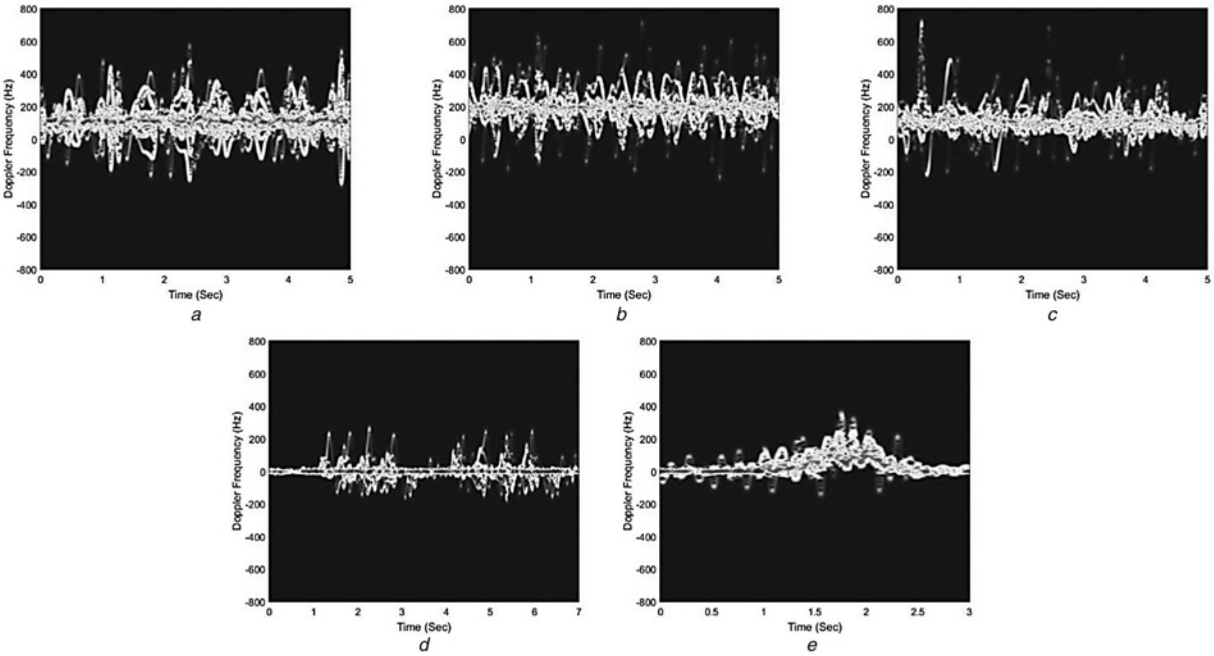

Fig. 1 *Spectrograms for several different human activities, as simulated from Kinect-based motion capture data for a 15 GHz radar with a PRF of 2.4 kHz*
a Walking
b Running
c Random
d Boxing
e Jumping

of length N is defined as

$$X_k = \sum_{n=0}^{N-1} x_n \cos\left[\frac{\pi}{N}(n+1)k\right], \quad \text{for } k = 0, \ldots, N-1 \tag{3}$$

The cepstrum, $c(n)$, is defined as the inverse DFT of the log magnitude of the DFT of an input $x(n)$ signal

$$c(n) = \Im^{-1}\{\log|\Im\{x(n)\}|\} \tag{4}$$

where $\Im\{\cdot\}$ is the Fourier transform. Any desired number of the DCT coefficients X_k or cepstrum coefficients $c(n)$ may be used as features. Cepstrum coefficients are also closely related to MFCC, which are computed by taking first filtering the signal according to a mel-frequency filter bank that emulates human perception of sound. LPC coefficients, on the other hand, are based on the more general principle of representing the current signal as a linear combination of past values

$$\hat{x}(n) = \sum_{k=1}^{p} d(k)x(n-k), \tag{5}$$

where $a(k)$ are the LPCs and p is the total number of LPCs. LPCs are computed by minimising the difference in error using any of a number of techniques, such as a Levinson–Durbin recursion.

To minimise the total number of features, component analysis techniques, such as PCA, ICA, and singular value decomposition have also been applied to micro-Doppler signatures. In PCA, for instance, the minimum number of orthogonal vectors that can represent the entire dataset is sought. Once the orthogonal decomposition is computed, the resulting eigenvalues may be exploited as features.

Although all these features, either alone or in combinations, have been utilised for micro-Doppler classification, each feature is affected differently by the radar's parameters and test scenario. These influences are now considered in turn using, as an example, classification between running, walking, jumping, and boxing.

3.1 Impact of radar system parameters

Pulse-Doppler radar systems typically transmit a linear frequency modulation or chirp signal, which is a function of the transmit frequency, BW, pulse duration, and PRF. These parameters in turn influence the measurement capabilities of the radar; for example, range resolution depends upon BW, while Doppler resolution depends upon PRF, and the Doppler shift induced is affected by transmit frequency. The impact of transmit frequency and PRF is investigated by computing the classification performance attained using just one feature at a time on a kNN classifier with five neighbours.

A database of simulated signatures is generated using the Kinect-based micro-Doppler signature simulator for nine different transmit frequencies, eight different people, and four different activities at an aspect angle of 0° and PRF of 2.4 kHz, yielding a total for 288 signatures. The duration of the signatures was 24 s for walking and running signatures, 1.5 s for jumping signatures, and 3.5 s for boxing signatures. Sixty per cent of this database is randomly selected as the training set, while the remaining 40% of the signatures are used as test data. For PRF, similar train/test databases are generated with all parameters remaining the same, except that the transmit frequency was kept constant at 15 GHz, while eight different PRFs were utilised, yielding a database of 256 signatures.

The features examined in this study include: (i) physical features: mean torso Doppler frequency, mean of upper and lower envelopes, BW of torso response, total BW, and difference of envelope means (outer BW); (ii) the first three cepstrum coefficients; (iii) the first ten DCT coefficients; and (iv) 100 LPC coefficients. Figs. 2*a* and *b* show the performance for each type of feature, computed by jointly using all features of a given type, as well as the classification performance attained by each feature individually, shown separately for physical features in Figs. 2*c* and 2*d*.

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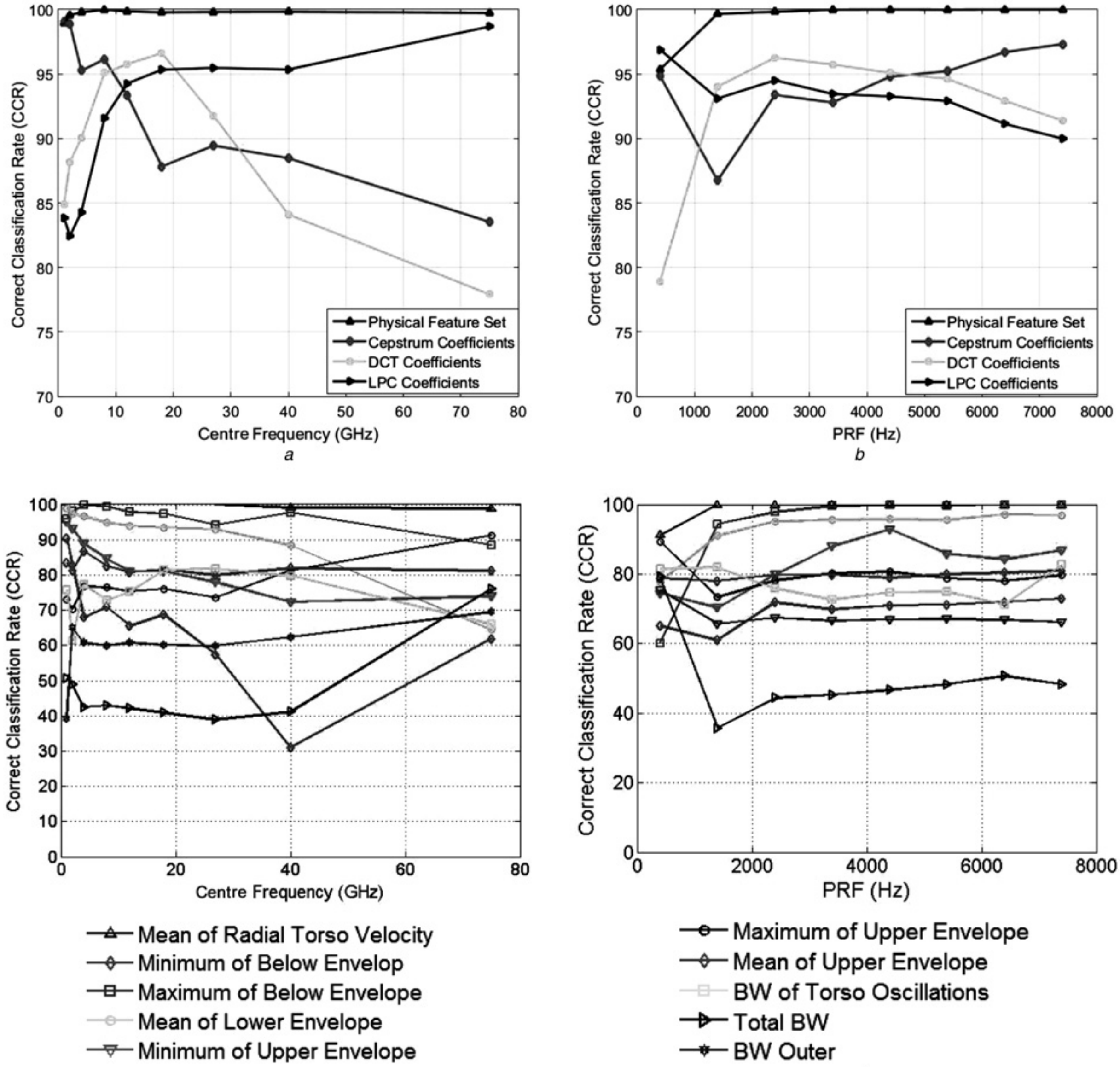

Fig. 2 *Influence on radar system parameters on the classification performance of walking, running, boxing and jumping as yielded by different sets of features: (a) and (b), joint use of all features of a specified feature type; (c) and (d), use of each physical feature individually*

a Impact of transmit frequency – feature types
b Impact of PRF
c Impact of transmit frequency – individual physical features
d Impact of PRF – individual physical features

While above 10 GHz physical features and LPC coefficients provide a more or less unchanging level of performance, cepstrum and DCT coefficients appear to be greatly affected by transmit frequency. In fact, DCT coefficients peak between 10 and 20 GHz, suggesting that use of these features would be preferable for such X and Ku band radars. PRF appears to have much less an effect on features, with just DCT coefficients suffering from a performance degradation at PRF's below 1.5 kHz.

3.2 Impact of signal-to-noise ratio (SNR)

One of the most significant environmental factors, which unlike the radar system parameters is not under operator control, is the SNR. It is expected that performance degrades as the clutter levels increases; however, from a feature selection point of view, choosing features that are robust in noisy environments is a practical requirement to ensure performance in varying scenarios. To assess the impact of SNR, a database of 288 simulated signatures is generated for nine different SNRs. Independent, identically distributed, complex Gaussian noise was generated at each tested SNR and added to the noiseless simulated received signal and the spectrogram computed. This procedure was repeated 100 times at each SNR for each feature set, and the results averaged to find the reported classification result.

Fig. 3 shows the variation of classification performance as a function of SNR, when just a single feature is used. Average classification results are reported according to type of feature. While all features exhibit the expected drop in performance as noise levels increase, the overall performance drop experienced by physical features and cepstrum coefficients is much greater than that experienced by DCT and LPC coefficients. Thus, in high clutter environments, DCT and LPC coefficients would be preferable over other possible features.

3.3 Impact of antenna–target aspect angle

Radar inherently measures not just range but the radial velocity of targets; thus, the aspect angle between the radar line-of-sight and

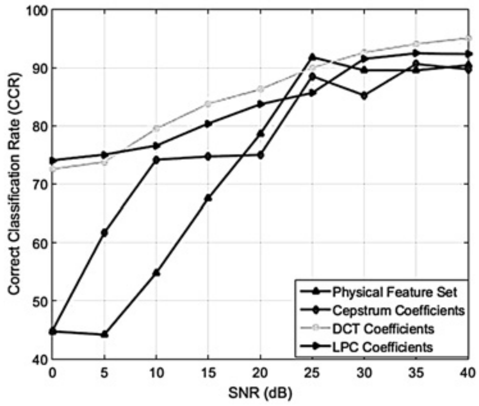

Fig. 3 *Robustness of average classification between running, walking, boxing, and jumping for different types of features under noise*

Database generated using Kinect-based micro-Doppler simulator for nine different SNRs, eight different people and four different activities at an aspect angle of 0°, a transmit frequency of 15 GHz and PRF of 2.4 kHz

the direction of target motion is a critical factor affecting the micro-Doppler signature. The most easily distinguishable signatures are obtained when the target is directly moving towards or away from the radar (0° aspect angle), resulting in maximum Doppler spread. As the aspect angle increases, the radial velocity component seen by the radar decreases, causing the total Doppler spread of the micro-Doppler signature to likewise decrease. The resulting signature appears increasingly 'squished' in frequency and the accuracy with which features are extracted likewise decrease. For example, although total Doppler BW may be a good feature in distinguishing between running and walking in general, when the target moves tangentially to the radar line-of-sight, the total Doppler spread is so small that hardly any difference can be noticed between running and walking signatures.

To assess the impact of aspect angle, a database of 416 simulated signatures is generated for 13 different aspect angles. Classification performance according to feature type is given as a function of aspect angle in Fig. 4. All features experience increasingly degraded performance as the aspect angle increases towards 90°. However, DCT coefficients experience the least drop, while cepstrum and LPC coefficients appear to be the most affected by angle.

3.4 Impact of dwell time

Because most micro-Doppler signatures are the result of periodic vibrations or rotations, the duration over which a target is observed has a significant impact on micro-Doppler features. Good classification performance often depends on being able to accurately extract information about these periodicities. For example, in the case of human motion, the frequency of torso, arm, and leg oscillations is important to discriminate between walking, running, and a more generalised activity such as random motion.

To assess the impact of dwell time, a database of 320 simulated signatures is generated for ten different durations. Fig. 5 shows classification results as a function of dwell time, computed from using all features jointly for each feature type. Here, DCT coefficients yield consistent results even for quite short dwell times. Physical features are the most affected by dwell, however, as the dwell increases they are the most capable in differentiating the suttle differences between random motion and walking, as well as random motion and running; hence, the overall better performance achieved for longer dwells.

In summary, the efficacy of any given feature depends on not just system parameters in operator control, such as transmit frequency and PRF, but also on factors outside of operator control, such as SNR, aspect angle and dwell time. However, the efficacy of a feature also depends on the classification problem at hand. In the next section, feature selection approaches to selecting a subset that maximises classification performance are discussed.

4 Feature selection

There are two main approaches to selecting an optimal subset of features for classification: filter methods and wrapper methods [27]. Filter methods assess the relevance of features by using a metric of class separability, such as correlation, Euclidean or Battacharya distance, mutual information, and the *t*-test. Features that score high are selected, while those with a low score are discarded. An important advantage of filter methods is that they are independent of the classifier subsequently used. The feature selection and classification stages are decoupled so that any classifier desired may be applied to the subset chosen by the filter method. A down side to this decoupling, however, is that that any interaction with the classifier is ignored.

Wrapper methods, on the other hand, utilise a brute force search in the feature space to find which combination yields the greatest

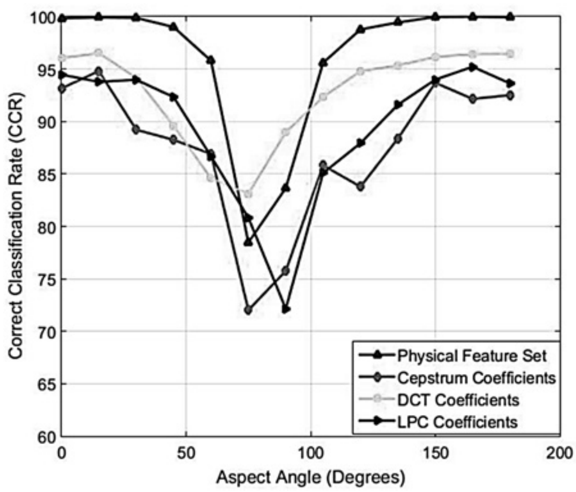

Fig. 4 *Dependency of average classification performance between walking, running, boxing and jumping on aspect angle for various types of features*

Database generated using Kinect-based micro-Doppler simulator for 13 different aspect angles, eight different people and four different activities at an aspect angle of 0°, a transmit frequency of 15 GHz and PRF of 2.4 kHz

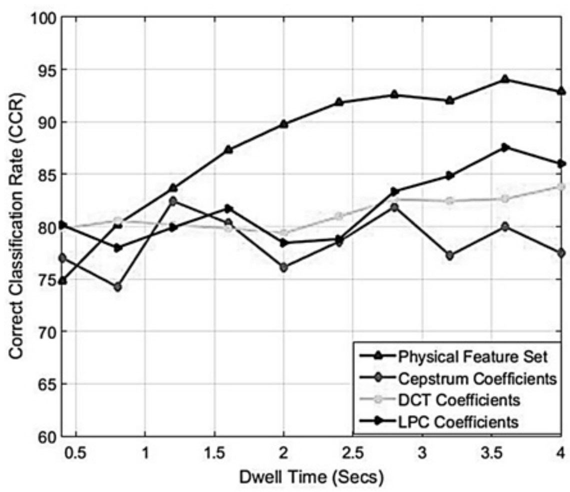

Fig. 5 *Dependency of classification performance between walking, running, boxing, and jumping on dwell time for various types of features*

Database generated using Kinect-based micro-Doppler simulator for ten different dwell times, eight different people and four different activities at an aspect angle of 0°, a transmit frequency of 15 GHz and PRF of 2.4 kHz classification performance. Rather than use a metric, the performance is directly computing using a specific classifier, so that if a different classifier was utilised, the selected feature subset would need to be re-computed. As the search space increases exponentially with the number of features to be evaluated, wrappers tend to be much more computationally intensive than filter methods. Thus, heuristic search methods are typically used. Two common search strategies are sequential forward selection (SFS) and sequential backward elimination (SBE). SFS selects features yielding the highest value of a pre-defined objective function, such as the correct classification rate for a given classifier:

(i) Start with an empty set $\boldsymbol{F}(\boldsymbol{\emptyset})$.
(ii) Select the next feature, x, as the one that yields the greatest classification performance when used together with previously selected features.
(iii) Update the selected feature set as $\boldsymbol{F}_{\boldsymbol{k+1}} = \boldsymbol{F}_{\boldsymbol{k}} + x$, and increment k.
(iv) Repeat Step 2 until the total number of desired features is selected.

The SBE algorithm functions in a similar fashion, except that this time all features are included in the initial feature list, and features are removed one-by-one at each iteration based on classification performance.

In this work, the t-test [28], as a representative filter method, and SFS [29], as a representative wrapper method, are used to select an optimal feature subset from all micro-Doppler features previously utilised: ten physical features, ten DCT coefficients, three cepstrum coefficients, and 100 LPC coefficients. The t-test is a statistical method used to assess the difference in the mean between two classes. The t-statistic value for the ith feature in the cth class can be defined as

$$t_{ic} = \frac{\bar{x}_{ic} - \bar{x}_i}{M_c(S_i - S_0)} \tag{6}$$

where $\bar{x}_{ic}$ is the mean of the ith feature in the cth class and $\bar{x}_i$ is the mean of the ith feature for all classes. S_i is the within class standard deviation of the ith feature, while S_0 is the median S_i value for all features. This standard deviation may be computed as

$$S_i^2 = \frac{1}{N - C}\sum_{c=1}^{C}\sum_{j\in c}\left(x_{ij} - \bar{x}_{ic}\right)^2 \tag{7}$$

where N is the number of all samples in the C classes and x_{ij} is the ith feature of the jth sample. The constant M_c is defined in terms of the number of samples, n_c, in a class c as follows

$$M_c = \sqrt{\frac{1}{n_c} + \frac{1}{N}} \tag{8}$$

The performance of the t-test is compared against the performance of the SFS in Fig. 6, which shows the correct classification rate achieved for four classes – walking, running, boxing, and jumping – using a kNN = 5 classifier when a varying number of features is selected using both methods. This result clearly shows the benefit of feature selection – both algorithms yield their best performance when a small, carefully selected subset of features is used. For example, the t-test filter actually yields peak performance when 40 features are utilised, with just 10 features giving near-peak performance. The SFS wrapper method yields peak performance with just eight features. Moreover, regardless of the feature set size, it may be observed that the SFS wrapper outperforms the t-test filter method, with a difference of roughly 5% in classification performance for ten features.

The impact of feature selection on classification performance, especially under sub-optimal operational conditions can be observed from the results shown in Tables 1 and 2. Consider a situation where a 15 GHz radar with 2.4 kHz PRF is illuminating a

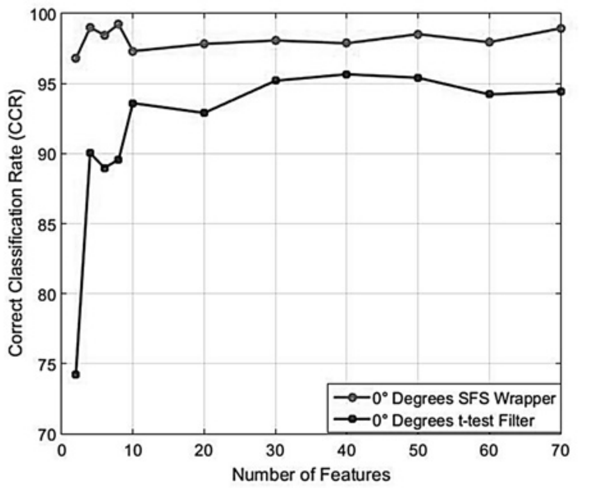

Fig. 6 *Influence of selected feature subset size on t-test and SFS wrapper method*

Table 1 Confusion matrix for when all 123 features are used

Class				
Activity	Walking	Running	Random motion	Jumping
walking	0.78	–	0.22	–
running	0.20	0.76	0.40	–
random motion	0.35	–	0.65	–
jumping	0.80	–	–	0.92

Table 2 Confusion matrix for when 10 features are selected

Class				
Activity	Walking	Running	Random motion	Jumping
walking	0.83	–	0.17	–
running	–	1.00	–	–
random motion	0.26	–	0.74	–
jumping	–	–	0.10	0.90

target with an SNR of 20 dB and an aspect angle of 60° for just 1.5 s. When all features are used, an overall classification performance of 77.8% is achieved; however, this rate improves to 86.6% with just ten selected features – approximately a 9% improvement.

5 Adaptive feature selection

As shown in Section 3, classification performance is highly dependent not just on system parameters in control of the operator, but also on scene dependent conditions, such as the duration over which a target is illumination and the aspect angle of motion relative to the radar line-of-sight. Through feature selection, the classification performance of the radar processor may be maximised for a given situation. However, in some situations the target trajectory may be dynamic enough that pre-selection of a set of features based on training data according to a certain line-of-sight in fact only optimises performance for a very small section of the collected data. As an example, consider the problem of identifying a person walking indoors, where many paths are curvilinear. More specifically, suppose an X-band (15 GHz) radar with a PRF of 2.4 kHz equipped with an antenna of 60° beamwidth observes a person walking along a circle, as shown in Fig. 7*a*. Although the beamwidth is 60°, we assume that the target

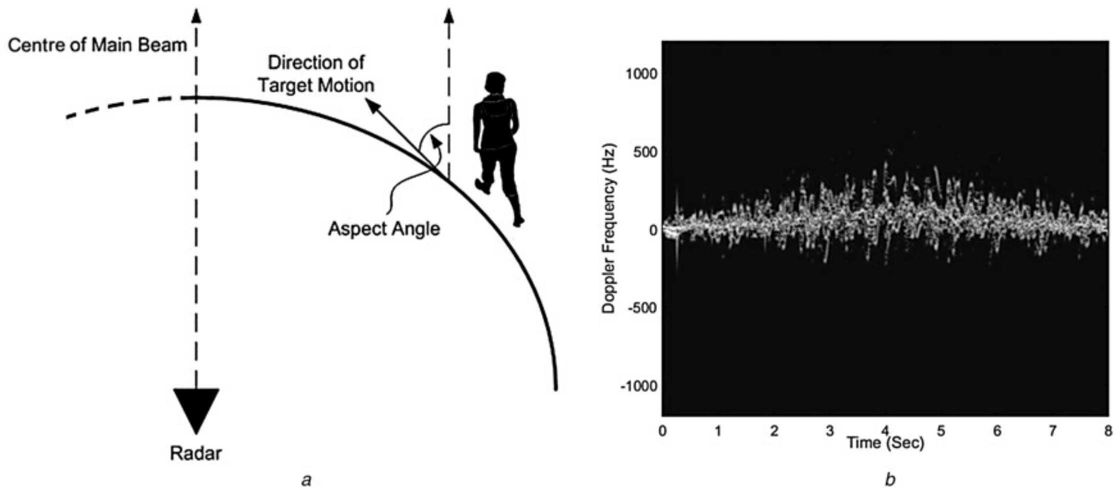

Fig. 7 *Person walking along a circle*

a Radar–target geometry
b Resulting spectrogram for a quarter-circle

returns from the sidelobes can enable the radar to receive reflections from the target even when at nearly 90°. The resulting spectrogram extracted from the radar data is shown in Fig. 7*b*. Suppose now that a subject of 10 features is selected from all possible 123 features to classify the data using a kNN-5 classifier. Fig. 8 shows the performance for the *t*-test filter, SFS wrapper, and PCA algorithms as a function of dwell time. For short dwell times, the angular change incurred during the data collect is smaller, so that greater classification performance is attained. However, as the dwell time increases and more of the circle is traversed, the angular change is so much that despite the training set containing data collected at multiple angles, the classifier cannot correctly account for this change, and the misclassification rate increases dramatically. Indeed, over the entire 3 s dwell, the performance of all methods drops to about 5%. Thus, for highly changeable, dynamic target trajectories, conventional processing, even with feature selection, does not yield desired results.

Alternatively, this work proposes implementation of adaptive feature selection for such situations. Rather than process the entire data collect as a single signature, the data is processed as multiple, shorter duration segments. As was shown in Section 3, generally shortening the dwell time reduces performance. To increase the temporal sampling, segments are extracted such that they have a certain amount of overlap relative to each other. This overlapping segmentation procedure is illustrated in Fig. 9 for the quarter-circle trajectory processing with segment duration of 1 s and overlap of 0.5 s, yielding a total of 15 segments that are classified independently.

First, the segment duration is selected by plotting the variation in classification performance over dwell time for a linear trajectory, shown in Fig. 10*a*. The duration yielding maximum performance using ten features is selected; in this case, 0.7 s. Next, given this choice, the variation of classification performance for different overlap durations is computed for the circular trajectory, shown in Fig. 10*b*. Again, the overlap yielding maximum performance is selected. Once the data is segmented, each segment is classified independently using a feature set that is optimal for the aspect angle of that particular segment, thereby compensating for variations in the path traversed. Classification results are tallied to compute the result for the overall trajectory. This method is summarised by the flow chart given in Fig. 11.

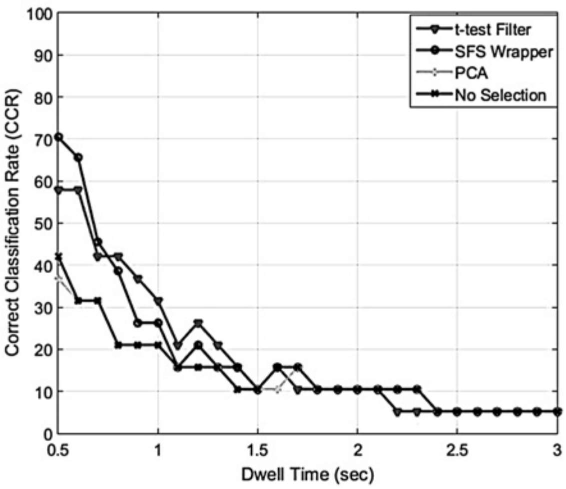

Fig. 8 *Performance of feature selection and dimension reduction algorithms for varying dwell times of data collected for a person walking along a quarter-circle trajectory*

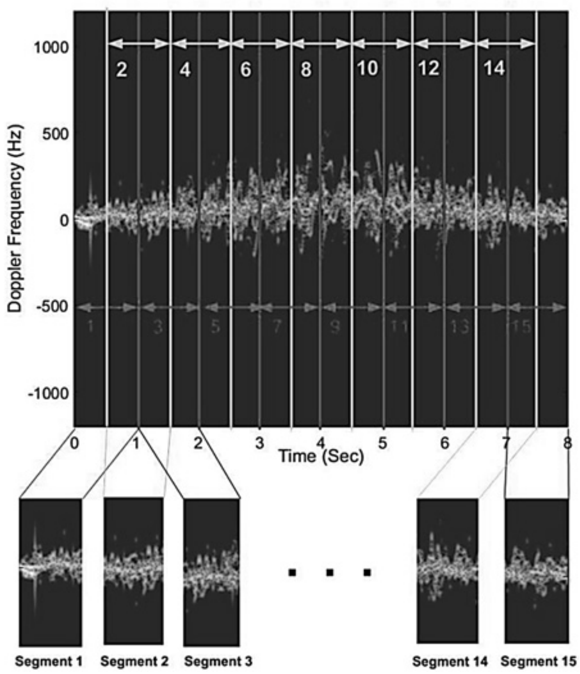

Fig. 9 *Illustration of overlapping segmentation procedure*

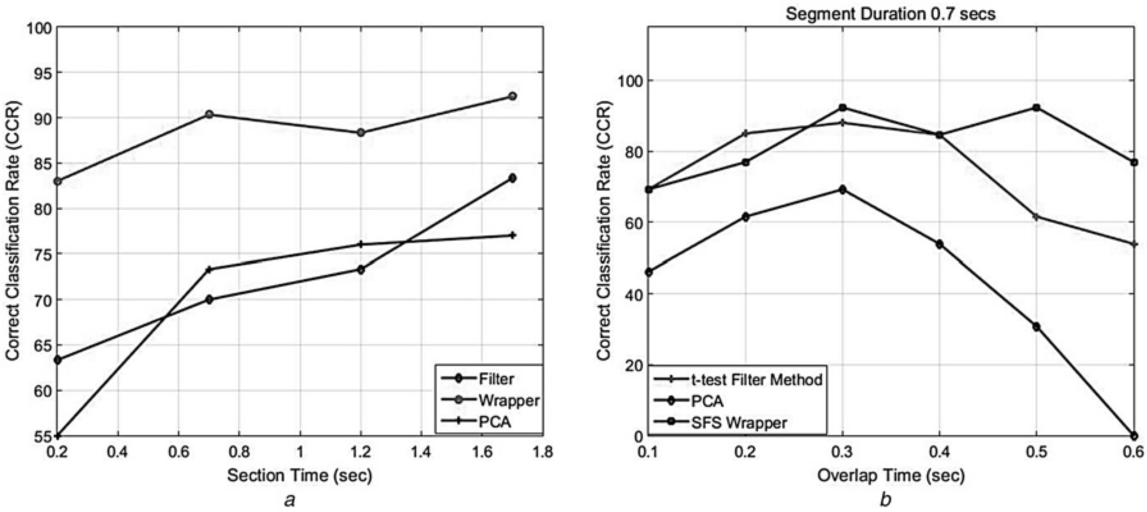

Fig. 10 *Choice of*

a Segment duration
b Overlap duration in adaptive feature selection method

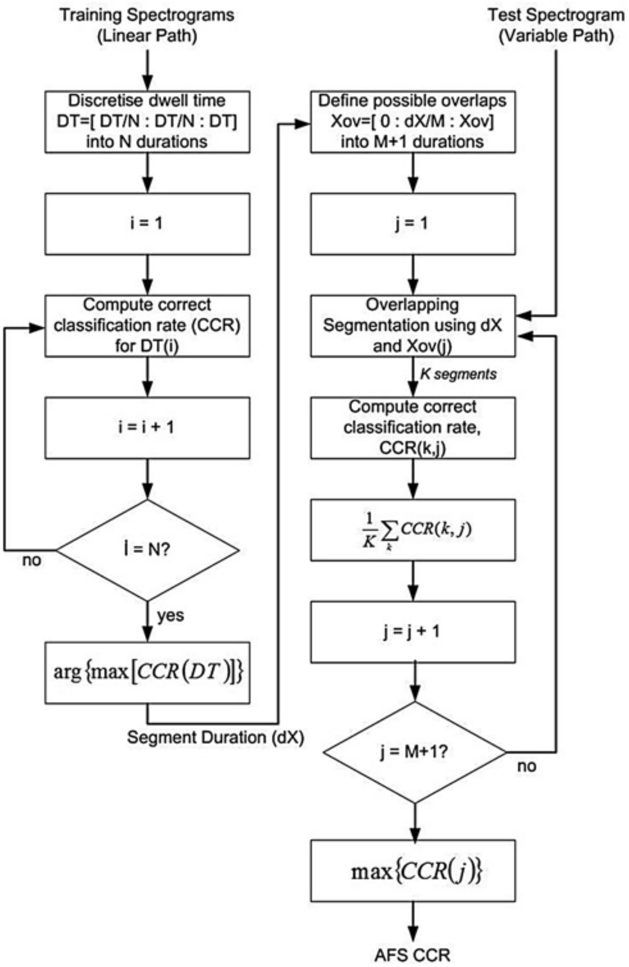

Fig. 11 *Flow chart for adaptive feature selection algorithm*

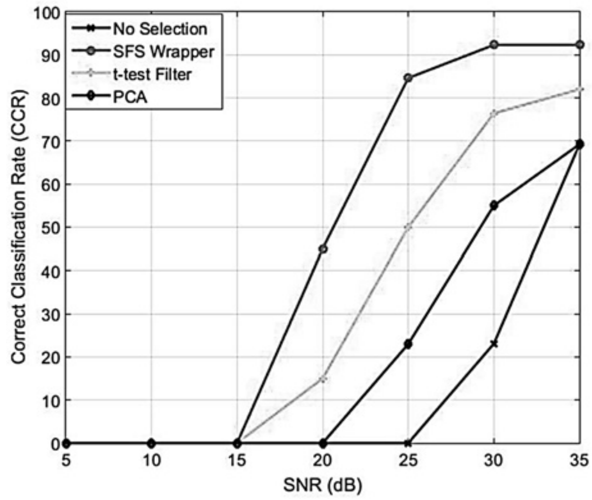

Fig. 12 *Classification results obtained using adaptive feature selection with a segment duration of 0.7 s and an overlap of 0.3 s for different feature selection algorithms as a function of SNR*

The benefits of adaptive feature selection are quite pronounced in the results shown in Fig. 12, where the performance of different feature selection algorithms applied adaptively on the data with a segment duration of 0.7 s and an overlap of 0.3 s is compared. The rate at which the subject is correctly identified as walking is plotted as a function of SNR. When no feature selection is applied at all, walking along the half-circle trajectory is correctly determined at a rate 70% in a nearly uncluttered environment (SNR = 35 dB). Below 25 dB, walking is never successfully recognised. On the other hand, when the SFS wrapper approach is utilised adaptively to select ten features, this rate rises to just above 90% at 35 dB, drops slightly to about 85% at 25 dB, and plummets to no correct classifications below 15 dB. As expected from previous discussions and analytical comparisons of feature selection algorithms, the wrapper outperforms the *t*-test filter method, while both feature selection algorithms surpass the results yielded by dimension reduction with PCA.

6 Conclusion

In this work, the necessity and performance gains attainable using feature selection to optimise performance under a variety of system parameters, such as transmit frequency and PRI, as well as operational conditions, such as SNR, dwell time, and aspect angle, is shown for a variety of feature selection approaches (filter and wrapper). The performance gains attainable from feature selection are compared to those obtained from dimension reduction. The robustness of micro-Doppler features is assessed, and adaptive feature selection is proposed to improve classification performance for highly variable target trajectories, while also minimising the total number of features utilised. The results show that use of adaptive feature selection can improve classification performance by 30% at 35 dB and 85% at 25 dB in comparison with the results achieved when no feature selection stage is included in the processing.

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