Automatic Classification of Human Motions using Doppler Radar

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Abstract—This paper presents a new approach to classify human motions using a Doppler radar for applications in security and surveillance. Traditionally, the Doppler radar is an effective tool for detecting the position and velocity of a moving target, even in adverse weather conditions and from a long range. In this paper, we are interested in using the Doppler radar to recognize the micro-motions exhibited by people. In the proposed approach, a frequency modulated continuous wave radar is applied to scan the target, and the short-time Fourier transform is used to convert the radar signal into spectrogram. Then, the new two-directional, two-dimensional principal component analysis and linear discriminant analysis are performed to obtain the feature vectors. This approach is more computationally efficient than the traditional principal component analysis. Finally, support vector machines are applied to classify feature vectors into different human motions. Evaluated on a radar data set with three types of motions, the proposed approach has a classification rate of 91.9%.

I. INTRODUCTION

Human movement classification using radars has become an emerging research field with numerous civilian and military applications, such as surveillance, search and rescue, and health care [1]–[3]. Singh *et al.* [2] developed a radar system to detect people behind a wall. Palmer *et al.* [3] used radar and gait analysis to detect people having concussion symptoms. In contrast to optical-based systems such as digital cameras, radars can operate in adverse weather conditions from a long range and they are less affected by clothing choices.

When the transmitted signal from a Doppler radar is reflected by a moving target, its carrier frequency is shifted depending on the target's relative velocity. In addition, micro motions of the target, such as vibrations, rotations or swings, induce frequency modulations on the returned signal, which are known as micro-Doppler effects. An articulated target such as a human has body parts moving at different velocities. These body parts cause different frequency shifts and generate unique micro-Doppler signatures.

Most existing studies on human micro-Doppler focus on the analysis of individual components of the body based on simulated data that obtained by using electromagnetic wave scattering model or computer animation software like Maya [4]–[6]. Some researches have

been done in classifying of human motions via micro-Doppler signatures. Youngwook and Hao [7] [8] developed a classification approach to distinguish seven different human activities: running, walking, walking without moving arms, crawling, boxing, boxing while moving forward, and sitting relatively still. In their approach, the short-time Fourier transform (STFT) is used to examine the time-varying micro-Doppler signatures. Short windows of radar signals are converted into spectrograms. Noise in the spectrograms is removed by applying a threshold, computed from the background signal when no target is present. Then, six features are extracted to characterize the micro-Doppler signatures. Support vector machine (SVM) and feed-forward neural network are employed to classify the seven human motions.

Instead of choosing a fixed set of features from the spectrogram, Tivive *et al.* [9] developed a neural network that extracts micro-Doppler features through learning. Their neural network has three stages. The first stage has directional nonlinear filters to extract motion energy and directional contrast from the spectrogram. The second stage comprises adaptive nonlinear filters to learn intrinsic motion features, and the third stage is for classification. They use neural network and support vector machine to classify three types of human arm motions while walking: free-arm motion (two-arm swing), partial-arm motion (one-arm swing), and no-arm motion.

Orovic *et al.* [10], [11] proposed an approach to classify human gaits, based on time-frequency representation. Time-frequency analysis is performed on the radar signals by using the multi-window S-method (also called Hermite S-method). Support functions are defined to remove the main motion (such as torso and leg motion) and other relative strong components, and reveal the weak arm movements. Features are then extracted based on the envelopes of the arms in the time-frequency plane. The upper and lower envelopes are described respectively by the positive and negative frequency points, with respect to the torso motion component. The distance between the two envelopes is used to determine if the person is walking with or without arm swing. The distance between the envelopes is larger for walking with arm-swing than without arm-swing. The shape of the envelopes is used to differentiate a person walking with one-arm or two-arm swing. The performance of this method depends

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how accurately the envelope is extracted.

Another classification approach for micro-Doppler signature was proposed by Smith *et al.* [12]. They compute the power spectrum of short-window of radar signals and employ principle component analysis to extract Doppler features. Then, a naive Bayesian classifier is applied to differentiate three moving targets: wheeled vehicles, tracked vehicles and people.

In this paper, we propose a method based on two-directional, two-dimensional discriminant analysis for micro-Doppler signatures classification. The proposed method firstly transforms the radar signals to spectrograms via the short-time Fourier transform. Then local windows centered on the torso motion component are extracted. Two-directional two-dimensional Principal Component Analysis (2D2-PCA) and two-directional two-dimensional Linear Discriminant Analysis (2D2-LDA) are applied to extract micro-Doppler features for classification.

The remainder of this paper is organized as follows. Section II presents the proposed subspace analysis method for classifying micro-Doppler signatures. Section III presents the experimental results and analysis of the method. Section IV gives the concluding remarks.

II. PROPOSED APPROACH

The proposed approach consists of three stages: time-frequency analysis, feature extraction, and classification, as shown in Fig. 1. First, the short-time Fourier transform is employed to convert the radar signal to a joint time-frequency representation that describes the frequency content of the signal at different time instances. Next, the two-directional, two-dimensional forms of principal component analysis and linear discriminant analysis are applied for feature extraction. Finally, support vector machines are used to classify the micro-Doppler signatures of human movements.

Fig. 1. Overview of the proposed approach.

A. Time-Frequency Analysis

Fourier transform is widely used to analyze the frequency contents of a signal, but it lacks localized time information [13]. Therefore, to analyze radar signals with time-varying frequency contents, a joint time-frequency representation is needed. In this paper, the spectrogram is applied to create a time-varying spectral representation for radar signals.

For a discrete signal $x[n]$, the short-time Fourier transform is defined as

$$X[n, k] = \sum_{r=-\infty}^{\infty} x[r] w[r-n] e^{-j2\pi rk/N}, \quad k = 0, 1, \dots, N-1, \quad (1)$$

where n is the discrete-time index, k is the discrete frequency index, N is the number of frequency points, and $w[n]$ is a window function. The idea of STFT is to multiply the Fourier transform of a signal with a window function that slides in time. The window size is chosen to make the signal of interest stable over the duration. The spectrogram of $x[n]$ is computed by taking the squared magnitude of the STFT:

$$S(n, k) = |X[n, k]|^2. \quad (2)$$

Figure 2 presents the spectrograms for three types of human motions: normal walking, walking while carrying an object in one hand, and walking while holding an object with two hands. The spine of each spectrogram represents the torso motion of the person. In this case, the spectrogram has only positive Doppler as the person is moving towards the radar. The periodic peaks denote the arms, legs, and feet motions of the person. These spectrograms show that different human motions exhibit different micro-Doppler signatures, which can be used for classification.

B. Feature Extraction

In our approach, the spectrogram is cast as an image and features are extracted from this image as the micro-Doppler signatures. Instead of processing the entire spectrogram, we propose to extract features from sliding local windows centered at the torso frequency points. These torso frequency points form the ‘spine’ of the spectrogram. Note that most micro-motions reside in the local windows near the spectrogram spine. For feature extraction, we locate the spectrogram spine by computing the maximum power spectrum at each time instance and then applying a smoothing median filter (see Fig. 3). Using selected local windows reduces the amount of data and produces features that are invariant to the target’s speed.

We propose to use two-directional, two-dimensional form of principal component analysis (2D2-PCA) and linear discriminant analysis (2D2-LDA) to extract features from the extracted local windows. This form of discriminant analysis has been shown to be more computationally efficient than the classical PCA and LDA [14], [15]. Moreover, 2D2-PCA and 2D2-LDA preserve the spatial topology of the 2-D input. Compared to the classical PCA and LDA, 2D2-PCA and 2D2-LDA use covariance matrices that are much smaller in size and can be computed more efficiently and accurately, even on a small training set. Next, we describe these two feature extraction techniques.

Fig. 2. Example spectrograms of three different types of human motions: (a) normal walking; (b) walking while carrying an object in one hand; (c) walking while holding an object with two hands. See the electronic color figure.

Fig. 3. Example of identifying the spine of the spectrogram.

1) *Two-Directional, Two-Dimensional PCA*: Consider a set of P training samples where each sample is an image of size $M \times N$ pixels: $\mathbf{A}_i \in \mathbb{R}^{M \times N}$, $i = 1, 2, \dots, P$. In our case, every local window is a training sample. The mean of all the samples is

$$\bar{\mathbf{A}} = \frac{1}{P} \sum_{i=1}^P \mathbf{A}_i. \quad (3)$$

For the horizontal direction, let $\Phi \in \mathbb{R}^{N \times D}$ be a projection matrix with unitary columns. An image $\mathbf{A}$ is projected onto Φ to yield a $M \times D$ matrix: $\mathbf{Y} = \mathbf{A}\Phi$. The projection matrix is found as follows. First, the image covariance matrix $\mathbf{H}$ in the horizontal direction for the given training set is calculated:

$$\mathbf{H} = \frac{1}{P} \sum_{i=1}^P (\mathbf{A}_i - \bar{\mathbf{A}})^T (\mathbf{A}_i - \bar{\mathbf{A}}). \quad (4)$$

Second, the optimal projection matrix Φ is obtained by maximizing the generalized total scatter:

$$J(\Phi) = \Phi^T \mathbf{H} \Phi. \quad (5)$$

The columns of Φ are the eigenvectors of $\mathbf{H}$ with the D largest eigenvalues. The value of D is selected so that

$$\frac{\sum_{i=1}^D \lambda_i}{\sum_{i=1}^M \lambda_i} \geq \theta, \quad (6)$$

where θ is a predefined threshold, and λ_i are the M eigenvalues of $\mathbf{H}$ sorted in the descending order: $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_M$.

Similarly, for the vertical direction, let $\Omega \in \mathbb{R}^{M \times E}$ be a projection matrix with unitary columns. An image $\mathbf{A}$ is projected onto Ω to yield a $E \times N$ matrix: $\mathbf{X} = \Omega^T \mathbf{A}$. The projection matrix is found by firstly computing the image covariance matrix in the vertical direction:

$$\mathbf{V} = \frac{1}{P} \sum_{i=1}^P (\mathbf{A}_i - \bar{\mathbf{A}})(\mathbf{A}_i - \bar{\mathbf{A}})^T, \quad (7)$$

and then maximizing the following generalized total scatter:

$$J(\Omega) = \Omega^T \mathbf{V} \Omega. \quad (8)$$

The columns of the optimal projection matrix Ω are the eigenvectors of $\mathbf{V}$ that correspond to the E largest eigenvalues. The value of E is determined similarly to Eq. (6).

For a given input image $\mathbf{A}$ of size $M \times N$, a feature matrix $\mathbf{C}_{\text{PCA}}$ of size $E \times D$ can be obtained by applying projection matrices Φ and Ω simultaneously:

$$\mathbf{C}_{\text{PCA}} = \Omega^T \mathbf{A} \Phi. \quad (9)$$

2) *Two-Directional, Two-Dimensional LDA*: In contrast to 2D2-PCA, the 2D2-LDA technique includes class information during feature extraction. Let K be the number of human motion categories. Let P be the total number of training samples and P_k be the number of training samples in the k -th class. The j -th sample image in the k -th class is denoted as $\mathbf{A}_{jk} \in \mathbb{R}^{M \times N}$, where $j = 1, 2, \dots, P_k$ and $k = 1, 2, \dots, K$.

Let $\bar{\mathbf{A}}_k$ be the mean image of training samples in the k -th class. Let $\bar{\mathbf{A}}$ be the mean image of the training samples in all classes. In the horizontal direction, the

between-class scatter matrix $\mathbf{H}_b$ and within-class scatter matrix $\mathbf{H}_w$ are defined as

$$\mathbf{H}_b = \frac{1}{P} \sum_{k=1}^K P_k (\bar{\mathbf{A}}_k - \bar{\mathbf{A}})^T (\bar{\mathbf{A}}_k - \bar{\mathbf{A}}), \quad (10)$$

$$\mathbf{H}_w = \frac{1}{P} \sum_{k=1}^K \sum_{j=1}^{P_k} (\mathbf{A}_{jk} - \bar{\mathbf{A}}_k)^T (\mathbf{A}_{jk} - \bar{\mathbf{A}}_k). \quad (11)$$

The generalized Fisher criterion for the horizontal direction is defined by

$$J(\Psi) = \frac{\Psi^T \mathbf{H}_b \Psi}{\Psi^T \mathbf{H}_w \Psi}, \quad (12)$$

For the vertical direction, the image between-class scatter matrix $\mathbf{V}_b$ and image within-class scatter matrix $\mathbf{V}_w$ are given by

$$\mathbf{V}_b = \frac{1}{P} \sum_{k=1}^K P_k (\bar{\mathbf{A}}_k - \bar{\mathbf{A}})(\bar{\mathbf{A}}_k - \bar{\mathbf{A}})^T, \quad (13)$$

$$\mathbf{V}_w = \frac{1}{P} \sum_{k=1}^K \sum_{j=1}^{P_k} (\mathbf{A}_{jk} - \bar{\mathbf{A}}_k)(\mathbf{A}_{jk} - \bar{\mathbf{A}}_k)^T. \quad (14)$$

The generalized Fisher criterion for the vertical direction is defined by

$$J(\Theta) = \frac{\Theta^T \mathbf{V}_b \Theta}{\Theta^T \mathbf{V}_w \Theta} \quad (15)$$

The idea of 2D2-LDA technique is to find the projection matrices Ψ and Θ that maximize $J(\Psi)$ and $J(\Theta)$, respectively. The optimal projection matrices Ψ and Θ can be obtained by computing the eigenvectors of $\mathbf{H}_w^{-1} \mathbf{H}_b$ and $\mathbf{V}_w^{-1} \mathbf{V}_b$. For 2D2-LDA, the feature matrix is given by

$$\mathbf{C}_{\text{LDA}} = \Theta^T \mathbf{A} \Psi. \quad (16)$$

The local windows of the spectrogram are projected to the feature space using 2D2-PCA or 2D2-LDA technique. The resulting feature matrices $\mathbf{C}_{\text{PCA}}$ and $\mathbf{C}_{\text{LDA}}$ are then converted to feature vectors for classification.

C. Classification

In the classification stage, support vector machines are used to discriminate the various types of human motions. In machine learning, SVM is a widely used classifier due to its high generalization ability. For a two-class problem, the key idea of SVM is to determine the separating hyperplane with the highest margins to the two classes. A margin is the distance from the hyperplane to the nearest input vector. The input vectors on the margin planes are known as the support vectors.

Consider a set of P training feature vectors $\mathbf{x}_i \in \mathbb{R}^d$ and the corresponding labels $y_i \in [+1, -1]$, where

$i = 1, 2, \dots, P$. SVM training can be expressed as an optimization problem:

$$\text{maximizing } \left\{ \frac{1}{2} \mathbf{w}^T \mathbf{w} + C \sum_{i=1}^P \xi_i \right\} \quad (17)$$

subject to

$$y_i (\mathbf{w}^T \mathbf{x}_i + b) \geq 1 - \xi_i \quad \text{for all } i, \quad (18)$$

where $\mathbf{w}$ is the vector normal to the hyperplane, b is a bias term, ξ_i is a non-negative slack variable, and C is a penalty parameter representing the trade-off between maximizing the margin and minimizing the training error. This optimization is a dual form:

$$\text{maximizing } \Psi(\alpha) = \sum_{i=1}^P \alpha_i - \frac{1}{2} \sum_{i,j=1}^M \alpha_i \alpha_j y_i y_j \mathbf{x}_i^T \mathbf{x}_j \quad (19)$$

subject to

$$\sum_{i=1}^P \alpha_i y_i = 0, \quad \text{and } 0 \leq \alpha_i \leq C \quad \text{for all } i. \quad (20)$$

Once the optimal α_i has been computed, the decision function for SVM is

$$y_p(\mathbf{x}) = \text{sgn} \left\{ \sum_{i=1}^P y_i \alpha_i \psi(\mathbf{x}_i, \mathbf{x}) + b \right\}. \quad (21)$$

Here, $\psi(\cdot, \cdot)$ is a kernel function that maps the input feature vectors to a higher dimensional space (to improve class separation). If y_p is positive, the feature vector $\mathbf{x}$ belongs to class +1 and vice versa. In this paper, the linear kernel is used:

$$\psi(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j. \quad (22)$$

For a multi-class problem involving K classes, we apply the one-versus-one approach that requires $K(K-1)/2$ two-class SVM classifiers, each of which is trained on two classes. The final classification output is obtained by combining all two-class SVM classifiers with a majority voting scheme.

III. RESULTS AND ANALYSIS

The proposed method is applied to recognize three types of human motions: (i) two-arm motion, which corresponds to walking normally (2-AM), (ii) one-arm motion characterized by walking while carrying an object in one hand (1-AM), and (iii) no-arm motion characterized by walking while holding a heavy object with two hands (0-AM). Recognizing these human motions are useful in surveillance applications.

A. Doppler radar data

The radar data were collected at the University of Wollongong, Australia in an outdoor environment. A Frequency Modulated Continuous Wave radar operating at 24 GHz was used to scan moving subjects (people). Each subject was walking along the line of sight towards or away from the radar. The distance between the subject and the radar is between 1 m and 55 m. Radar signals were recorded for 30 seconds and digitized at a rate of 7812 samples/second. There were seven subjects; each subject repeated the three types of motions for three times (Fig. 4).

To evaluate the classification performance of different algorithms, the 3-fold cross-validation was applied. The entire radar data were partitioned into three subsets. For each fold, a subset was used for testing, whereas the other two subsets were used for training. This was repeated three times, and the classification rates were averaged.

B. Parameter Analysis

To capture the micro-Doppler signatures, a Hamming window was used in the STFT and the overlap was set to 50%. The time-frequency resolution of the spectrogram depends on the width of the Hamming window. A long Hamming window improves the frequency resolution, whereas a short Hamming window improves the time resolution.

Let S_h be the width of the Hamming window, and S_l be the width of the local window. The duration in seconds of the radar signal segment to be classified is given by $t_x = [S_l (S_h - N_o) + N_o] / F_s$, where N_o is the number of overlapping samples in the STFT and F_s is the sampling rate.

To find suitable Hamming window and local window, preliminary experiments were conducted on a training set, which was partitioned into two subsets: Subset 1 was used for preliminary training and Subset 2 was used for validation.

- The Hamming window has a width S_h varied from 256 to 768 with a step of 128. That is, the length of the STFT window was varied from 32.8 to 98.3 ms.
- The local window has a height (along the frequency axis) of 200, and a width varied from 50 to 300 with a step of 50.
- For each pair (S_h, S_l) , an SVM classifier with the linear kernel was trained on Subset 1 and classification rate on Subset 2 was recorded. This step was repeated three times and the classification rates were averaged.

Table I shows the average classification rate for each pair (S_h, S_l) . The highest classification rates were achieved for $(S_h = 384, S_l = 300)$ and $(S_h = 512, S_l = 150)$. With these two pairs, the required durations of radar signal segments are $t_x = 7.4$ s and

TABLE I
CLASSIFICATION RATES (%) OF 2D2-PCA METHOD ON A VALIDATION SET FOR DIFFERENT SIZES OF HAMMING WINDOW AND LOCAL WINDOW.

Local window S_l	Hamming window S_h				
	256	384	512	640	768
50	80.7	83.5	84.0	85.5	79.6
100	83.2	83.6	85.6	86.5	82.5
150	83.9	86.9	89.8	87.6	84.9
200	86.1	88.6	88.8	87.6	83.0
250	86.1	86.7	87.1	86.3	78.2
300	87.5	91.7	87.6	80.3	78.2

$t_x = 4.9$ s, respectively. To enable shorter radar signal segments, we selected the parameter pair $(S_h = 512, S_l = 150)$; this pair was used for system evaluation on the test set.

C. Comparison of classification methods

The proposed methods were compared with two other feature extraction methods: (i) classical 1D PCA; (ii) combination of DFT and PCA [12]. The SVM classifier with the linear kernel was used by all methods. For each method, 2000 local windows were randomly chosen from each class for training and eigenvectors were selected using threshold $\theta = 0.9$. For the proposed methods, the local rectangular window centered on the torso spine was used. For the classical PCA, the local window reshaped as a vector was used. We also implemented the method proposed in [12], where the power spectrum of short-frame of radar signals is computed and PCA is employed to extract Doppler features. In the experiments, we extracted overlapping short frames of one-second duration for classification.

The classification rates, obtained using the 3-fold cross-validation, on the test set for the four methods are shown in Table II. The proposed 2D2-PCA method has an average classification rate of 91.9%, whereas 2D2-LDA has a classification rate of 75.2%. Compared to the proposed 2D2-PCA method, the classical 1D PCA achieves similar classification performance. However, the covariance matrix for the classical PCA has about 900 million entries, whereas the covariance matrices for the 2D2-PCA and 2D2-LDA have fewer than 40,000 entries. The method combining the DFT and PCA has a classification rate of only 65.4%. This result indicates that the DFT is not suitable for analyzing the non-stationary radar signal, produced by moving targets. Furthermore, a longer frame of radar signal is needed, but this will increase the size of the covariance matrix.

The confusion matrix for the 2D2-PCA approach is shown in Table III. The main diagonal entries are the correct classification rates for each human motion. The off-diagonal entries indicate the misclassification rates. Results for 0-AM, 1-AM and 2-AM show that 99.98% discrimination between the 0-AM and other classes can be achieved with the proposed approach. Error occurs

(a)

(b)

(c)

Fig. 4. Photos taken during radar signal acquisition: (a) normal walking (2-AM); (b) walking while carrying an object in one hand (1-AM); (c) walking while holding an object with two hands (0-AM).

TABLE II
CLASSIFICATION RATES ON THE TEST SET OF DIFFERENT METHODS.

Method	Average classification rate (%)
2D2-PCA	91.9 ± 3.8
2D2-LDA	75.2 ± 2.1
Classical 1D PCA	92.1 ± 2.0
DFT + PCA [12]	65.4 ± 3.8

mainly for the 1-AM and 2-AM classes. However, the overall result indicates that the proposed method is effective in classifying human motions based on micro-Doppler signatures.

TABLE III
CONFUSION MATRIX FOR THE 2D2-PCA APPROACH. THE ENTRY AT (ROW r , COLUMN c) IS THE PERCENTAGE OF HUMAN MOTION r THAT IS CLASSIFIED AS HUMAN MOTION c .

	0-AM	1-AM	2-AM
0-AM	99.98	0.02	0.00
1-AM	3.05	86.52	10.43
2-AM	1.39	9.41	89.20

IV. CONCLUSION

This paper investigated the automatic classification of human motions using Doppler radar. Doppler radar can operate in adverse weather conditions from a long range and it is less affected by clothing choices. We proposed two methods based on the new two-directional, two-dimensional forms of principal component analysis and linear discriminant analysis to extract micro-Doppler signatures from the spectrogram. Instead of processing the entire spectrogram, local rectangular windows centered on the torso frequency are processed for feature extraction; this scheme is less affected by the speed of the moving target. Evaluated on a dataset involving three types of human motions, the proposed 2D2-PCA method achieved a classification rate of 91.9% when classifying short-frame signal of 4.9 s. In future work, alignment method will be investigated to improve the performance of PCA feature extraction.

REFERENCES

- [1] A. Boissier and C. D. Loisy, "Urban surveillance use of continuous wave radar for monitoring human activity," Department Surface Radar, Technical Report, 2009.
- [2] S. Singh, Q. Liang, D. Chen, and L. Sheng, "Sense through wall human detection using uwb radar," *EURASIP Journal on Wireless Communications and Networking*, vol. 2011, no. 1, p. 20, 2011.
- [3] J. W. Palmer, K. F. Bing, A. C. Sharma, and E. F. Greneker, "Detecting concussion impairment with radar using gait analysis techniques," in *IEEE Radar Conference*, 2011, pp. 222–225.
- [4] V. C. Chen, *The micro-Doppler effect in radar*. Artech House, 2011.
- [5] V. C. Chen, W. J. Miceli, and B. Himed, "Micro-doppler analysis in ISAR - review and perspectives," in *International Radar Conference - Surveillance for a Safer World*, 2009, pp. 1–6.
- [6] G. Kirose, "Animating a human body mesh with maya for doppler signature computer modeling," Army Research Lab, Tech. Rep. ARL-TN-0351, 2009.
- [7] K. Youngwook and L. Hao, "Human activity classification based on micro-doppler signatures using an artificial neural network," in *IEEE Antennas and Propagation Society International Symposium*, 2008, pp. 1–4.
- [8] —, "Human activity classification based on micro-doppler signatures using a support vector machine," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, no. 5, pp. 1328–1337, 2009.
- [9] F. H. C. Tivive, A. Bouzerdoum, and M. G. Amin, "A human gait classification method based on radar doppler spectrograms," *EURASIP Journal on Advances in Signal Processing*, vol. 2010, pp. 1–12, 2010.
- [10] I. Orovic, S. Stankovic, and M. Amin, "A new approach for classification of human gait based on time-frequency feature representations," *Signal Processing*, vol. 91, no. 6, pp. 1448–1456, 2011.
- [11] I. Orovic, S. Stankovic, T. Thayaparan, and L. Stankovic, "Multiwindow s-method for instantaneous frequency estimation and its application in radar signal analysis," *IET Signal Processing*, vol. 4, no. 4, pp. 363–370, 2010.
- [12] G. E. Smith, K. Woodbridge, and C. J. Baker, "Naive bayesian radar micro-doppler recognition," in *International Conference on Radar*, 2008, pp. 111–116.
- [13] T. Thayaparan, S. Abrol, E. Riseborough, L. Stankovic, D. Lamothe, and G. Duff, "Analysis of radar micro-doppler signatures from experimental helicopter and human data," *IET, Radar, Sonar and Navigation*, vol. 1, no. 4, pp. 289–299, 2007.
- [14] D. Zhang and Z. Zhou, "(2D)2PCA: Two-directional two-dimensional PCA for efficient face representation and recognition," *Neurocomputing*, vol. 69, no. 13, pp. 224–231, 2005.
- [15] S. Noushath, G. Hemantha Kumar, and P. Shivakumara, "(2D)2LDA: An efficient approach for face recognition," *Pattern Recognition*, vol. 39, no. 7, pp. 1396–1400, 2006.