Pseudo-Zernike Moments Based Radar Micro-Doppler Classification

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***Abstract*— Reliable micro-Doppler signature classification requires the use of robust features describing uniquely the micro-motion. Moreover, future applications of micro-Doppler classification will require meaningful representation of the observed target by using a limited set of values. In this paper the application of the pseudo-Zernike moments for micro-Doppler classification is introduced demonstrating the effectiveness of the proposed approach by classifying real data. The use of pseudo-Zernike moments allows invariant features to be obtained that are able to discriminate the content of two-dimensional matrices with a small number of coefficients.**

I. Introduction

The analysis of radar micro-Doppler was introduced by Chen in [1] and widely treated in [2], demonstrating the potential of micro-Doppler information for target classification and micro-motion analysis. In the last decade the analysis of micro-Doppler signatures has been investigated for different families of radar systems [3], demonstrating the effectiveness of models and potential of radar micro-Doppler. Despite the quasi-complete knowledge of the phenomenon and its representation [2], an open problem related to the exploitation of micro-Doppler signatures is the realization of a reliable, robust and efficient procedure to classify targets in different observation conditions. Different approaches have been applied to classify micro-Doppler signatures, for example in [4] and [5] a template-based approach with interesting results was introduced, while in [6] and [7] a combination of information extracted from the Cadence Velocity Diagram (CVD) of the received data were used with the aim to remove acquisition dependence in the micro-Doppler feature. In [8] a Mean Frequency Profile (MFP) based approach has been presented achieving good results with low complexity.

In this paper we present a novel micro-Doppler signature extraction method that is based on pseudo-Zernike moments [9]. The family of geometric moments represented by Hu [10], Zernike [11], and pseudo-Zernike [9], have been widely used in image processing for pattern recognition. These moments can provide interesting characteristics such as position, scale, and rotational invariance. Zernike moments, unlike Hu moments, are obtained using a set of orthogonal polynomials, namely Zernike polynomials, that are independent. This is an important property as independent moments allow us to obtain more information considering the same number of coefficients. Pseudo-Zernike moments introduced by Bhatia in [9] improve Zernike moments by reducing the noise sensitivity compared to Zernike moments and increasing the number of moments available for a given order of the polynomial. For these reasons the pseudo-Zernike moments were selected as features to discriminate different micro-Doppler signatures, in the novel approach described in this paper.

The remainder of the paper is organized as follows. Section II introduces the pseudo-Zernike moments theory, and the novel feature extraction algorithm is described. The effectiveness of the proposed approach is demonstrated in Section III, where classification results on real data are presented. Section IV concludes the paper.

II. Pseudo-Zernike Moments Based Features

In this section, a novel feature for radar micro-Doppler classification is introduced. The approach is based on the use of pseudo-Zernike moments [9], in order to obtain reliable feature vectors with relatively small dimension and low computational complexity. The novel feature benefits of the specific properties of the pseudo-Zernike moments such as invariance with respect to translation and rotation and in particular the scale invariance can be included if required by the specific applications.

In the following subsections the theory defining the pseudo-Zernike moments is introduced, followed by the novel feature extraction algorithm.

A. Pseudo-Zernike Moments

Let $f(x,y)$ be a non-negative real defined image, i.e. $f(x,y) \geq 0$. The moments of $f(x,y)$ of order (or degree) $n+l$ are defined as the projection of the function $f(x,y)$ on the monomials $x^n y^l$, by the integral [10]

$$M_{n,l} = \iint x^n y^l f(x,y)\, dx\, dy. \tag{1}$$

Pseudo-Zernike polynomials are a set of orthogonal functions with simple rotation properties [9], that can be written in the form

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$$W_{n,l}(x,y,\rho) = W_{n,l}(\rho\cos\theta, \rho\sin\theta, \rho) = S_{n,l}(\rho)\, e^{jl\theta}, \quad (2)$$

where j is the imaginary unit, $x = \rho\cos\theta$, $y = \rho\sin\theta$, l is an integer, whereas $S_{n,l}(\rho)$ is a polynomial (called radial polynomial) in ρ of degree n not smaller than l. These functions form a complete basis and satisfy, on the unit circle (i.e. for $x^2 + y^2 \leq 1$), the orthogonality relation

$$\iint\limits_{x^2+y^2\leq 1} W^*_{n,l}(x,y)\, W_{m,k}(x,y)\, dx\, dy = \frac{\pi}{n+1}\delta_{mn}\delta_{kl}, \quad (3)$$

where the symbol $(\cdot)^*$ indicates the complex conjugate operator, and δ_{mn} is the Kronecker delta function, i.e.

$$\delta_{mn} = \begin{cases} 1 & \text{if} \quad m = n \\ 0 & \text{if} \quad m \neq n \end{cases}.$$

As given in [9], the radial polynomials, $S_{n,l}(\rho)$, have the following explicit expressions

$$S_{n,l}(\rho) = \sum_{k=0}^{n-|l|} \frac{(-1)^k\,(2n+1-k)!}{k!\,(n+|l|+1-k)!\,(n-|l|-k)!}\rho^{n-k}, \quad (4)$$

where $n \geq 0$ and l are integers such that $n \geq |l|$. Finally, the complex pseudo-Zernike moments (obtained projecting $f(x,y)$ on the pseudo-Zernike polynomials) are defined as

$$\psi_{n,l} = \frac{n+1}{\pi}\int_0^{2\pi}\int_0^1 W^*_{n,l}(\rho,\theta)\, f(\rho\cos\theta, \rho\sin\theta)\rho d\rho d\theta. \quad (5)$$

Notice that, the number of linearly independent pseudo-Zernike polynomials is $(n+1)^2$. Moreover, an important characteristic of the pseudo-Zernike moments is the simple rotational transformation property; indeed, the moment requires only a phase factor for the rotation [9].

B. Feature Extraction Algorithm

The proposed micro-Doppler feature extraction algorithm is shown in Fig. 1. The signal containing the micro-Doppler components is pre-processed to have zero mean and unit variance.

The first step is the computation of the spectrogram of the signal. The choice of the spectrogram, rather than other time-frequency distributions, is motivated by its robustness with respect to interference terms present in the so-called energy distributions [12]. An example of the spectrogram of $s(t)$ of a running human observed with a 16 GHz carrier frequency radar [13], [14], [15], is shown in Fig. 2-a.

The CVD introduced in [6], [16] to extract micro-Doppler features, is defined as the Fourier Transform of the spectrogram along each frequency bin. An example of the CVD obtained from the spectrogram in Fig. 2-a is shown in Fig. 2-b. From the CVD useful information can be extracted such

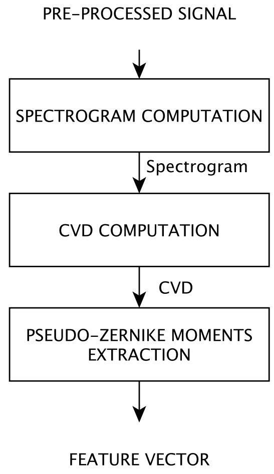
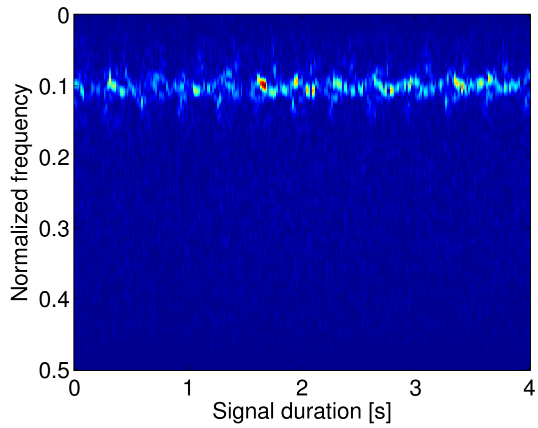
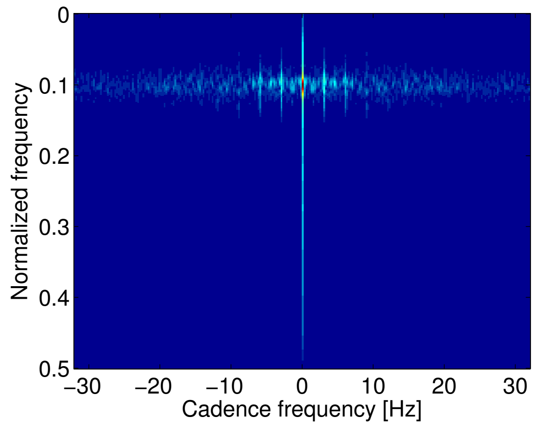


Fig. 1. Block scheme of the proposed feature extraction algorithm.



(a) Spectrogram



(b) CVD

Fig. 2. Spectrogram (a) and CVD (b) from the returns relative to a running man. The observation time is 4 s.

as the period of each components and their maximum micro-

Doppler shifts. The CVD is computed as second step of the proposed algorithm.

The third step of the algorithm is the projection of the CVD onto basis constituted by the pseudo-Zernike polynomials. The polynomials depend on the CVD size only and can be pre-computed and used to populate a look up table. As the pseudo-Zernike polynomials are defined on the unit circle the CVD dimension is scaled, before the coefficient is computed, to avoid information loss. The output of this stage is the set of $(n+1)^2$ magnitudes of the pseudo-Zernike coefficients; the modulus is used in order to obtain the rotational invariance of the coefficients. The resulting feature vector, $\boldsymbol{F}$, is normalized using the following linear rescaling

$$\tilde{\boldsymbol{F}} = \frac{\boldsymbol{F} - \mu_{\boldsymbol{F}}}{\sigma_{\boldsymbol{F}}}, \tag{6}$$

where $\mu_{\boldsymbol{F}}$ and $\sigma_{\boldsymbol{F}}$ are the mean and standard deviation of the feature vector. These values are then used to populate the micro-Doppler feature to be used as input to a classifier.

Classification of extracted feature vectors is then performed using a Support Vector Machine (SVM) classifier with a Radial Basis Function (RBF) kernel, employing a cross-validation grid search for selection of cost function and kernel parameters. The one-against-all approach [17] was used to perform multi-class classification.

III. Experimental Results on Real Radar Data

To analyze the performance of the proposed algorithm, the *correct classification* (defined as the number of correct classified objects over the total number of analyzed objects) has been considered as a figure of merit. The algorithm has been tested on real Ku band radar data, with short range within radar and target ($100 - 1000$ m) [13], [14], [15]. The analysis has been conducted on the entire 4 s time observation window and on shorter time windows (2, 1 and 0.5 seconds), extracted from the beginning of the 4 s sequence. In this way, it is possible to test the algorithm with respect to the variation of the available observation time.

Attention has been focused on 5 different classes of data, included in the same class the case of a target moving toward and away from the radar location. A summary of the classes and acquisitions is reported below for a total of 362 acquisitions:

- class 1. Person running toward/away from the radar (284 s - 71 samples);
- class 2. Person walking toward/away from the radar (396 s - 99 samples);
- class 3. Person crawling (72 s - 18 samples);
- class 4. Group of people running toward/away from the radar (200 s - 50 samples);
- class 5. Group of people walking toward/away from the radar (496 s - 124 samples).

From all the available samples, 70% are used for training, while the other 30% are used for testing. In order to statistically characterize the classifier and its performance, a Monte Carlo approach has been applied, using different selections of the training and test sets of the data chosen randomly for each class. To estimate the classifier performance, 50 different experimental cases have been evaluated, reporting the mean and standard deviation (or degree of reliability). The spectrogram is computed using $N = 512$ points for the DFT computation, and a Hamming window of length $M = 256$, with 50% overlap. Notice that, the choice of the number of DFT points depends on the acquisition system (i.e. Pulse Repetition Frequency) and the expected time dynamic of the targets (e.g. humans, animals rather than helicopters).

Fig. 3 shows the average correct classification versus the pseudo-Zernike moments order for different signal's duration, and with the corresponding degree of reliability. The average correct classification values are also summarized in Table I.

Analyzing the result of Fig. 3 and Table I, it is clear that performances increases with the pseudo-Zernike moments order. In particular, it is sufficient to consider the pseudo-Zernike moments of order 5 (36 coefficients) to provide the 95% correct classification. Furthermore, as expected, as the acquisition time of the considered signals reduces, the classification performance experiences a reduction due to the reduced amount of micro-Doppler information contained in the analyzed signal (see Figs. 3-a to 3-d). Moreover, for comparison purposes, the 20-components MFP-based classifier suggested in [8] is also considered. As the curves of Fig. 3 show, the proposed classification algorithm can achieve better performance than the MFP-based, if a sufficient high moments order is chosen. Finally, the proposed classification algorithm has been compared also with the Time-Frequency Distribution - Direction Features (TFD-DF) technique proposed in [7]. As the curves show, the TFD-DF classifier outperforms the pseudo-Zernike based one if a 0.5 s signal length is considered; however, as the duration of the signals increases, the proposed algorithm achieves an higher probability of correct classification than the TFD-DF.

To further analyze the behavior of the proposed classification algorithm, in Table II the confusion matrix related to signals of 4 s length, using pseudo-Zernike moments of order 5, is reported. This matrix gives more information about the behavior of the classifier than the single value represented by the correct classification. Specifically, this confusion matrix allows to better understand the types of error performed by the classifier. For instance, in classifying class 1 (see row 1 of the matrix), even if the algorithm never chooses classes 3, 4, and 5, in the 4.8% of times it chooses class 2, performing a bad classification. Notice that, in this paper we have reported only one confusion matrix for simplicity purposes; in fact for each Monte Carlo run, it is possible to compute a different confusion matrix. However, the average correct classification gives a synthetic value that is sufficient to assess the performance of such a classifier.

IV. Conclusions

In this paper a novel approach for micro-Doppler feature extraction has been presented. The proposed algorithm exploits the properties of the pseudo-Zernike moments to

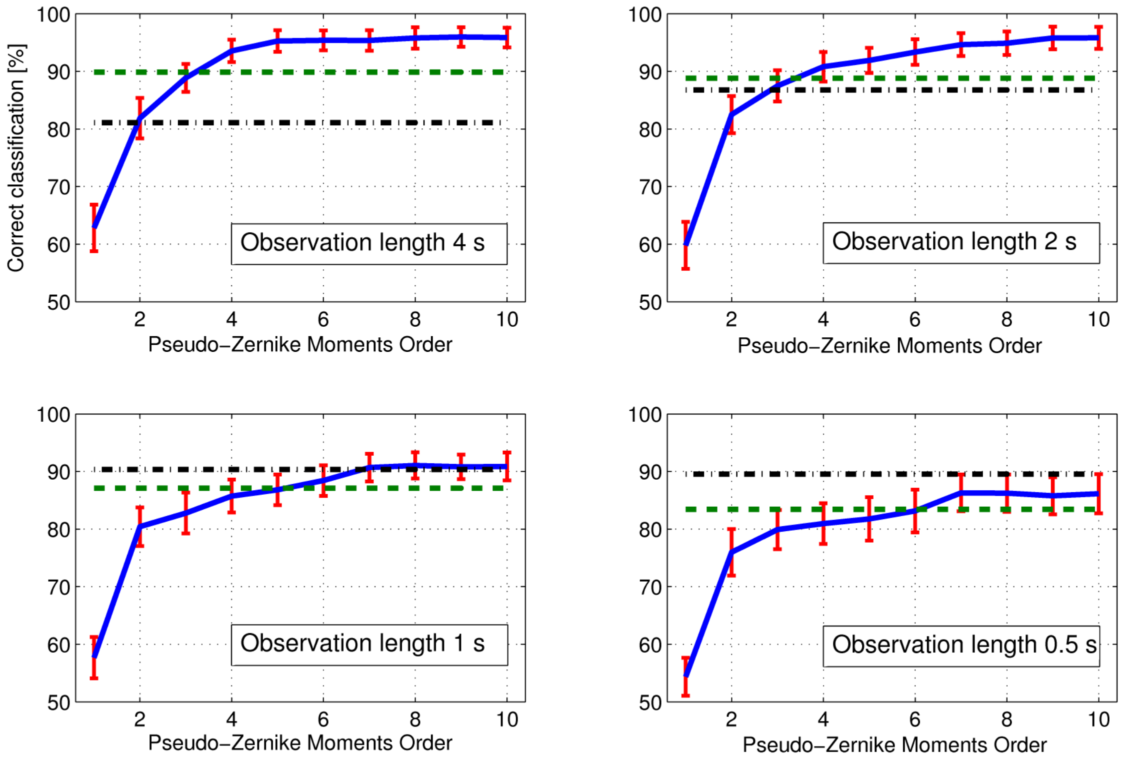


Fig. 3. Correct classification (%) versus pseudo-Zernike moments order. The solid line represents the average correct classification (over 50 runs) with its corresponding degree of reliability, the dashed curve is related to the MFP-based classifier proposed in [8], whereas the dot-dashed curve refers to the TFD-DF classifier given in [7]. Subplots refer to different signal lengths (i.e. 4, 2, 1 and 0.5 s, respectively).

TABLE I

AVERAGE CORRECT CLASSIFICATION (%) FOR DIFFERENT OBSERVATION TIME WINDOWS AND PSEUDO-ZERNIKE MOMENT ORDERS.

Time [s]	Pseudo-Zernike Moments Order: **1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
4	62.8	81.8	88.8	93.5	95.2	95.3	95.3	95.7	95.9	95.8
2	59.7	82.4	87.4	90.8	91.8	93.3	94.6	94.8	95.7	95.8
1	57.6	80.4	82.7	85.7	86.8	88.4	90.6	91.0	90.8	90.8
0.5	54.3	75.9	79.9	80.9	81.7	83.1	86.2	86.2	85.7	86.1

TABLE II

CONFUSION MATRIX RELATED TO 4 S SIGNALS LENGTH, OBTAINED FOR PSEUDO-ZERNIKE MOMENTS OF ORDER 5 FROM A SINGLE RUN.

class number	class number: 1	2	3	4	5
1	95.2%	4.8%	0%	0%	0%
2	0%	96.5%	3.5%	0%	0%
3	0%	0%	80%	0%	20%
4	0%	0%	0%	93.3%	6.7%
5	0%	2.7%	0%	0%	97.3%

extract robust features with a limited number of values. The moments are applied to the Cadence Velocity Diagram of the micro-Doppler signature in order to minimize the feature acquisition dependence. Moreover the invariant properties of the novel feature, together with the opportunity to extract a desired accuracy from the data, open to many ATR (Automatic Target Recognition) applications. To demonstrate the use of the pseudo-Zernike moments in ATR, the novel features have been tested on real micro-Doppler data producing high classification accuracy.

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