

# Performance Analysis of Co-Located and Distributed MIMO Radar for Micro-Doppler Classification

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**Abstract**—Over the past few years, the use of Multiple Input Multiple Output (MIMO) radar has gained increased attention as a way to mitigate the degradation of micro-Doppler classification performance incurred when the aspect angle approaches 90 degrees. In this work, the efficacy of co-located MIMO radar is compared with that of distributed MIMO. The performance analysis is accomplished for three different classification problems: 1) discrimination of a walking group of people from a running group of people; 2) identification of individual human activities, and 3) classification of different types of walking. In the co-located configuration each radar is placed side by side so as to form a line. In the distributed configuration, the radar positions are separated to observe the subjects from different angles. Starting from the cadence velocity diagram (CVD), the Pseudo-Zernike moments based features are extracted because of their robustness with respect to unwanted scalar and angular dependencies. Two different approaches to integrate the features obtained from multi-aspect data are compared: concatenation and principal component analysis (PCA). Results show that a distributed MIMO configuration and use of PCA to fuse multi-perspective features yields higher classification performance as compared to a co-located configuration or feature vector concatenation.

## I. INTRODUCTION

A typical radar system transmits electromagnetic waves and receives echoes scattering from a target. If the target is not stationary, the received signal is modulated as consequence of the known Doppler effect. The main Doppler shift is directly related to the targets velocity toward the radar. Any other secondary motion of the target, such as rotation or vibration, may introduce additional modulation around the main Doppler shift. This phenomenon, which is known as micro-Doppler effect, is widely described by Chen in [1]. The micro-Doppler information may be used to extract reliable information for target recognition. For example, a remote detection of humans and animals is examined in [2], ballistic missile warhead recognition in [3], while discrimination for helicopters is examined in [4] and human activity classification in [5], [6].

However, as several recent works have shown [7], [8], the performance of micro-Doppler classification algorithms is heavily dependent upon the aspect angle of the target relative to the radar's line-of-sight. For example, in [9], a

correct classification rate of 95% is obtained when the aspect angle is 0 degrees, while this rate drops to 65% when the aspect angle is 90 degrees. Because this effect is caused by radar only measuring radial, not absolute, velocity, the use of multiple radars to collect multi-perspective data has been proposed to improve classification performance [7]. The Multiple Input Multiple Output (MIMO) concept, which has been widely used in communications, was first investigated for radar applications by Fishler in [10]. Widely separated radars were shown to yield an improvement in detection performance in [11], while in [12] a novel technique was proposed to improve output SINR for co-located arrays. In [13], the effect of vibrating targets on MIMO Synthetic Aperture Radar (SAR) was investigated by considering target micro-Doppler. In [14], a majority voting scheme was utilized to improve the classification performance of armed/unarmed personnel from a three node, linearly aligned, multi-static radar network. Although in [15], information theoretic feature selection was used to choose which node in a radar network was best positioned to give the best possible classification result, a detailed performance analysis of different MIMO configurations for micro-Doppler classification has yet to be investigated.

In this work, the micro-Doppler classification performance attainable using co-located and distributed MIMO configurations is evaluated using features fused through two different approaches: concatenation and principal component analysis (PCA). There are many different features that have been proposed in the literature for micro-Doppler classification, including physical features, transform-based features, and even speech features, such as mel-frequency cepstrum coefficients (MFCC) and linear predictive coding. In this work, however, a recently proposed novel feature set extracted using pseudo-Zernike moments is utilized. Pseudo-Zernike moments are geometric moments introduced by Hu [16] enhanced in [17] and improved by showing orthogonality in [18]. This approach provides interesting elements of robustness with respect to unwanted dependencies such as angle and scale dependencies in micro-Doppler signatures [19]. Performance analysis is

conducted for three different but important classes of micro-Doppler classification: 1) discrimination of a walking group of people from a running group of people; 2) identification of individual human activities, and 3) classification of different types of walking.

The remainder of the paper is organized as follows. Section II gives information about the experimental test setup and programmable radar hardware used to collect data. Subsequently, Section III describes the micro-Doppler analysis techniques employed, while results for the different MIMO configurations are presented and discussed in Section IV.

## II. EXPERIMENTAL TEST SETUP

All experimental data was collected using two National Instruments (NI) Universal Software Defined Radio Peripheral (USRP) RIO 2943r units, each of which has two channels functioning as a transmitter and a receiver, thereby establishing a 4-node MIMO network. The channels in each USRP share the same oscillator, and thus are capable of transmitting at exactly the same center frequency. When two devices are operated simultaneously, however, slight differences in transmit frequency are possible. Thus, each USRP was synchronized through a common reference signal. Each USRP was programmed to transmit a CW waveform, thus requiring a total of eight printed circuit board (PCB) directional antennas. Each antenna utilized has a 5 - 6 dBi directional gain and operates over a 850 MHz to 6.5 GHz frequency range. To avoid channel confusion, each channel transmitted at the same 4.4 GHz center frequency, but with varying modulation of 7, 13, 19, and 24 kHz sinusoids. Experiments were conducted for three different classification problems:

- 1) Group Classification, distinguishing between group of walking people and running people;
- 2) Person Classification, making an discrimination between a walking, running or crawling person;
- 3) Walking Classification, categorizing person who is walking, walking with a backpack or walking with a limp.

Towards this aim, a database of micro-Doppler signatures was constructed from radar measurements of human motion collected in an indoor facility, and in particular in an approximately 30 meter square room without any special covering for clutter suppression. Data is collected for two different configurations: 1) co-located and 2) distributed positioning of the 4x4 MIMO system depicted on Figure 1. For each configuration, human motion has been observed over 3 different angles, namely 30°, 60° and 90°, relative to the radar's observation direction. Activities observed include

- Walking
- Running
- Crawling
- Walking with a backpack
- Limping
- Group Walking
- Group Running

Thus, 16 different micro-Doppler signatures were recorded by the 4 x 4 MIMO system for each test run. Each activity

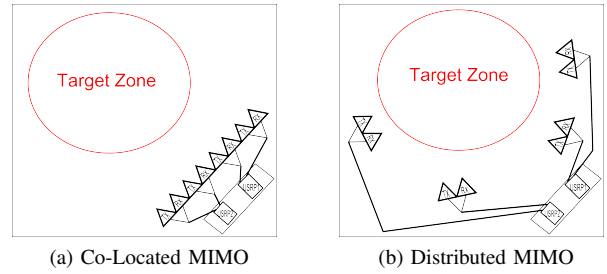


Fig. 1: MIMO configurations experimentally tested.

was recorded for a duration of 60 seconds, as enacted by 4 test subjects, thereby yielding a total of 240 recordings in the micro-Doppler database.

## III. MICRO-DOPPLER CLASSIFICATION

In this work, the micro-Doppler signature is represented in the time-frequency domain using a Short-Time Fourier Transform (STFT), or spectrogram, which was preferred over other time-frequency representations due to its robustness to interference [20]. First the received echoes  $s_{rx}^k(n)$  are formed into a zero mean and unit variance signal  $\tilde{s}_{rx}(n)$ . The pre-processed received signal  $\tilde{s}_{rx}(n)$  contains  $k^{th}$  channels micro-Doppler components and consist of  $N_s$  samples. The spectrogram is computed with the modulus of short time Fourier transform (STFT) of each  $k^{th}$  signal  $\tilde{s}_{rx}(n)$  as follows

$$\chi(v, k) = \left| \sum_{n=1}^{N_s-1} \tilde{s}_{rx} h^*(n-k) e^{j\frac{2\pi v n}{N_s}} \right| \quad (1)$$

$$k = 0, \dots, K-1$$

where  $K$  is the total number of channels,  $v$  is the normalized frequency and  $h^*(\cdot)$  is the smoothing window.

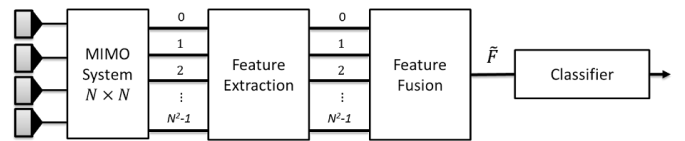


Fig. 2: Block Scheme of the Algorithm

After computation of the spectrogram, the classification process then proceeds through extraction of features that exhibit statistical differences for the classes under consideration. In MIMO systems, however, individual feature vectors are obtained for each node in the network. Thus, after feature extraction, a single, composite feature vector formed from the individual feature vectors is computed and supplied to the classifier. The overall micro-Doppler classification process is shown in 2.

### A. Feature Extraction

Features are extracted from the spectrogram by first computing the cadence velocity diagram (CVD), which may be found from

$$\Delta(v, \epsilon) = \left| \sum_{k=1}^{K-1} \chi(v, k) e^{j \frac{2\pi v \epsilon}{K}} \right| \quad (2)$$

where  $\epsilon$  is the cadence frequency. The motivation of using CVD is its robustness and lack of dependence upon the initial target position [20]. Each CVD obtained from all channels is then projected onto a basis constituted by pseudo-Zernike polynomials. Before calculating moments, normalization and CVD dimensional scaling should be done as the pseudo-Zernike polynomials are defined on the unit circle. This ensures the prevention of information loss due to dimension mismatch. The normalized CVD is acquired with the following formula;

$$\bar{\Delta}^k(v, \epsilon) = \frac{\Delta^k(v, \epsilon) - \min_{v, \epsilon} \Delta^k(v, \epsilon)}{\max_{v, \epsilon} [\Delta^k(v, \epsilon) - \min_{v, \epsilon} \Delta^k(v, \epsilon)]} \quad (3)$$

Finally, the pseudo-Zernike moments are computed from the normalized CVD. The feature extraction process is summarized in Figure 3.

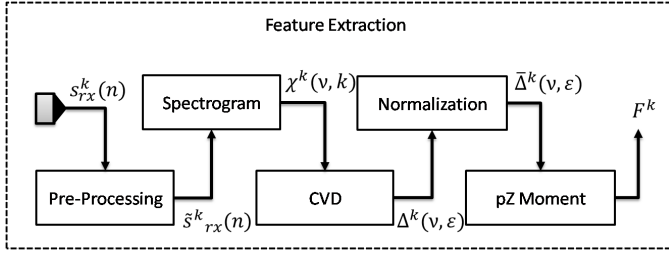


Fig. 3: Feature Extraction Scheme

Features are obtained by projecting  $\bar{\Delta}^k(v, \epsilon)$  on the pseudo Zernike polynomials of order  $n$  which can be written in the following form

$$W_{n,l}(x, y, \rho) = W_{n,l}(\rho \cos \theta, \rho \sin \theta, \rho) = S_{n,l}(\rho) e^{j l \theta} \quad (4)$$

where the radial polynomials  $S_{n,l}(\rho)$  are expressed as

$$S_{n,l}(\rho) = \sum_{k=0}^{n-|l|} \frac{(-1)^k (2n+1-k)!}{k!(n+|l|+1-k)!(n-|l|-k)!} \rho^{n-k} \quad (5)$$

Exploiting (4), the pseudo-Zernike moments are defined as

$$\psi_{n,l} = \frac{n+1}{\pi} \int_0^{2\pi} \int_0^1 W_{n,l}^*(\rho, \theta) f(\rho \cos \theta, \rho \sin \theta) \rho d\rho d\theta \quad (6)$$

By using  $\bar{\Delta}^k(v, \epsilon)$  into (6), the pseudo-Zernike coefficients can be obtained and if  $n^{th}$  order pseudo-Zernike polynomials are used,  $(n+1)^2$  sized output vectors is acquired. Hence the feature vector of  $k^{th}$  channel is

$$F^k = \left[ |\psi_{0,0}|, \dots, |\psi_{N,-N}| \right] \quad (7)$$

Lastly, this output vectors are statistically normalized using the following linear re-scaling

$$\tilde{F}^k = \frac{F^k - \mu_{F^k}}{\sigma_{F^k}} \quad (8)$$

where  $\mu_{F^k}$  and  $\sigma_{F^k}$  are the mean and standard deviation of the  $F$  the feature vector. As seen in Figure 4, signal  $s_{rx}^k(n)$

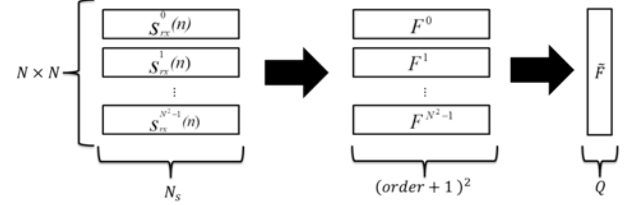


Fig. 4: General Flow of the Algorithm

where  $k = 0, 1, \dots, N^2 - 1$  is obtained from 4x4 MIMO system with  $N_s$  samples. After the feature extraction stage,  $F^k, k = 0, 1, \dots, N^2 - 1$  acquired with length  $(order+1)^2$  where  $order$  is the pseudo-Zernike polynomials order. Since we have 16 data vector so the same number of feature vector, an algorithm should be used in order to make a feature vector from feature channel matrix for classifier. Last stage is to acquire a feature vector  $F$  whose dimension is  $Q$  associated with the selection algorithm.

1) *Feature Fusion*: In the 4x4 MIMO system used for this work, a total of 16 different feature vectors are obtained after the feature extraction process. Especially in distributed localization, the target is observed from different perspectives so the feature vectors from different channels might include added information helpful for classification. Two different approaches for fusing the individual feature vectors into a final, overall feature vector are considered in this paper 1) concatenation of all the features from each channel; and 2) principal component analysis (PCA).

Concatenation creates a vector of size  $1 \times 16N$  from  $16 \times N$  matrix where  $N$  is the number of features related to pseudo-Zernike moments order introduced in the previous section. While creating the feature vector, it exploits all features from all channels respectively regardless of any elimination. PCA, on the other hand, reduces the dimension of the feature space by computing an orthogonal basis that spans the entire feature space, thereby ensuring the minimum correlation between PCA feature generated. Although in PCA the relevancy of features (i.e. distance between classes) is not optimized, it is quite efficient in terms of computational time and amount of memory utilized [21].

## IV. RESULTS

To statistically discriminate between different classes based on micro-Doppler analysis using pseudo-Zernike feature vectors, a support vector machine (SVM) classifier is used together with a Monte Carlo approach. %70 of the data is used to train SVM classifier and the rest is used for testing. The classification results obtained for concatenation and PCA

features for co-located and distributed MIMO configuration is given in Table I and Table II. From these results, it is seen that in all cases, PCA yielded better results than concatenation of features. Moreover, when PCA was applied, the distributed MIMO configuration outperformed the co-located MIMO configuration for all classification problems considered. When concatenation was applied, the distributed configuration performed best, with the exception of the case of individual classification, in which concatenation yielded similar results to that of PCA.

TABLE I: Classification Results of Co-Locate Configuration

Co-Located 4x4 MIMO: $P_C(\%)$		
	Concatenation of All Features	PCA
Group Classification	94.07	96.57
Individual Classification	93.23	92.39
Walking Classification	75.76	80.60

TABLE II: Classification Results of Distributed Configuration

Distributed 4x4 MIMO: $P_C(\%)$		
	Concatenation of All Features	PCA
Group Classification	96.16	98.80
Individual Classification	93.02	95.67
Walking Classification	78.03	81.60

## V. CONCLUSION

In this paper, the performance improvements attainable with multi-perspective data and the importance of sensor positioning is demonstrated. More specifically, it was found that a distributed configuration yields greater classification performance than a co-located configuration. Two different methods for feature-level fusion of radar data is explored: concatenation and PCA. It was found that through dimension reduction PCA yields superior results to concatenation. Classification results are shown for three different human activity recognition problems: 1) group classification, 2) individual classification, and 3) walking classification (normal, limping, and carrying a backpack).

## VI. ACKNOWLEDGEMENTS

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