Krogager Decomposition and Pseudo-Zernike Moments for Polarimetric Distributed ATR

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OVERVIEW

- Introduction
- Krogager Polarimetric Decomposition
- Pseudo-Zernike Moments
- Algorithm Description
- Simulations Set-Up
- Results
- Conclusions and Future Plans

Introduction

- Automatic Target Recognition (ATR) refers to different tasks, one of which is the ***classification*** of the target: once that a target has been detected, it is assigned to a specific class. This process can help to distinguish between allied and enemy targets.
- In a battlefield scenario multiple sources of information are often available, such as spatial, temporal, frequency, waveform and polarization ***diversities***.
- Aim: development of an automatic target classification algorithm which exploits both spatial and polarization diversities.

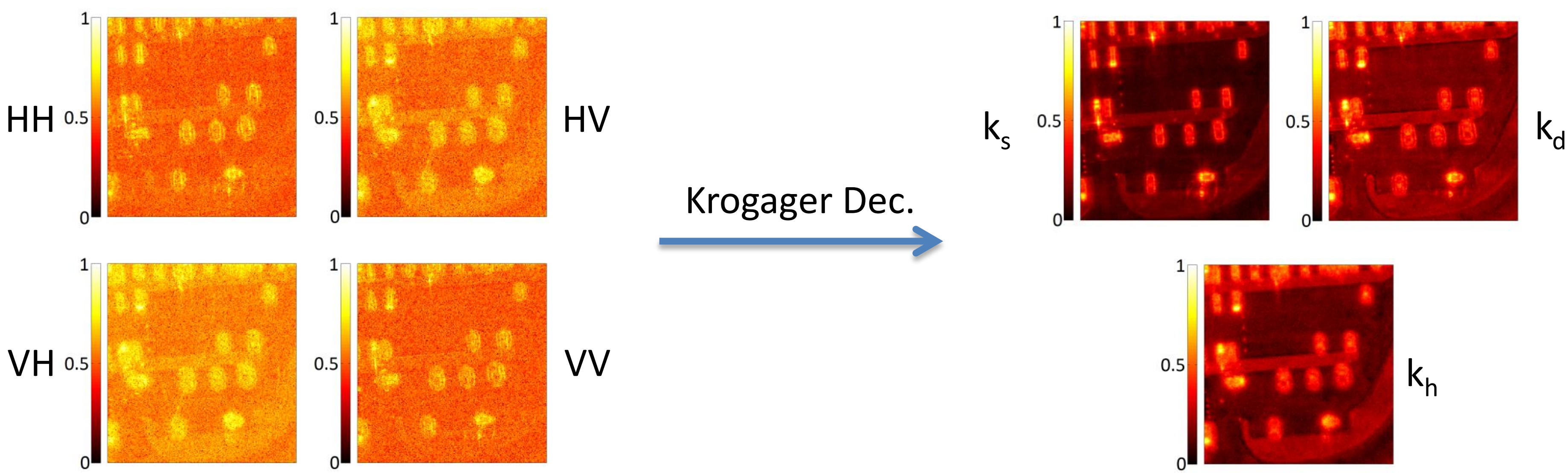
Krogager Polarimetric Decomposition

The Krogager decomposition (Krogager, 1990) is defined as:

$$\boldsymbol{S}_{(RL)} = \begin{bmatrix} S_{RR} & S_{RL} \\ S_{LR} & S_{LL} \end{bmatrix} = e^{i\phi}\left\{k_s e^{i\phi_s}\begin{bmatrix} 0 & i \\ i & 0 \end{bmatrix} + k_d \begin{bmatrix} e^{i2\eta} & 0 \\ 0 & -e^{-i2\eta} \end{bmatrix} + k_h \begin{bmatrix} e^{i2\eta} & 0 \\ 0 & 0 \end{bmatrix}\right\} \quad (1)$$

where $\boldsymbol{S}_{(RL)}$ is the circular polarimetric scattering matrix. The real-valued quatities k_s, k_d and k_h can be interpreted as scattering coefficients from a ***sphere***, a ***diplane*** and a ***helix***, respectively. They are computed as:

$$k_s = |S_{RL}| \qquad k_d = \min(|S_{RR}|, |S_{LL}|) \qquad k_h = \mathrm{abs}(|S_{RR}| - |S_{LL}|) \qquad (2)$$



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ADVANTAGES

- This decomposition is the most suitable in ***dividing man-made targets from natural targets***.
- The components k_s, k_d and k_h are ***roll invariant***.

DRAWBACKS

- The Krogager decomposition is ***not capable*** of distinguish ***between different man-made targets***.

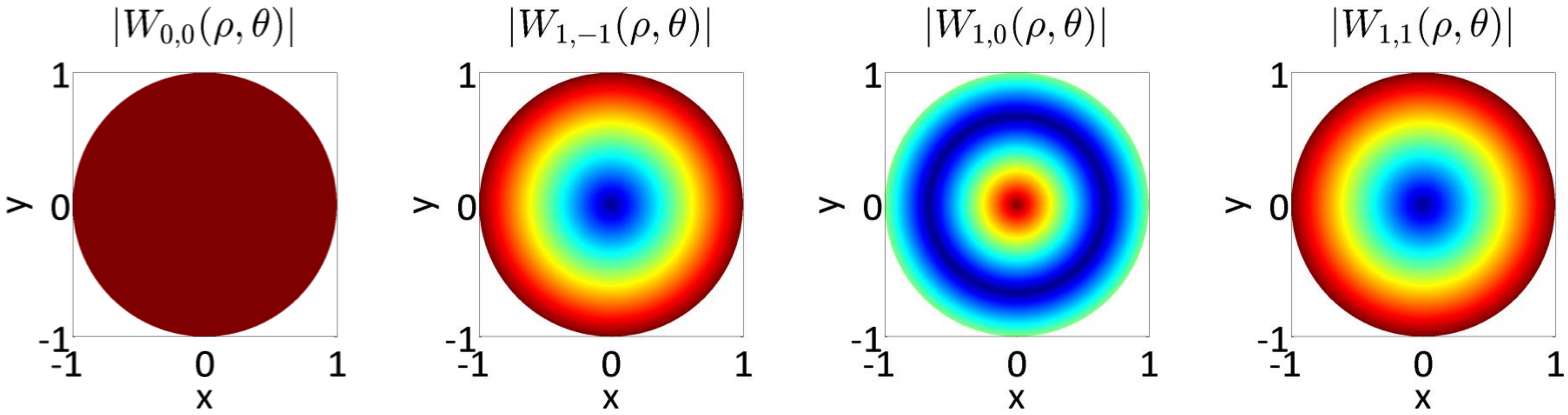
Pseudo-Zernike Moments

The pseudo-Zernike moments (Bhatia and Wolf, 1954) of an image $f(x, y)$ are geometric moments computed as the ***projection of the image*** itself on a ***basis of 2D-polynomials*** which are defined on the unit circle. They are calculated as:

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

where

$$W_{n,l}(\rho, \theta) = \sum_{m=0}^{n-|l|} \frac{\rho^{n-m}(-1)^m (2n+1-m)!}{m!\,(n+|l|+1-m)!\,(n-|l|-m)!} e^{il\theta} \qquad \rho \le 1 \qquad (2)$$



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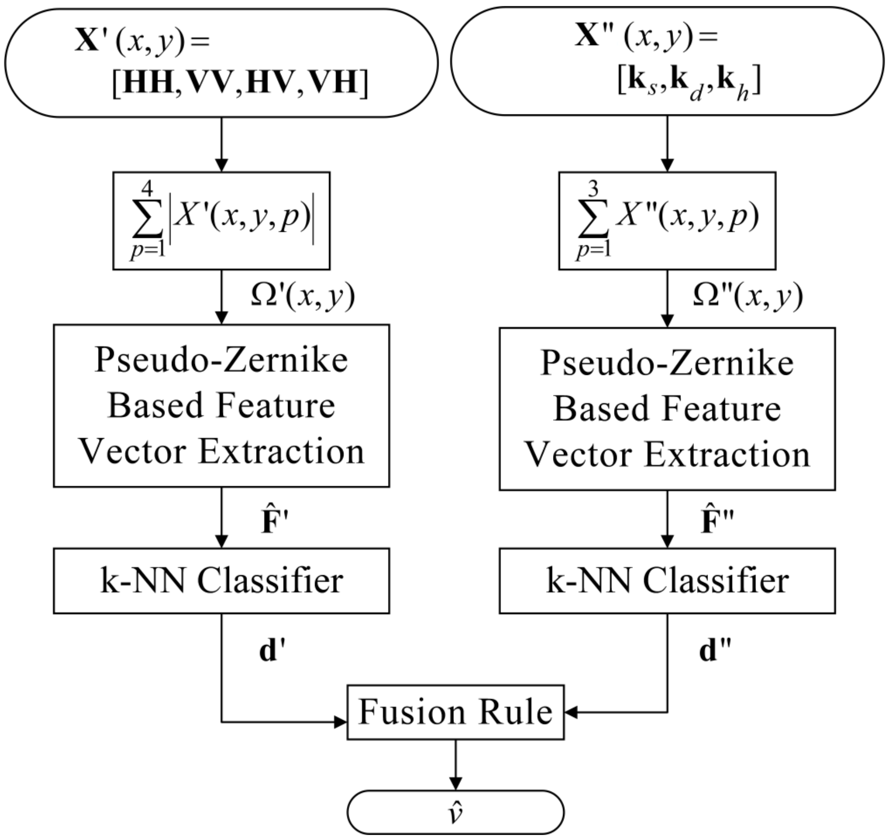
Properties

- The pseudo-Zernike moments are ***independent***, since the pseudo-Zernike polynomials are orthogonal on the unit circle;
- With respect to the Zernike moments, the pseudo-Zernike moments are ***less sensitive to noise*** and are ***more for a given order***.
- The ***modulus*** of the pseudo-Zernike moments is ***rotational invariant***.

ALGORITHM DESCRIPTION (1/3)

INTEGRATED INTENSITY-KROGAGER (IIK) APPROACH – SINGLE SOURCE



- $\boldsymbol{X}'(x,y)$ and $\boldsymbol{X}''(x,y)$: vectors whose elements are the **four polarimetric components** and the **three Krogager components**, respectively;
- **Feature vector**: $\widehat{\boldsymbol{F}} \in \mathbb{R}^{(n+1)^2}$
- **Score vector** $\boldsymbol{d} \in \mathbb{R}^{V}$: vector whose elements are the occurrences (normalized to k) of each class among the k nearest neighbours to $\widehat{\boldsymbol{F}}$;
- V is the **number of possible classes**;
- **Fusion rule**: $\boldsymbol{\lambda} = \boldsymbol{d}' + \boldsymbol{d}''$
- **Decision rule**:

$$\hat{v} = \begin{cases} \text{argmax}\,\boldsymbol{\lambda} & \text{if } \exists!\,(\max \boldsymbol{\lambda}) > T \\ unknown & \text{otherwise} \end{cases}$$

ALGORITHM DESCRIPTION (1/3)

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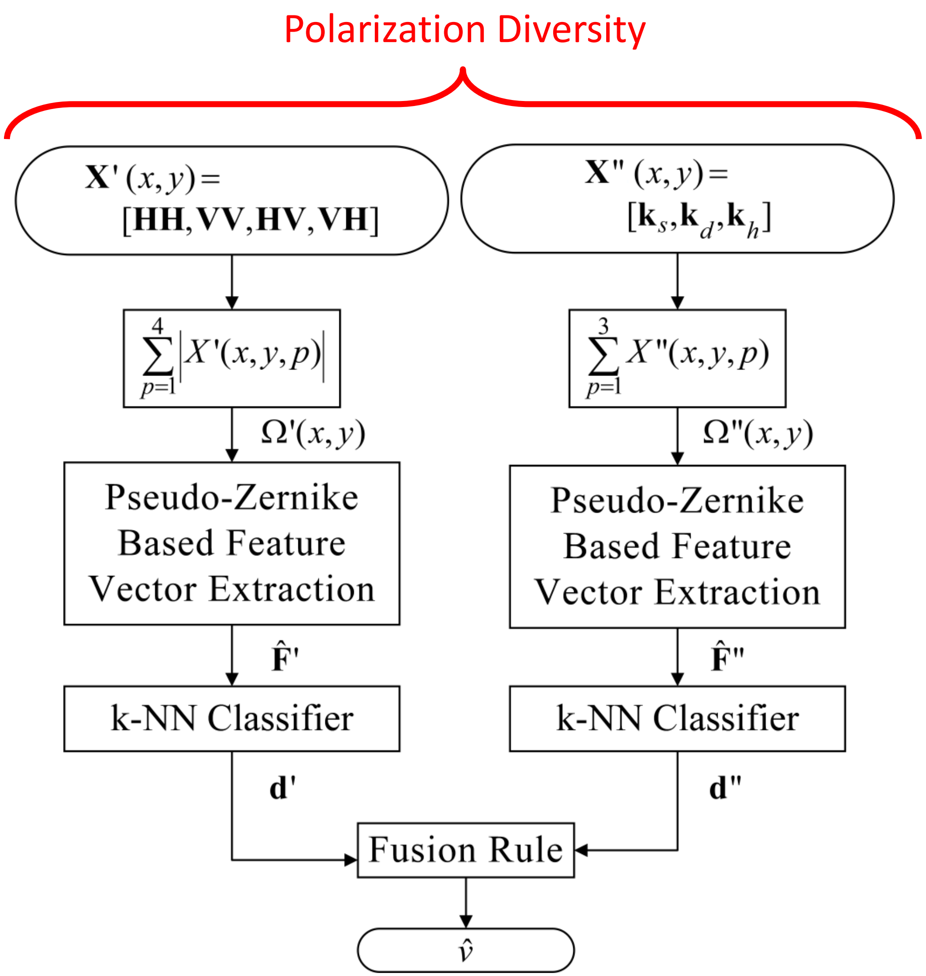

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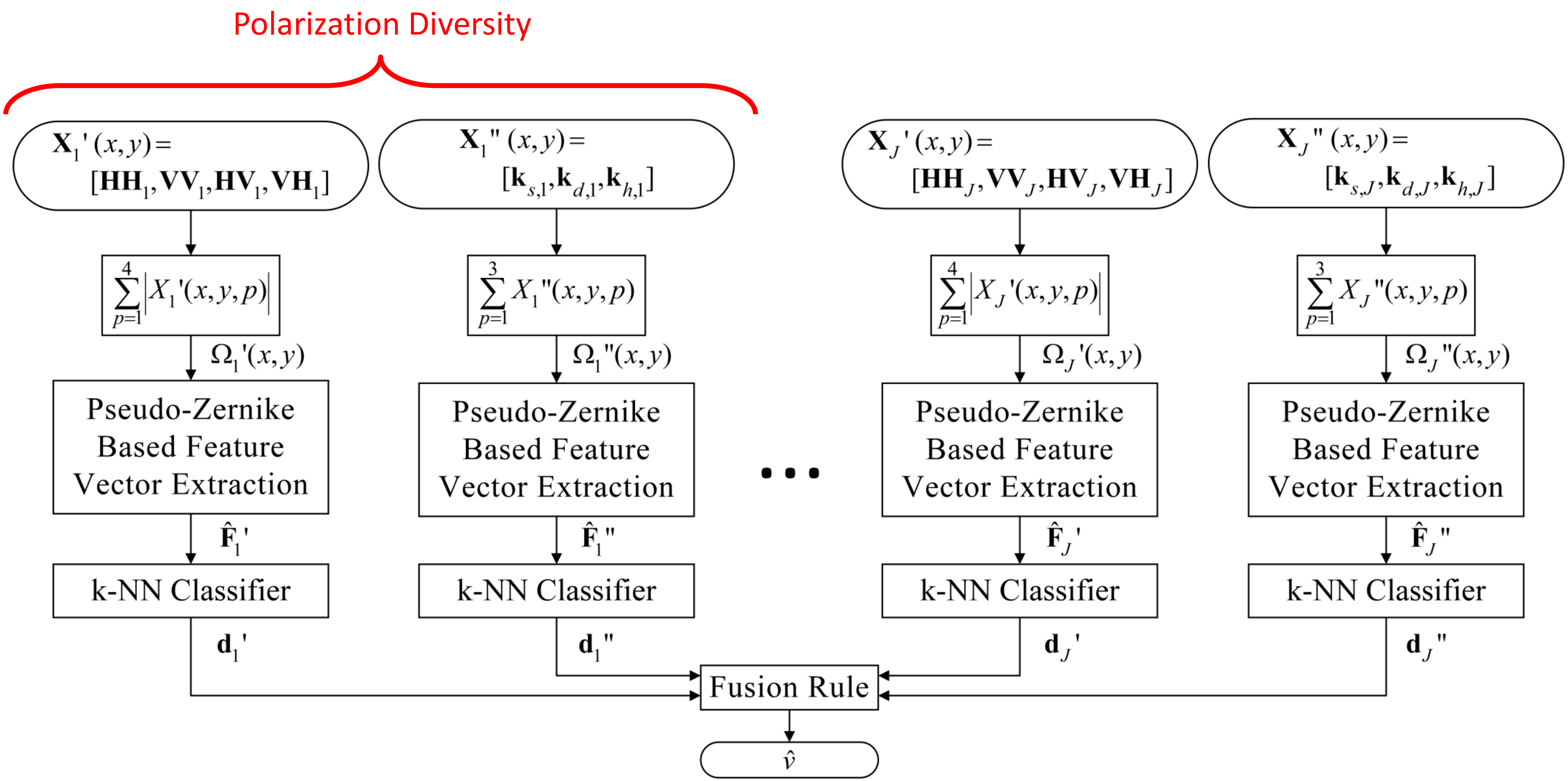
Algorithm Description (2/3)

Integrated Intensity-Krogager (IIK) Approach – Multi Source Extension

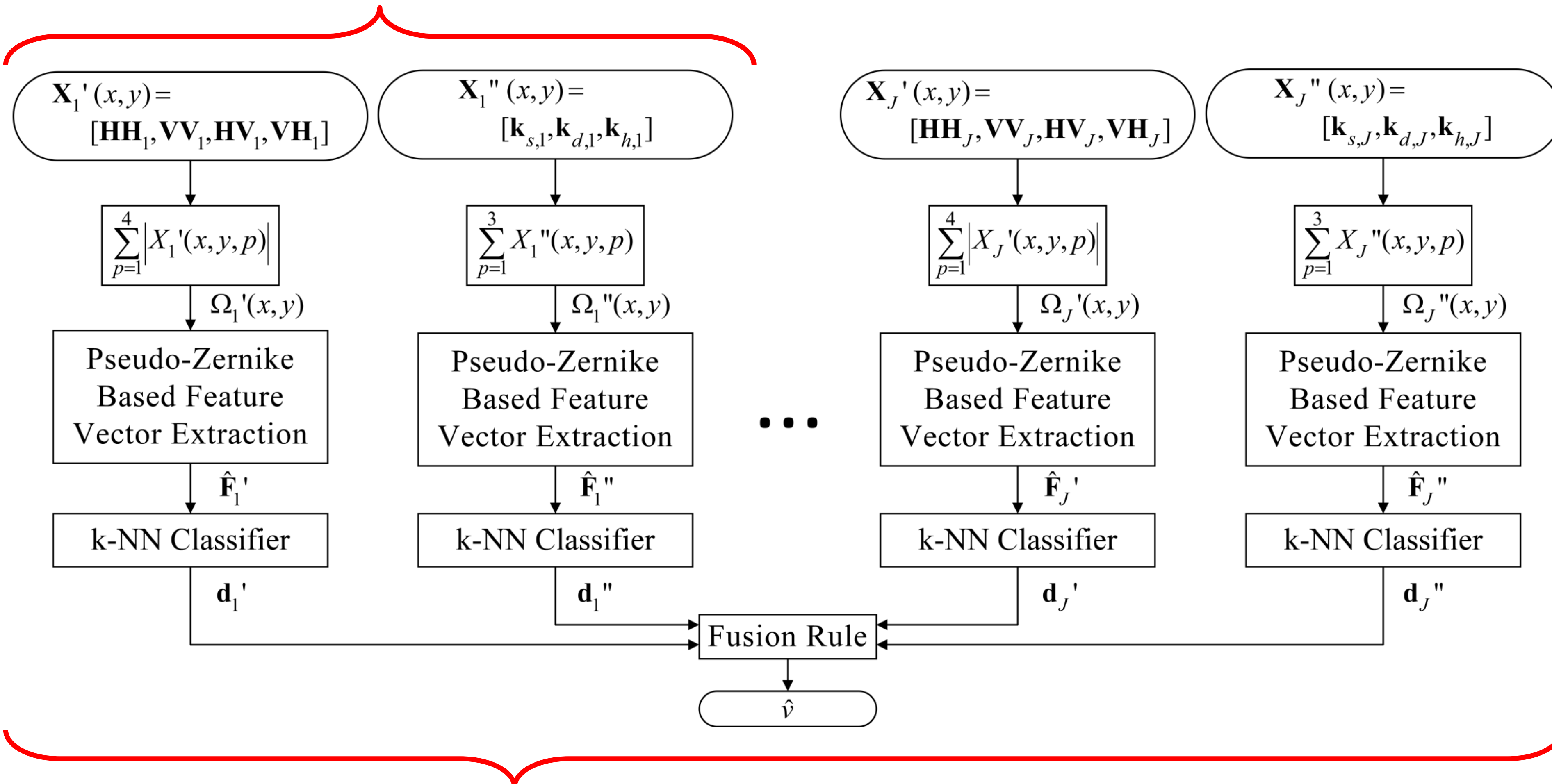


- **Fusion rule:** $\boldsymbol{\lambda} = \sum_{j=1}^{J} \boldsymbol{d}'_j + \sum_{j=1}^{J} \boldsymbol{d}''_j$

ALGORITHM DESCRIPTION (2/3)

INTEGRATED INTENSITY-KROGAGER (IIK) APPROACH – MULTI SOURCE EXTENSION

Polarization Diversity

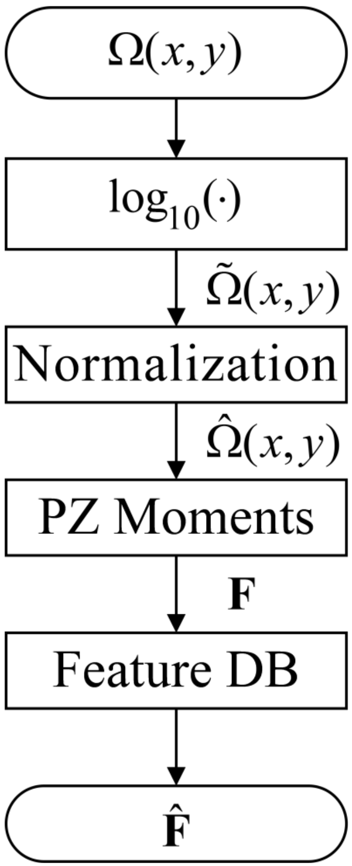


Spatial Diversity

- **Fusion rule:** $\lambda = \sum_{j=1}^{J} \boldsymbol{d}'_j + \sum_{j=1}^{J} \boldsymbol{d}''_j$

Algorithm Description (3/3)

Pseudo-Zernike Based Feature Vector Extraction



- **Reduction of the dynamic range**:

$$\tilde{\Omega}(x,y) = \log_{10}\big(\Omega\,(x,y)\big)$$

- **Image normalization**, computed in order to have features independent of the RCS:

$$\bar{\Omega}(x,y) = \tilde{\Omega}(x,y) - \min \tilde{\Omega}(x,y)$$

$$\hat{\Omega}(x,y) = \bar{\Omega}(x,y)/\max \bar{\Omega}\,(x,y)$$

- **Feature vector**, $(n+1)^2$ elements:

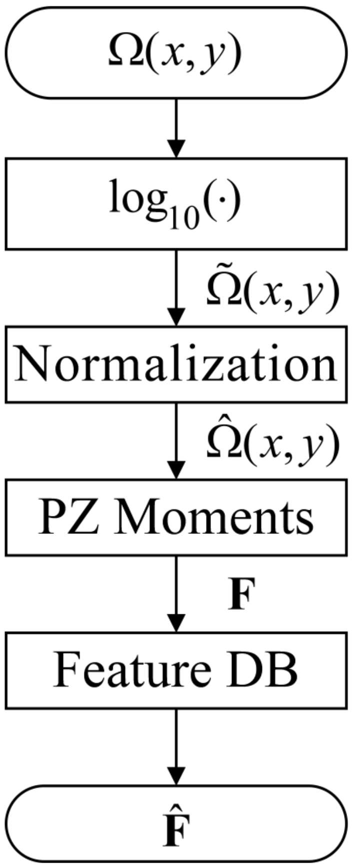
$$\boldsymbol{F} = \big[|\psi_{0,0}|, \dots, |\psi_{n,-n}|, |\psi_{n,-(n-1)}|, \dots, |\psi_{n,(n-1)}|, |\psi_{n,n}|\big]$$

- **Feature vector normalization**:

$$\widehat{\boldsymbol{F}} = \frac{\boldsymbol{F} - \mu_{\boldsymbol{F}}}{\sigma_{\boldsymbol{F}}}$$

ALGORITHM DESCRIPTION (3/3)

PSEUDO-ZERNIKE BASED FEATURE VECTOR EXTRACTION



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- **Feature vector normalization**:

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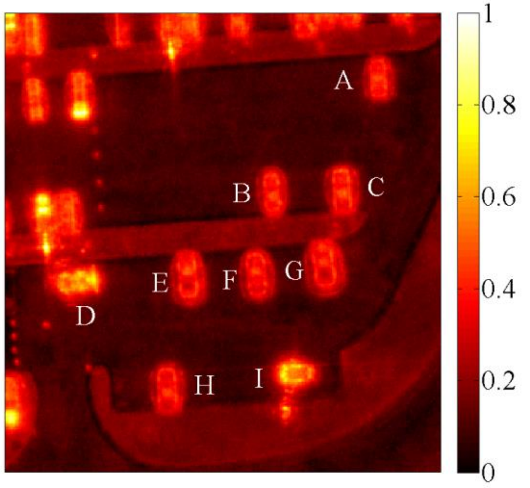
The **roll invariant property** of the Krogager decomposition and the **rotation invariant property** of the pseudo-Zernike moments make the algorithm **robust with respect to both the relative orientation of the target and the aspect angle**.

SIMULATIONS SET-UP (1/2)

GOTCHA DATASET

- Collection of real **full-polarimetric circular SAR** images.
- Airborne **X-Band** (9.6 GHz) sensor.
- **8 elevation angles**.
- Bandwidth 640 MHz, **range resolution ~23 cm**.
- **2880 full polarimetric images**, 360 for each pass.

The full synthetic aperture (360°) has been divided in **90 sub-apertures** of 4° in azimuth each, in order to have approximately **equal range-azimuth resolution cells**. The number of available images is reduced to 720.



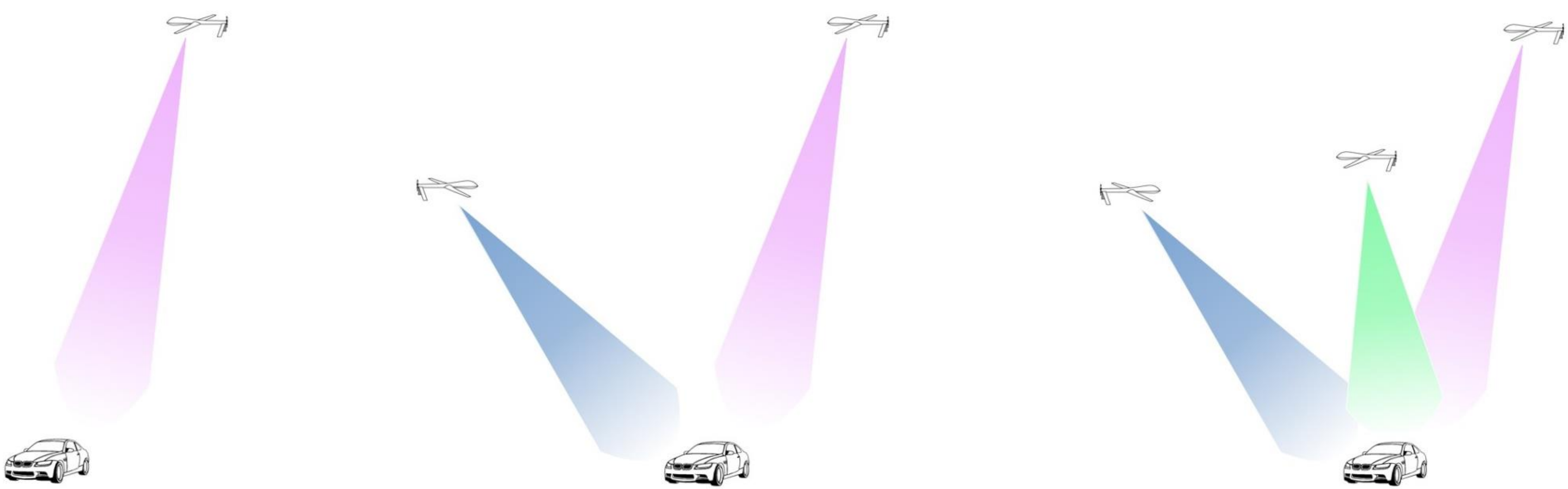
Simulations Set-Up (2/2)

Training Set

- It is formed by images coming from the **lowest altitude pass**.
- Two configurations: either **10 or 30 images for each vehicle**, selected each 36° or 12° in azimuth, respectively.

Test Set

- It is formed by **all but the images used for the training**.
- Three configurations: classification performed by using **one, two or three images** of the target.



One Image

Two Images

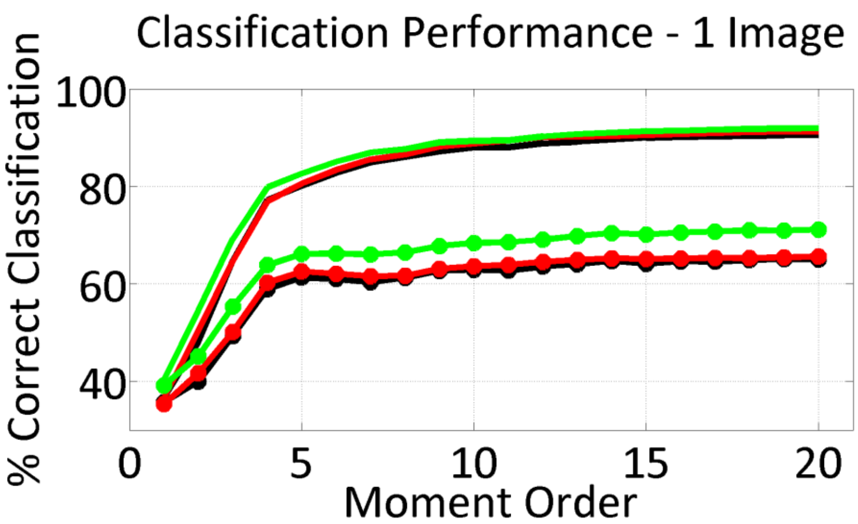
Three Images

RESULTS (1/2)

The IIK approach is compared with two similar algorithms:

- **Intensity Approach** (IA), presented in (Clemente et al., 2014), uses only the four polarimetric images of the target.
- **Krogager Approach** (KA) uses only the three Krogager components.

SINGLE SOURCE CLASSIFICATION

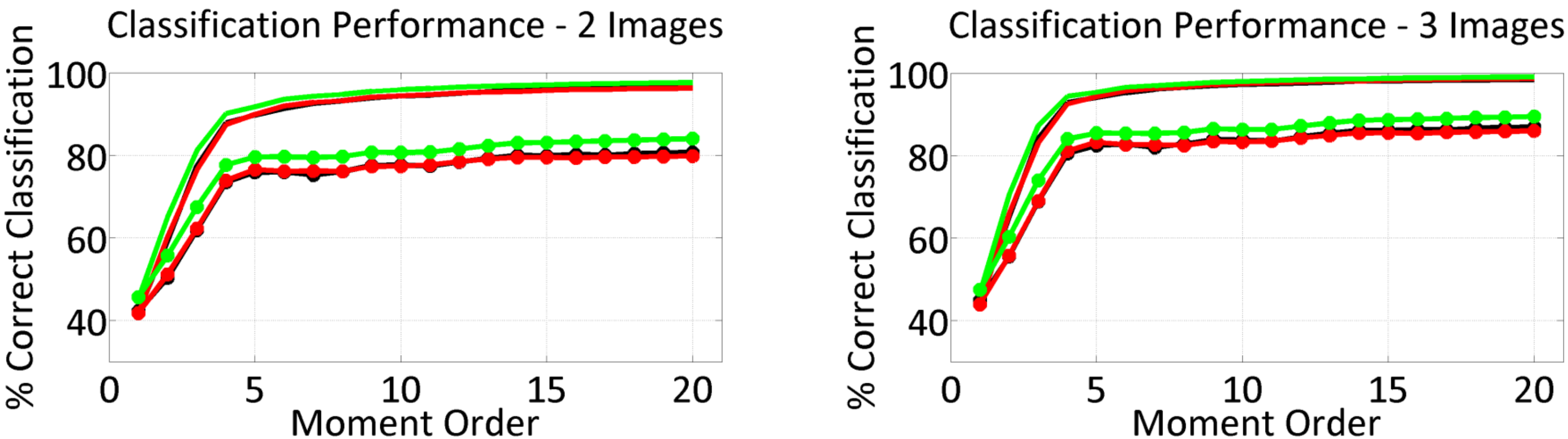


LEGEND

- 10 Training Images: IA, KA, IIK
- 30 Training Images: IA, KA, IIK

RESULTS (2/2)

MULTI SOURCE CLASSIFICATION



LEGEND

- 10 Training Images — IA, KA, IIK
- 30 Training Images — IA, KA, IIK

- Overall better performance, but once more the IIK approach achieves the best results.

SUMMARY

- The percentage of correct classification increases as the moment order increases, whereas the percentage of unknowns decreases.
- The IIK approach presents better performance than both the IA and the KA.
- The best improvements are achieved when the classifier is trained with 10 images.

Conclusions and Future Plans

- A novel automatic target classification algorithm for spatially-separated full-polarimetric SAR images was presented.
- The algorithm achieves better performance than the approach presented in a previous work in terms of both percentage of correct classification and percentage of unknowns.
- It is robust with respect to the relative orientation of the target and to the acquisition elevation angle, and it presents low computation complexity.
- The proposed framework can also be used with time series and multispectral images, as well as in low bit-rate distributed networks.
- Future work will deal with the development of a weighted fusion rule and the computation of optimal weights on varying the SAR depression angle.

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Thank you!

Any Question?

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