Complex-Valued Markov Random Field Based Feature Extraction for InSAR Images

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ABSTRACT

In this paper, complex-valued Markov random field (CMRF) parameters, namely the *interaction strength* and *variance*, which have been previously used for noise reduction in interferograms, are proposed for feature extraction from interferometric SAR (InSAR) images. A comparative performance evaluation has been carried out for feature extraction from InSAR and single-look complex (SLC) SAR images. A patch-based classification is performed for a small database of 3 forest classes. Also, a single image is tiled into small patches and unsupervised clustering is performed. The results are compared to that of another MRF-based complex-valued feature vector which consists of complex-mean and covariances.

INTRODUCTION

Automated understanding and interpretation of SAR images require the extraction of feature descriptors from complex-valued data. Most of the SAR applications make use of only the *amplitude* data ignoring the information hidden in the *phase* data. However, some recent studies take the phase information into account together with the amplitude. For instance, [1] presents the importance of phase data in terms of scattering behavior of targets, and in [2], the whole complex-valued SAR image is used to extract feature descriptors in order to be used for image classification and clustering purposes.

On the other hand, SAR interferometry inherently makes use of the phase difference between more than one complex-valued SAR images acquired from slightly different positions or at different times in order to derive surface topography or observe surface deformation. In this work, InSAR pairs are proposed to be used for feature extraction based on CMRF parameters.

INSAR GENERATION

Given two co-registered complex-valued SAR images of M x N pixels of the same scene, z_{master} and z_{slave}, the interferogram is obtained by :

$$z_{master} = \alpha_1 \cdot e^{j\psi_1}$$

$$z_{slave} = \alpha_2 \cdot e^{j\psi_2}$$

$$I = z_{master} \cdot z^*_{slave} = \alpha_1 \cdot \alpha_2 \cdot e^{j(\psi_1 - \psi_2)}$$

Once the interferogram is generated, the phase due to the curvature of the Earth is removed, i.e., the interferogram is flattened (I_{flat}).

FEATURE DESCRIPTOR BASED ON COMPLEX-VALUED MRF MODEL

Markov random field (MRF) is a well-known appropriate statistical model for parameter estimation of images [3]. According to Markovianity, given an M x N lattice L, the conditional probability that a pixel *s* has the value of z_s depends only on the neighboring pixels, which can be expressed as:

$$P(z_s | z_1, z_2, \ldots, z_{s-1}, z_{s+1}, \ldots, z_{M\times N}) = P(z_s | z_t, t \in N_s)$$

where $t \in N_s$ represents the neighboring pixels of *s*.

In order to model the complex-valued InSAR images based on Markovianity, a complex-valued MRF (CMRF) model is defined by adapting a complex-valued version of Ising model [4]:

$$P(z_s) = \frac{1}{Z} e^{-E_I(z_s)}$$

$$E_I(z_s) = \frac{1}{2\sigma^2}\left(\left| z_s - \sum_{t\in N_s} \Lambda^*_{st}\, z_t \right|^2\right)$$

z_s & z_t : Observed complex values of pixels *s* & *t*
Z : Partition function for normalization
$E_I(z_s)$: Pixel energy
Λ^*_{st} : Interaction strength between pixels *s* & *t*
σ^2 : Variance

For a neighborhood vector Q_s of site *s*, the model parameters Λ^*_{st} and σ^2 are estimated as [4]:

$$\hat{\Lambda}^* = \left[\sum_{s\in\mathcal{L}} z_s\, Q^*_s\right]\left[\sum_{s\in\mathcal{L}} Q_s\, Q^*_s\right]^{-1}$$

$$\hat{\sigma}^2 = \frac{1}{M\times N}\sum_{s\in\mathcal{L}}\left| z_s - \hat{\Lambda}^*\, Q_s \right|^2$$

$$FV_{CMRF} \equiv \left[\hat{\Lambda}^*,\, \hat{\sigma}^2\right]$$

CMRF feature vector for
$z = z_{master}$
$z = I_{flat}$

For performance comparison, complex-valued mean and covariances (CMC parameters) are computed for a patch size of *L* as follows [5]:

$$\mu = \frac{1}{L^2}\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} z_s(i,j)$$

$$K(\xi,\eta) = \frac{1}{L^2}\sum_{i'=0}^{L-1}\sum_{j'=0}^{L-1} z^*_s(i,j)\; z_s(i-\xi, j-\eta)$$

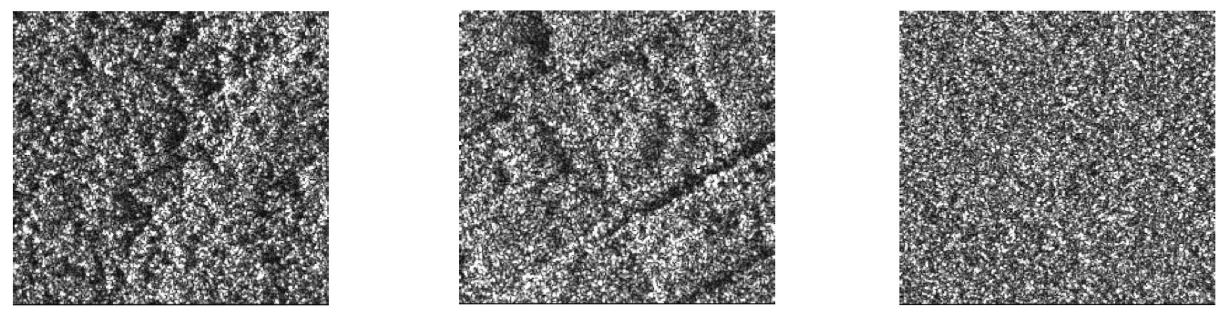
$$FV_{CMC} \equiv [\mu,\, K(0,0),\, K(1,0),\, K(0,1),\, K(1,1)]$$

CMC feature vector for
$z = z_{master}$
$z = I_{flat}$

EXPERIMENTAL RESULTS

1. Patch-based classification

Amazon forests (Brazil) *Forests from Munich-west* *Rain forests (Indonesia)*



- **Database:** 300 patches of size 256 x 256 pixels from 3 different forest classes
- **Feature descriptor:** 2nd order CMRF & CMC parameters from SLC & InSAR images
- **Classifier:** K-nearest neighbor (KNN) classifier with distance rule of Euclidean & k = 1
- **Training samples:** 5% of the samples (randomly chosen)
- The accuracies of 100 different runs for each classification experiment are averaged.

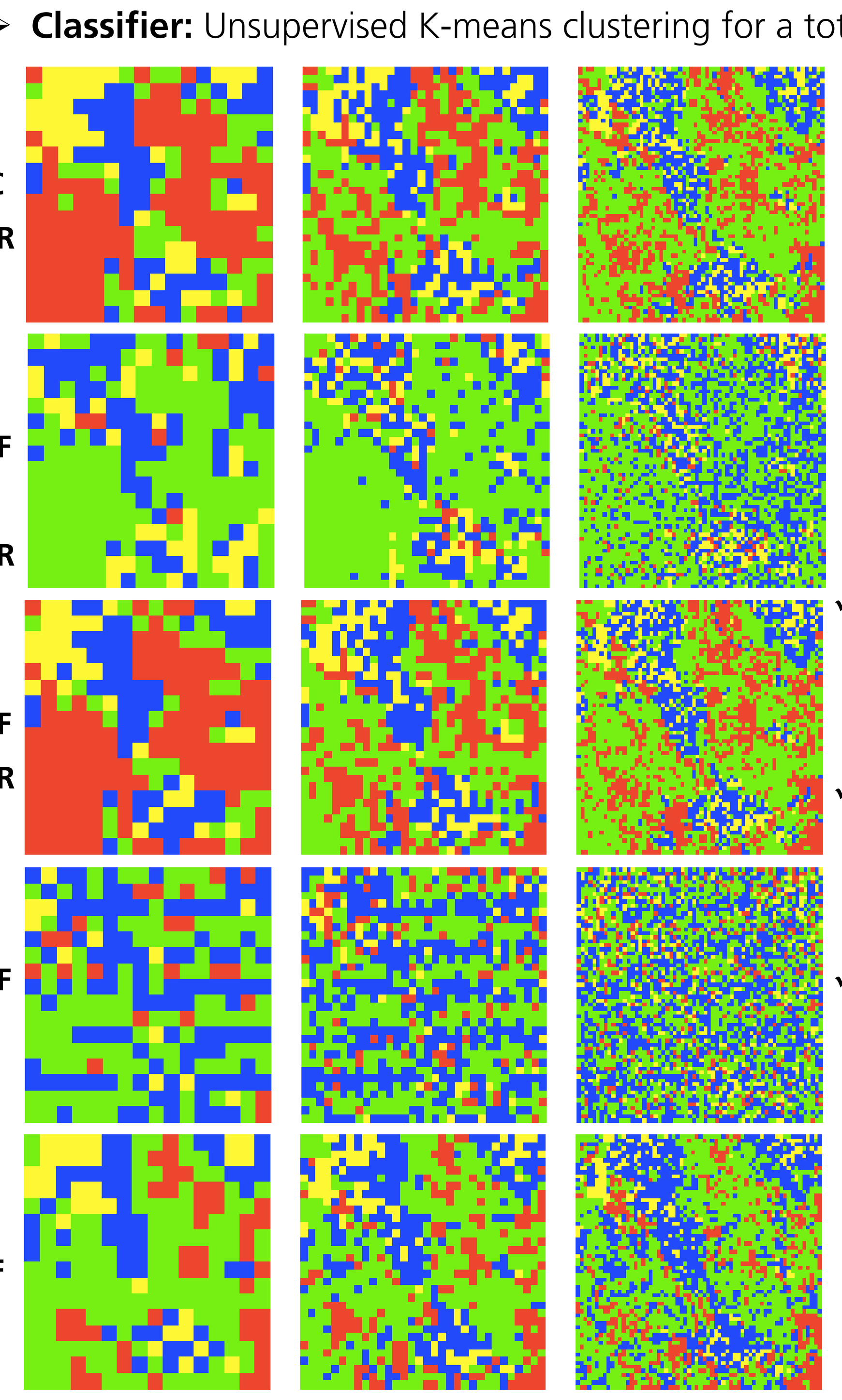
Method	Feature Vector	Class #1 Precision - Recall (%)	Class #2 Precision - Recall (%)	Class #3 Precision - Recall (%)
CMRF InSAR	FV01 = [abs(P1)]	100.0 - 100.0	100.0 - 100.0	100.0 - 100.0
CMRF SLC	FV02 = [abs(P1)]	60.23 - 53.00	58.04 - 65.00	100.0 - 100.0
CMRF InSAR	FV03 = [P1]	100.0 - 100.0	100.0 - 100.0	100.0 - 100.0
CMRF SLC	FV04 = [P1]	100.0 - 100.0	100.0 - 100.0	100.0 - 100.0
CMRF InSAR	FV05 = [abs(P1), log(P2)]	100.0 - 100.0	100.0 - 100.0	100.0 - 100.0
CMRF SLC	FV06 = [abs(P1), log(P2)]	100.0 - 100.0	100.0 - 100.0	100.0 - 100.0
CMRF InSAR	FV07 = [P1, log(P2)]	100.0 - 100.0	100.0 - 100.0	100.0 - 100.0
CMRF SLC	FV08 = [P1, log(P2)]	100.0 - 100.0	100.0 - 100.0	100.0 - 100.0
CMC InSAR	FV09 = log([P1, P2, P3, P4, P5])	59.85 - 79.00	94.79 - 91.00	62.50 - 45.00
CMC SLC	FV10 = log([P1, P2, P3, P4, P5])	77.61 - 52.00	55.14 - 59.00	42.86 - 54.00

- ✓ For both SLC & InSAR images, the use of CMRF interaction strength itself results in a better performance than that of its absolute value.
- ✓ Joint use of CMRF interaction strength & variance improves the classification of SLC images.
- ✓ For both CMC & CMRF, the use of InSAR image results in better classification performance.
- ✓ For both SLC & InSAR images, the performance of CMRF is better than that of CMC.

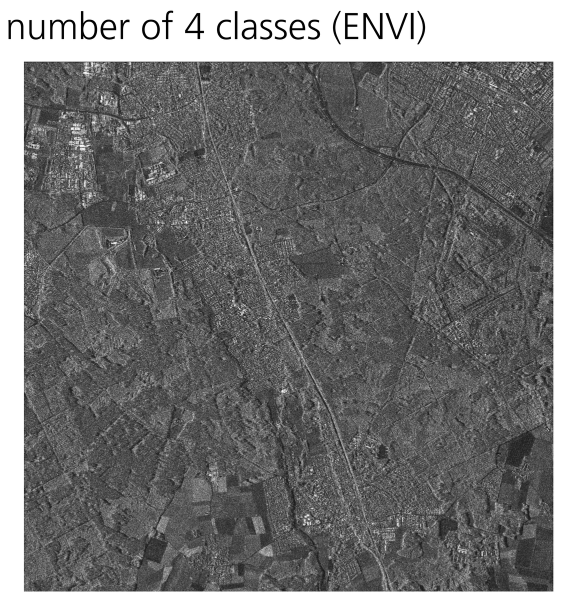
2. Clustering of a single image

- **Image:** 4096 x 4096 pixels from Munich (consists forest, agricultural area, urban)
  The whole image is tiled into L x L blocks (or patches) (L = 64, L = 128 and L = 256)
- **Feature descriptor:** 2nd order CMRF & CMC parameters from InSAR image, 2nd order CMRF parameters from SLC image. (CMC parameters are provided in a log-scale and the absolute value of the complex feature descriptors are used.)
- **Classifier:** Unsupervised K-means clustering for a total number of 4 classes (ENVI)

CMC INSAR
CMRF P1 INSAR
CMRF INSAR
CMRF P1 SLC
CMRF SLC



L = 256 L = 128 L = 64



- ✓ Using only the CMRF interaction strength, InSAR image yields a better performance than SLC image.
- ✓ Addition of the CMRF variance improves the clustering performance in both InSAR & SLC images.
- ✓ The clustering performance of CMC & CMRF are quite close for InSAR image. For a better evaluation, a supervised classification may be utilized. Also, the use of complex-valued feature vector itself instead of its absolute value is expected to enhance the clustering performance.

CONCLUSION AND FUTURE WORK

In this work, the use of InSAR images in feature extraction is emphasized through some experimental results. Also, a comparative study is carried out for two different MRF-based feature descriptors, and of these two, the superiority of CMRF features (interaction strength and variance) over CMC features (mean and covariances) is presented. A successful forest classification with accuracies equal or close to 100% is achieved by CMRF feature vectors. Since the initial results seem to be promising, the experiments will be extended to a larger InSAR database of more number of classes for a wide range of objects. In clustering of a single Munich image, the performance of CMC and CMRF feature vectors are comparable. A supervised classifier may be used for a more sophisticated performance evaluation.

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