MultiTemp 2015
8th International Workshop on the Analysis of Multitemporal Remote Sensing Images
July 22-24, 2015 Annecy, France

Change Detection of PolSAR imagery Using Mixture Model and Analytic Information Theory Divergence

Hui Song[1], Wen Yang[1,2], Xiao Jing Huang[1] and Xin. Xu[1]

[1]Signal Processing Laboratory, School of Electronic Information, Wuhan University, Wuhan 430079, China
[2]State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing (LIESMARS), Wuhan University, Wuhan 430072, China

SPMC http://dsp.whu.edu.cn Wuhan University
Signal Processing and Modern Communication Lab
武漢大學 电子信息学院
Electronic Information School, Wuhan University

OUTLINE

- **Introduction**
- **Proposed Method**
  - Region modeling by mixture models.
  - Analytic information theory divergence.
- **Experimental Results**
- **Conclusion**

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Change Detection Using PolSAR Data

Why using PolSAR data

- Synthetic aperture radar (SAR) remote sensing is currently one of the most effective technologies for a regular observation of the Earth's surface.
- Polarimetric SAR (PolSAR) images can provide more target scattering information, compared to single channel SAR images. Change detection using PolSAR data has shown great potential, such as land cover/land use changes, flooding mapping.

Change Detection of *PolSAR imagery* Using Mixture Model and Analytic Information Theory Divergence

Change Detection Using PolSAR Data

Why using Mixture Model

- Simple distributions (e.g., complex Gaussian for single-look data and complex Wishart for multi-look data) work well for homogeneous regions while complex irregular distributions are needed for modeling heterogeneous regions (e.g., K-$Wishart$, $\mathcal{G}_P^0$, $KummerU$, etc.).
- Learning an irregular distribution is much more complicated.
- Mixture of simple models can approximate complex models while do not increase much computation burden for model learning.

Change Detection of PolSAR imagery Using *Mixture Model* and Analytic Information Theory Divergence

Change Detection Using PolSAR Data

Why using Analytic Information Theory Divergence

- When comparing two mixture models, commonly used divergences such as kullback-leibler, Bhattacharyya, Hellinger, have no close-form expressions, numerical approach is needed.
- Divergence such as Cauchy-Schwarz divergence has analytic expression for exponential family mixture models (e.g., Gaussian, Wishart, etc.), the evaluation is fast and robust.

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Change Detection Using PolSAR Data

Common Change Detection Paradigms

- Unsupervised Change Detection, e.g., labeling of feature maps (different maps, DM)
- Supervised Change Detection, e.g., Comparison of individual classification maps (called Post-Classification Comparison, PCC)

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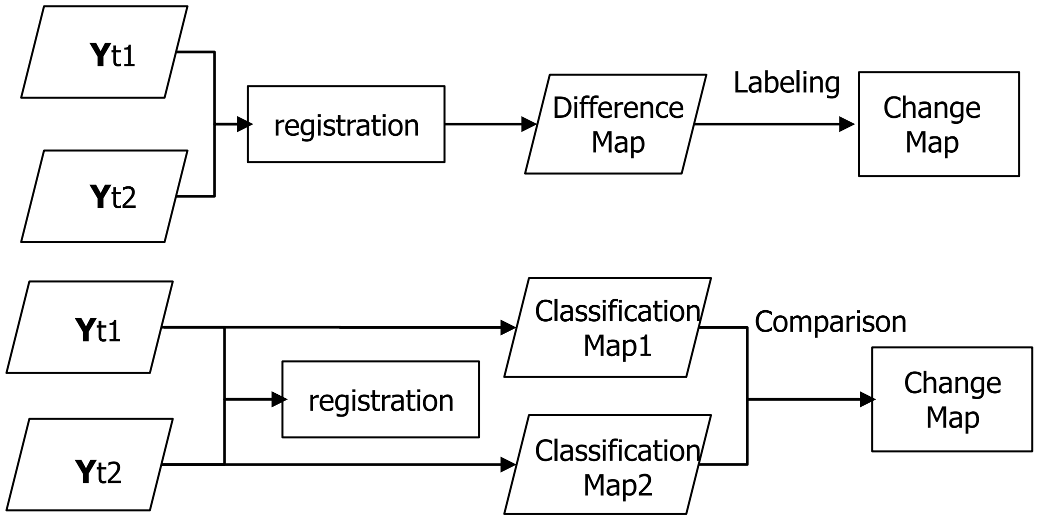

Fig.1 General frameworks of Change Detection for PolSAR images.
Top: Labeling of difference maps, Bottom: Post-Classification Comparison.

Change Detection Using PolSAR Data

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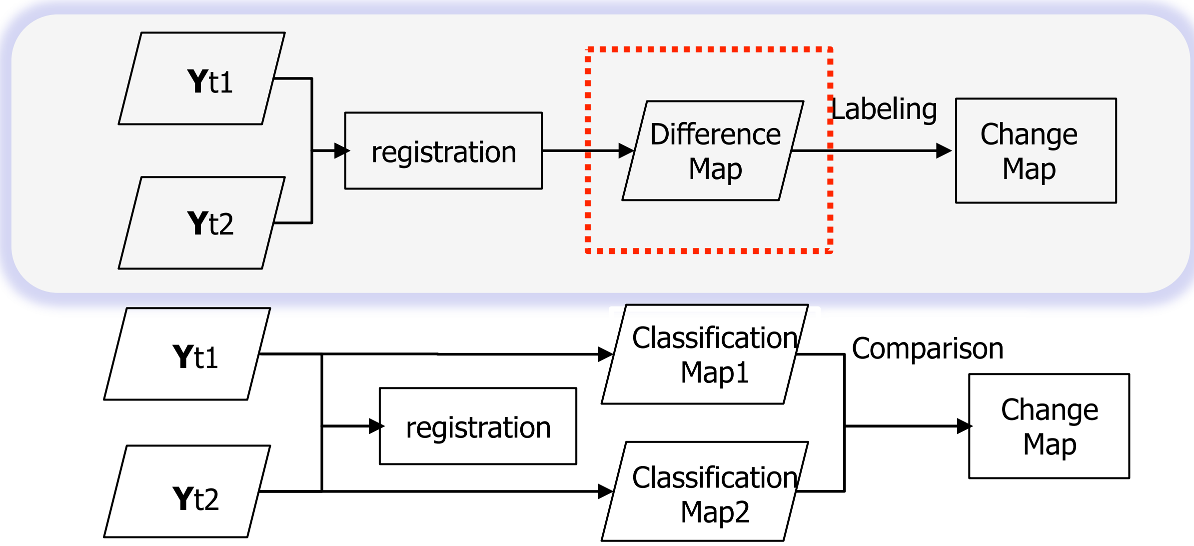

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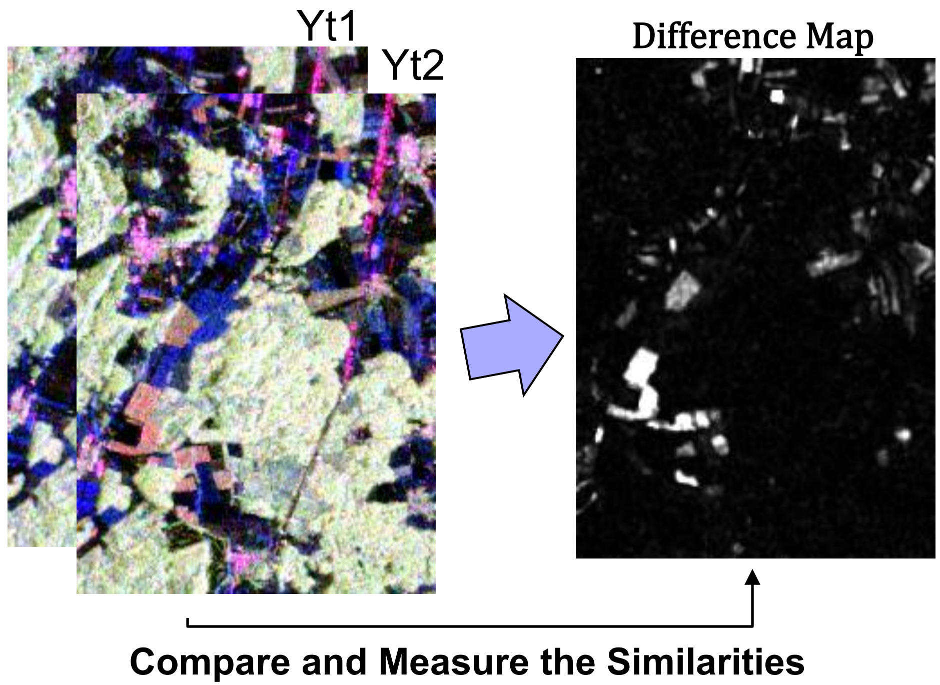
Top: Labeling of difference maps, Bottom: Post-Classification Comparison.

PolSAR images Change Detection: Proposed Method



Region-based Difference Map Generation

- The changes are measured based on local regions rather than pixels.
- Region information is modeled by using mixture model.

It consists of three main steps:

- Segment the multitemporal images into local regions by over-segmentation methods;
- Model each local region by a complex Wishart mixture model;
- For each pair of corresponding local regions, calculate their similarities using analytic information divergence- Cauchy Schwarz divergence.

PolSAR images Change Detection: Proposed Method

Learning the Mixture Model

$$m(X;\Phi)=\sum_{i=1}^{K} \omega_i \, p_F(X;\theta_i)$$

Model parameters $\Phi=(\omega_1, \omega_2, \ldots, \omega_K, \theta_1, \theta_2, \ldots, \theta_K)$

PolSAR images Change Detection: Proposed Method

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Model parameters $\Phi=(\omega_1,\omega_2,\ldots,\omega_K,\theta_1,\theta_2,\ldots,\theta_K)$

The density function of exponential family distribution

$$p(x;\lambda)=p_F(X;\theta)=\exp\{\langle t(x),\theta\rangle-F(\theta)+k(x)\}$$

$t(x)$-the sufficient statistic. F - a convex function called log-normalizer.

PolSAR images Change Detection: Proposed Method

Learning the Mixture Model

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The density function of exponential family distribution

$$p(x;\lambda)=p_F(X;\theta)=\exp\{\langle t(x),\theta\rangle-F(\theta)+k(x)\}$$

$t(x)$ - the sufficient statistic; θ – the natural parameters,
$F(\theta)$ - the log-normalizer; $k(x)$ - the carrier measure

Canonical decomposition of complex Wishart distribution $X \sim \mathcal{W}_C(p,n,\Sigma)$

$$\mathcal{W}_d(X;n,\Sigma)=\exp(\underbrace{\langle -X, n\Sigma^{-1}\rangle_F+\langle \log|X|, n\rangle}_{\langle t(x),\theta\rangle} - \underbrace{(\log\Gamma_d(n)+n\log|\Sigma|-dn\log n)}_{F(\theta)} - \underbrace{d\log|X|}_{-k(x)})$$

$$\begin{cases} t(X)=(\log|X|,-X) \\ \theta=(\theta_S,\Theta_M)=(n,n\Sigma^{-1}) \end{cases}$$

PolSAR images Change Detection: Proposed Method

Learning the Mixture Model

$$m(X;\Phi)=\sum_{i=1}^{K}\omega_i \, p_F(X;\theta_i)$$

A global learning scheme

- Learning a mixture model for the whole data set.
- Fix the component parameters and fit the mixture model for each local region.

The complex average log-likelihood of the mixture of exponential family densities

$$L(x_1, z_1, \dots, x_n, z_n \mid \omega, \theta) = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{K}\delta_j(z_i)\left(\log p_F(x_i \mid \theta_j) + lo\right.$$

PolSAR images Change Detection: Proposed Method

$L(x_1, z_1, \ldots, x_n, z_n; \omega, \theta) = 1/n \sum_{i=1}^{n} \sum_{j=1}^{K} \delta$

Learning the Mixture Model

Generic *k*-MLE for learning an exponential mixture model (Nielsen *et al.*)

0. **Initialization:** $\forall i \in \{i, \ldots, K\}$, let $\omega_i = 1/K$ and $\eta_i = t(x_i)$;

1. **Assignment:** $\forall i \in \{i, \ldots, n\}$, $z_i = \max_{1 \le j \le k} (\log p_F(x_i; \theta_j) + \log \omega_j)$; the cluster partition $\forall i \in \{i, \ldots, K\}$, $C_i = \{x_j \mid z_j = i\}$ and $\mathcal{X} = \bigcup_{i=1}^{K} C_i$;

2. **Update the $\boldsymbol{\eta}$ parameters:** $\eta_i = 1/|C_i| \sum_{x \in C_i} t(x_i)$.

   Goto step 1 unless local convergence of the complete likelihood is reached.

3 **Update the mixture weights:** $\forall i \in \{i, \ldots, K\}$, let $\omega_i = 1/|C_i|$.

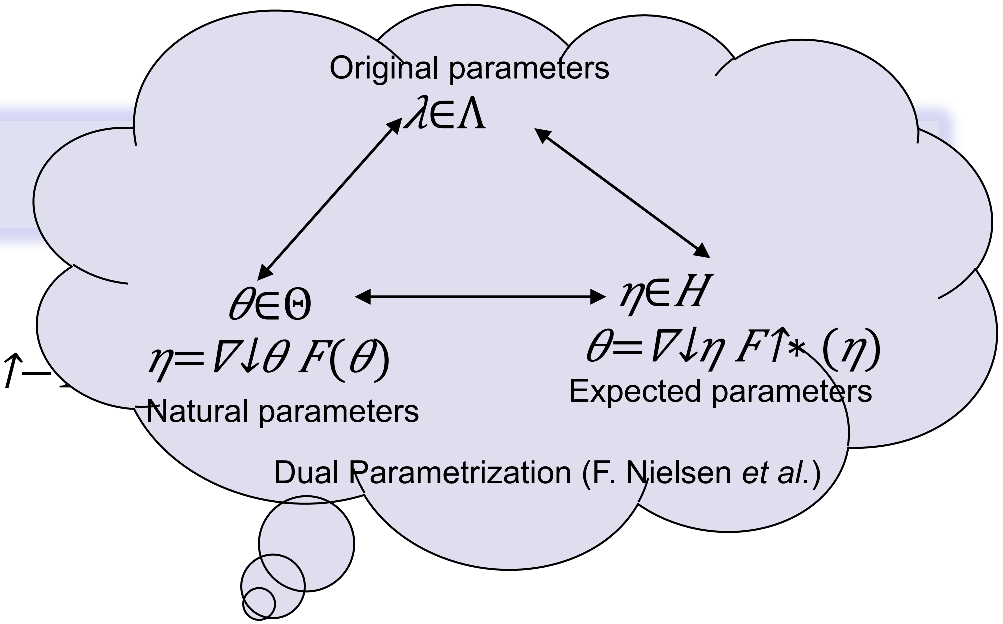
   Goto step 1 unless local convergence of the complete likelihood is reached.

Frank Nielsen, k-MLE: A fast algorithm for learning statistical mixture models, in *Proc.ICASSP* 2012

PolSAR images Change Detection: Proposed Method

The Wishart Mixture Model

$$m(X;\Phi)=\sum_{i=1}^{K}\omega_i\, p_F(X;\theta_i)$$



Parameter Estimation

$$t(X)=(\log|X|,-X) \quad \theta=(\theta_S,\Theta_M)=(n, n\Sigma^{-1} \ldots$$

$$\eta_i=\frac{1}{|C_i|}\sum_{x\in C_i} t(x_i)$$

$$\eta_M=-\theta_S\Theta_M^{-1} \quad \eta_s=\sum_{j=1}^{p}\Psi(\theta_S \ldots$$

PolSAR images Change Detection: Proposed Method

The Cauchy Schwarz divergence

$$d_{CS}(p||q) = -\log \frac{\int p(x)q(x)dx}{\sqrt{\int p(x)^2 dx \int q(x)^2 dx}}$$

It has analytic expression for mixture of exponential family densities

The mixture product term $\int m(x)m'(x)dx$

$$\int m(x)m'(x)dx = \sum_{i=1}^{k}\sum_{j=1}^{k'} \omega_i \omega'_j \int p_F(x;\theta_i)\, p_F(x;\theta'_j)\, dx$$
$$= \sum_{i=1}^{k}\sum_{j=1}^{k'} \omega_i \omega'_j \exp\{F(\theta_i + \theta'_j) - (F(\theta_i) + F(\theta'_j))\}$$

Frank Nielsen, Closed-form information-theoretic divergences for statistical mixtures, In *Proc. ICPR 2012*.

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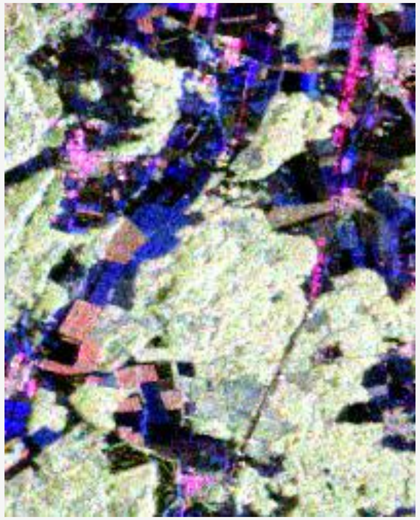
PolSAR images Change Detection: Experimental Results

Experimental Settings

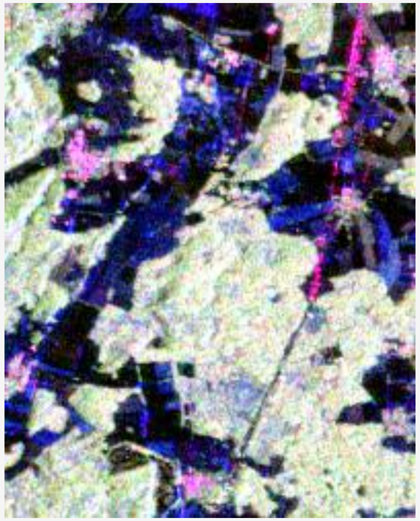
Algorithms:

- Pixel-level change detection approach that use the Bartlett distance
- Region-based change detection approach that use mixture model and Cauchy-Schwarz divergence.

Experimental Data



(a)



(b)

(c)

ALOS PALSAR data acquired in Hochstadt, Germany.

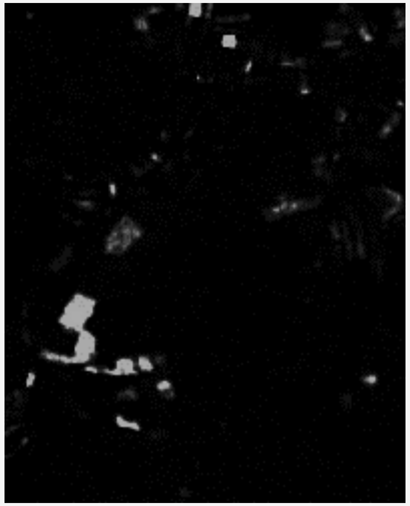
(a) Sep. 3, 2006;

(b) Apr. 2, 2007;

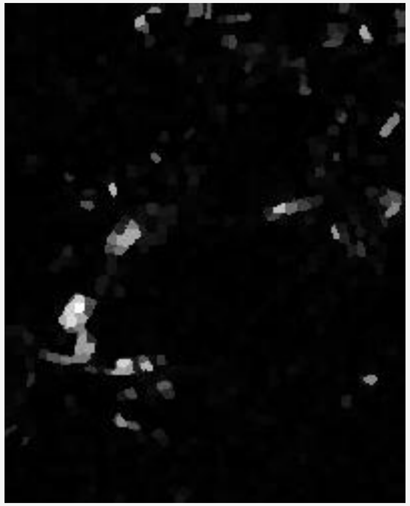
(c) The ground truth map of changed areas.

PolSAR images Change Detection: Experimental Results

Experimental Results (1)

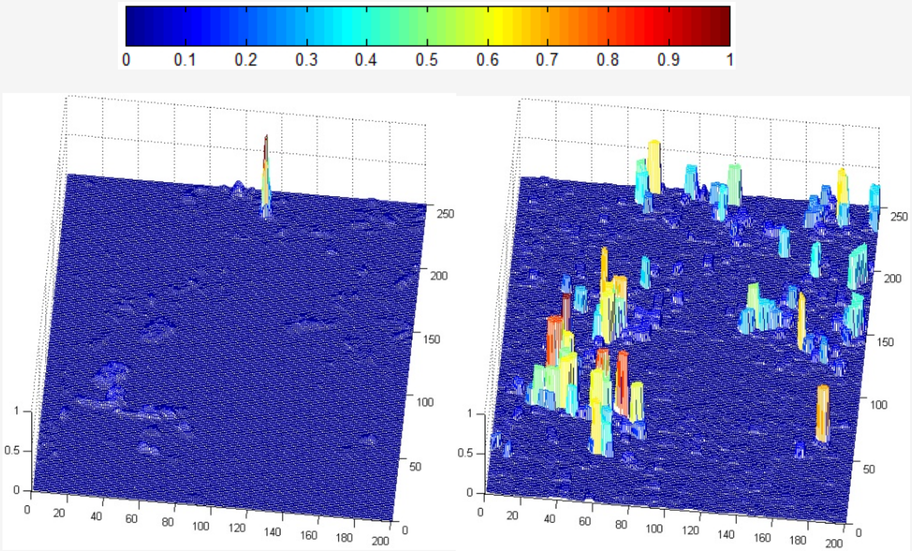


(a)



(b)

The difference maps generated by two schemes. (a) pixel-level DM. (b) region-based DM.

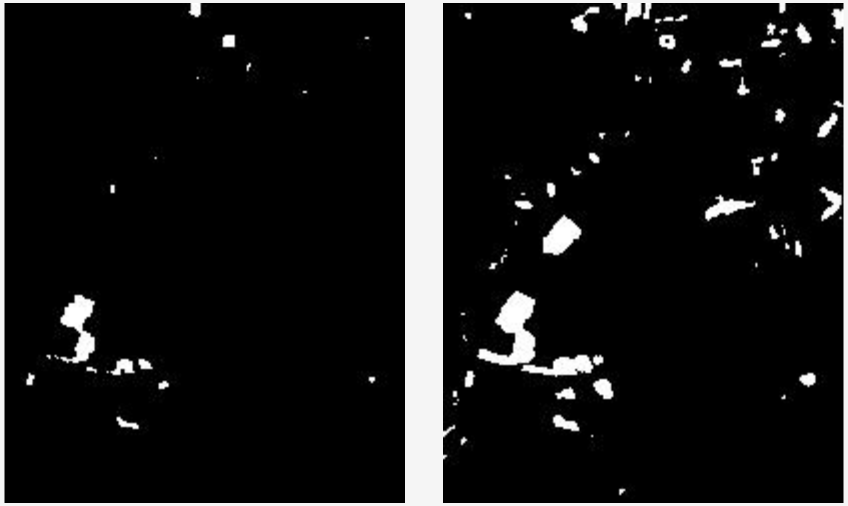


(c) (d)

3D plots of the two difference maps. They are adjusted to [0, 1] by linear mapping. (a) pixel-level DM. (b) region-based DM.

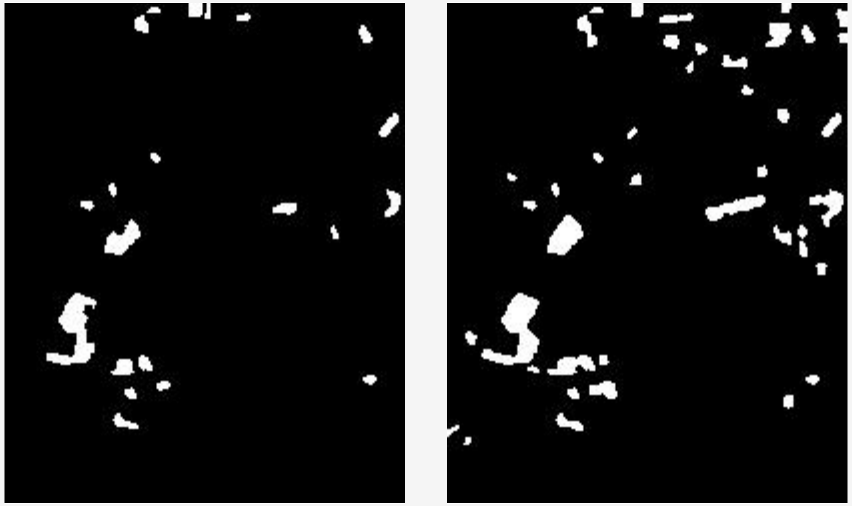
PolSAR images Change Detection: Experimental Results

Experimental Results (2)



(a) (b)

Results of pixel-level approach with Bartlett distance. (a) the initial segment obtained by K&I approach. (b) final result after MRF smoothing.

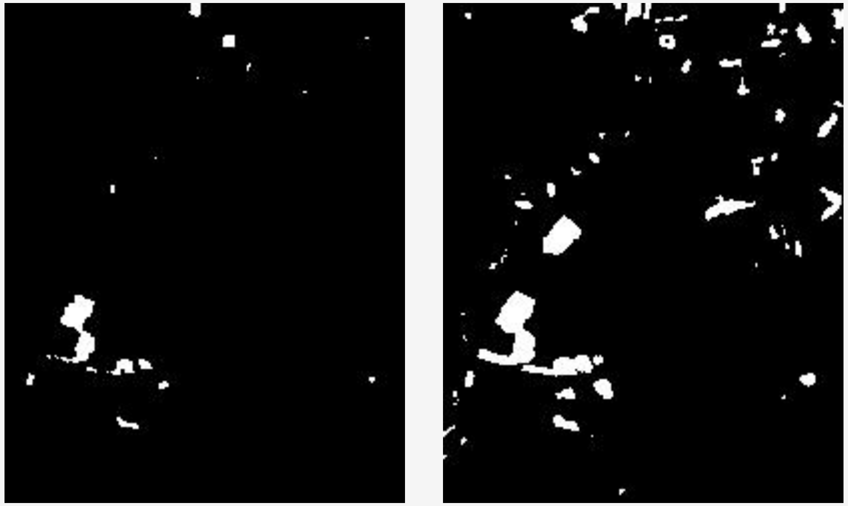


(c) (d)

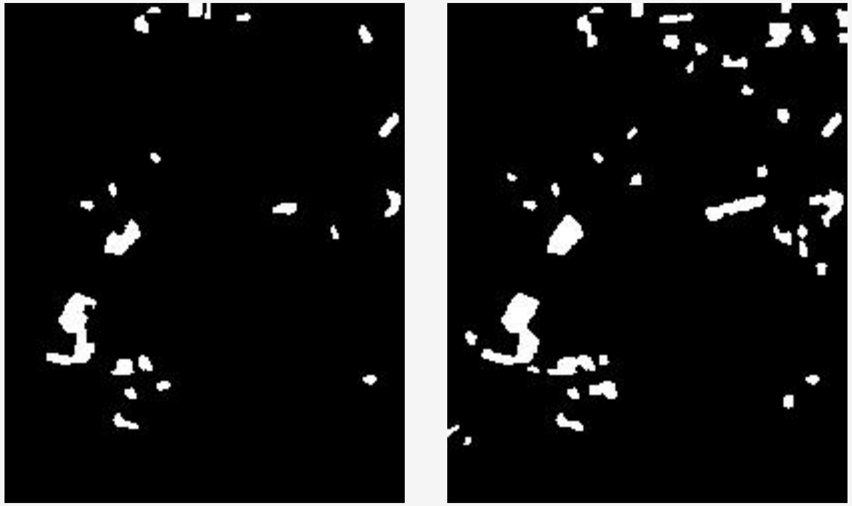
Results of the proposed region-based approach. (a) the initial segment obtained by K&I approach. (b) final result after MRF smoothing.

PolSAR images Change Detection: Experimental Results

Experimental Results (2)



(a) (b)



(c) (d)

Results of pixel-level approach with Bartlett measure. (a K&I approa smoothing.

Results of the proposed region-based btained ter MRF g

Method	Pu(%)	Pc(%)	OA(%)	Kappa
dB+MRF	99.20	68.57	97.55	0.7379
dCS+MRF	99.43	79.72	98.37	0.8319

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PolSAR images Change Detection: Conclusions

Summary

- Compared with the pixel-level approaches, the proposed region bassed scheme is more robust for noise.
- We modeled the local regions by mixture models, i.e., the complex Wishart mixture model and employed a fast and robust parameter estimation approach-kMLE for learning the model.
- The difference map is derived by using the analytic information theory divergence-Cauchy Schwarz (CS) divergence that measures the differences of corresponding mixture models.

PolSAR images Change Detection: Conclusions

Outlook

- The proposed approach involves some parameters, such as the size of the local regions, the number of components for the mixture models, etc. In our experiments, we set them to some empirical values, automatic optimal parameter selection should be exploited.
- Optimal segmentation of the Difference Map is still an open issue, and the parametric segmentation model we adopted is experimental, non-parametric decision methods such as a-contrario approach may be more suitable.
- Besides, we compare the similarities only in single scale, multi-scale information should be considered.
- More experiments should be done to test the performance of the proposed method.

Main References

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Thanks for your time!
Comments and Questions?