Fusion of Evidences in Intensity Channels for Edge Detection in PolSAR Images

Ongoing researches

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International Seminar on Advances in SAR Image Processing Technologies
March 29, 2021
9:00 Brasilia time
13:00 Rome time
17:30 Mumbai time
20:00 Beijing time
Zoom link: https://bit.ly/2NpcEeO
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Inter-institutional cooperation projects

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Ibmec

Database (PolSAR Image)

PolSAR Data

Table 1: Information from the PolSAR system.

Polarization	hh	hv	vv
hh	σ_{hh}	$\Re\big(\text{Cov}(\text{hh},\text{hv})\big) + \Im\big(\text{Cov}(\text{hh},\text{hv})\big)\hat{\jmath}$	$\Re\big(\text{Cov}(\text{hh},\text{vv})\big) + \Im\big(\text{Cov}(\text{hh},\text{vv})\big)\hat{\jmath}$
hv	-	σ_{hv}	$\Re\big(\text{Cov}(\text{hv},\text{vv})\big) + \Im\big(\text{Cov}(\text{hv},\text{vv})\big)\hat{\jmath}$
vv	-	-	σ_{vv}

Table 2: PolSAR intensity channels.

C_1	C_2	C_3
σ_{hh}	σ_{hv}	σ_{vv}

Image channels.

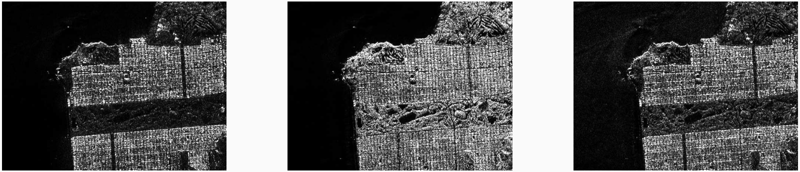


Figure 1: PolSAR images with polarization hh, hv e vv.

General Idea.

Fusion scheme

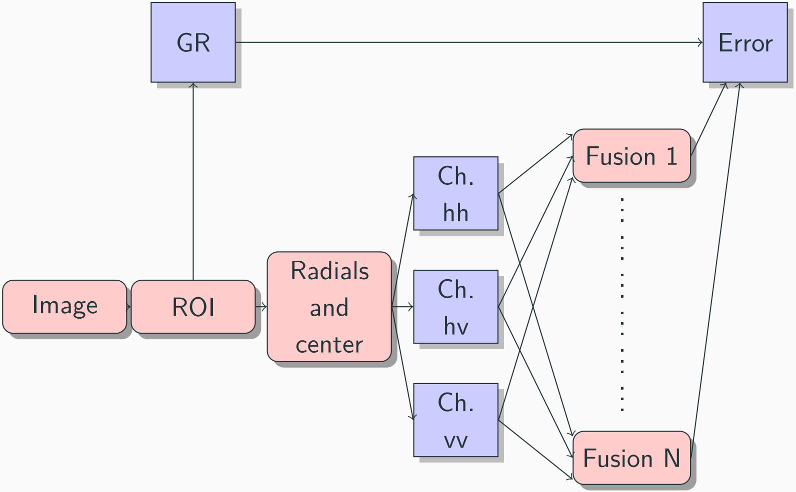


Figure 2: Fusion Scheme

Statistical modeling for PolSAR data (1 - Look)

- The complex scattering matrix **S**:

$$\mathbf{S} = \begin{bmatrix} S_{\mathrm{hh}} & S_{\mathrm{hv}} \\ S_{\mathrm{vv}} & S_{\mathrm{vv}} \end{bmatrix}. \tag{1}$$

- The medium of propagation of waves is reciprocal

$$\mathbf{s} = [S_{\mathrm{hh}}, S_{\mathrm{hv}}, S_{\mathrm{vv}}]^T.$$

Statistical modeling for PolSAR data (L - Looks) - Speckle

- The estimated sample covariance matrix:

$$\mathbf{Z} = \frac{1}{\mathsf{L}} \sum_{\ell=1}^{\mathsf{L}} \mathbf{s}_\ell {\mathbf{s}_\ell}^{\mathsf{H}}, \tag{2}$$

  - $\mathbf{s}_\ell$, $\ell = 1, \ldots, \mathsf{L}$;
  - L independent samples of complex vectors distributed as $\mathbf{s}$.
  - H denotes the conjugate complex number,

Statistical Modeling

The marginal distribution for intensity channel

$$f_Z(z;\mu,\mathsf{L}) = \frac{\mathsf{L}^{\mathsf{L}}}{\Gamma(\mathsf{L})\mu^{\mathsf{L}}} z^{\mathsf{L}-1} \exp\left\{-\frac{\mathsf{L}}{\mu}z\right\}, \tag{3}$$

where, $\mu > 0$ e $\mathsf{L} > 0$.

Apply natural logarithm,

$$\ln f_Z(z;\mu,\mathsf{L}) = \mathsf{L}\ln\frac{\mathsf{L}}{\mu} - \ln\Gamma(\mathsf{L}) + (\mathsf{L}-1)\ln z - \frac{\mathsf{L}}{\mu}z. \tag{4}$$

Statistical Modeling

MLE – Maximum Likelihood Estimator.

- Let a PolSAR image sample $\boldsymbol{z} = (z_1, \ldots, z_n)$.
- The log-likelihood is defined by,

$$\mathcal{L}(\boldsymbol{z}; \mu, \mathrm{L}) = \ln \prod_{k=1}^{n} f_Z(z_k; \mu, \mathrm{L})$$

$$\mathcal{L}(\boldsymbol{z}; \mu, \mathrm{L}) = \sum_{k=1}^{n} \ln f_Z(z_k; \mu, \mathrm{L}).$$

- Then,

$$\mathcal{L}(\boldsymbol{z}; \mu, \mathrm{L}) = n \left[\mathrm{L} \ln \frac{\mathrm{L}}{\mu} - \ln \Gamma(\mathrm{L}) \right] + \mathrm{L} \sum_{k=1}^{n} \ln z_k - \frac{\mathrm{L}}{\mu} \sum_{k=1}^{n} z_k. \tag{5}$$

OBS: Is it a flat function? Yes!!!!! (BFGS optimization is used.).

MLE – Maximum Likelihood Estimator.

- Splitting

$$\boldsymbol{z} = (\underbrace{z_1, z_2, \ldots, z_j}_{\boldsymbol{z}_{\mathrm{I}}}, \underbrace{z_{j+1}, z_{j+2}, \ldots, z_n}_{\boldsymbol{z}_{\mathrm{E}}}),$$

- Two models

$$\boldsymbol{Z}_{\mathrm{I}} \sim \Gamma(\mu_{\mathrm{I}}, \mathrm{L}_{\mathrm{I}}),$$

and,

$$\boldsymbol{Z}_{\mathrm{E}} \sim \Gamma(\mu_{\mathrm{E}}, \mathrm{L}_{\mathrm{E}}).$$

- To estimate the parameters we use the BFGS method

Statistical Modeling

MLE – The total log-likelihood is defined at pixel j by,

$$
\begin{aligned}
&\mathcal{L}(j;\widehat{\mu}_I,\widehat{\mathsf{L}}_I,\widehat{\mu}_E,\widehat{\mathsf{L}}_E) = \\
&\quad j\Big[\widehat{\mathsf{L}}_{\mathsf{I}}\ln(\widehat{\mathsf{L}}_{\mathsf{I}}/\widehat{\mu}_{\mathsf{I}}) - \ln\Gamma(\widehat{\mathsf{L}}_{\mathsf{I}})\Big] + \widehat{\mathsf{L}}_{\mathsf{I}}\sum_{k=1}^{j}\ln z_k - \frac{\widehat{\mathsf{L}}_{\mathsf{I}}}{\widehat{\mu}_{\mathsf{I}}}\sum_{k=1}^{j} z_k + \\
&\quad (n-j)\Big[\widehat{\mathsf{L}}_{\mathsf{E}}\ln(\widehat{\mathsf{L}}_{\mathsf{E}}/\widehat{\mu}_{\mathsf{E}}) - \ln\Gamma(\widehat{\mathsf{L}}_{\mathsf{E}})\Big] \\
&\quad + \widehat{\mathsf{L}}_{\mathsf{E}}\sum_{k=j+1}^{n}\ln z_k - \frac{\widehat{\mathsf{L}}_{\mathsf{E}}}{\widehat{\mu}_{\mathsf{E}}}\sum_{k=j+1}^{n} z_k,
\end{aligned}
\tag{6}
$$

$$
\widehat{\jmath} = \arg\max_{j\in[\min_s, N-\min_s]} \mathcal{L}(j;\widehat{\mu}_I,\widehat{\mathsf{L}}_I,\widehat{\mu}_E,\widehat{\mathsf{L}}_E),
$$

- Is it a non-differentiable function? Yes! GenSA.
- Are there oscillations in the extremities of the function? Yes! (Set a margin).

Evidence edge detection: Gambini Algorithm

for *Channel* $1 \leq c \leq n_c$ **do**

  for *Radial* **do**

    $\boldsymbol{z} = (z_1, z_2, \ldots, z_n) \leftarrow$ data collected around the radial;

    for $\min_s \leq j \leq n - \min_s$ **do**

      Splitting the sample as $\boldsymbol{z}_{\mathrm{I}} = (z_{\min_s}, \ldots, z_j)$ e $\boldsymbol{z}_{\mathrm{E}} = (z_{j+1}, \ldots, z_{n-\min_s})$;

      Compute $\left(\widehat{\mu}_{\mathrm{I}}, \widehat{\mathrm{L}}_{\mathrm{I}}\right)$ com $\boldsymbol{z}_{\mathrm{I}}$, e $\left(\widehat{\mu}_{\mathrm{E}}, \widehat{\mathrm{L}}_{\mathrm{E}}\right)$ com $\boldsymbol{z}_{\mathrm{E}}$;

      Compute the total log-likelihood at j with $\mathcal{L}\big(j; \widehat{\mu}_I, \widehat{\mathrm{L}}_I, \widehat{\mu}_E, \widehat{\mathrm{L}}_E\big)$;

    end

    $\widehat{\jmath} \leftarrow$ The value of j which maximizes the total log-likelihood function;

    return $(\widehat{x}, \widehat{y})$, the coordinates of each $\widehat{\jmath}$;

  end

  return The binary image $\widehat{\boldsymbol{\jmath}}_c$ with 1 at every $(\widehat{x}, \widehat{y})$, and 0 otherwise.

end

Evidence edge detection

Example with 25 radials in the ROI of the Flevoland image

Figure 3: Detection of evidence of edges in the channel hh.

Simple average Fusion – MS

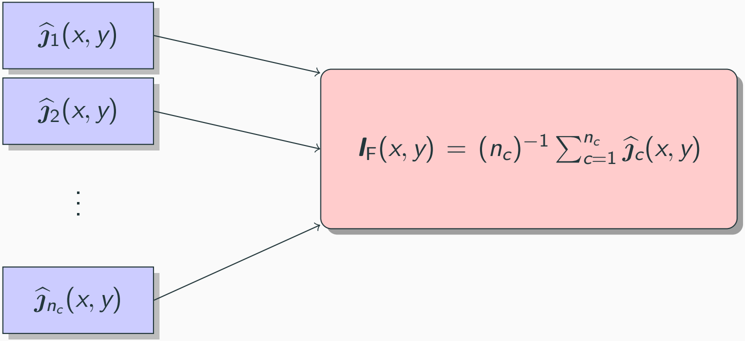


Figure 4: Simple average Fusion.

Fusion methods to edge detection

Discrete wavelet multi-resolution fusion – MR-DWT

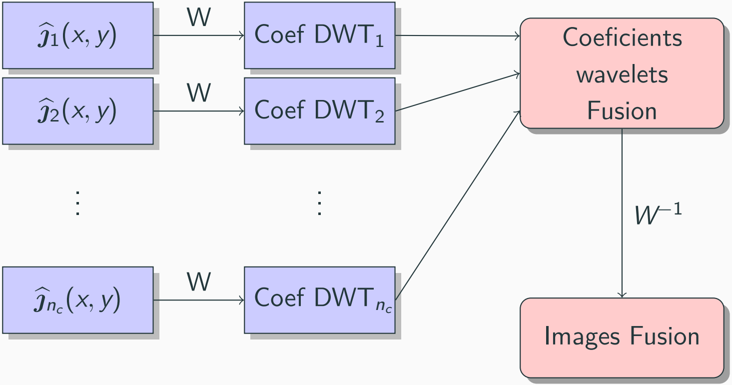


Figure 5: MR–DWT Fusion

- W is a wavelet transform.

Stationary wavelet multi-resolution fusion – MR-SWT

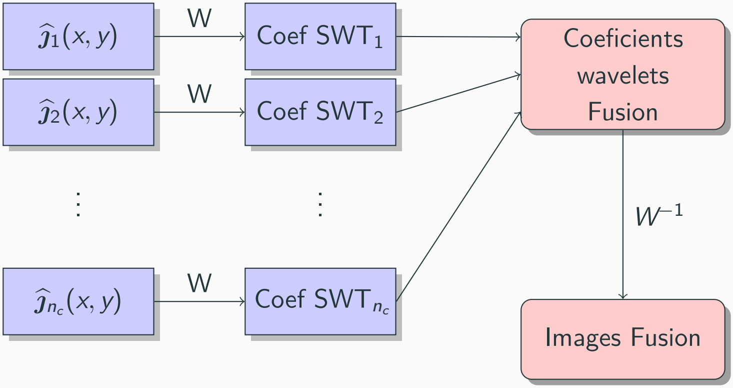


Figure 6: MR–SWT fusion.

- W is a wavelet transform.

Fusion methods to edge detection

PCA Fusion

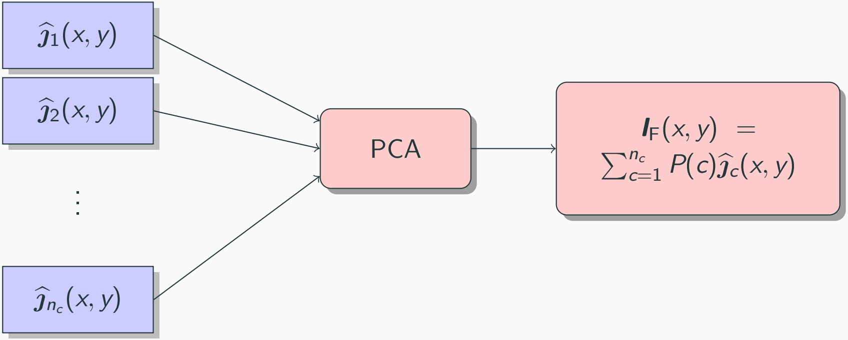


Figure 7: PCA Fusion.

Fusion methods to edge detection

ROC Fusion

- Parte I

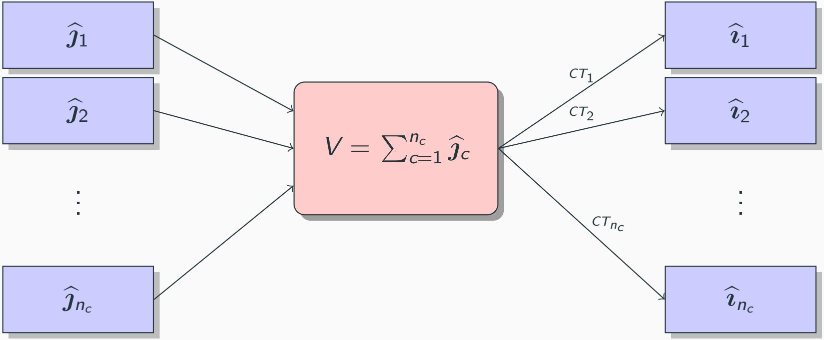


Figure 8: Fusion based in ROC statistics – Part I.

- CT_c are thresholds.

Fusion methods to edge detection

ROC fusion

- Part II - For each $\widehat{\imath}_t$

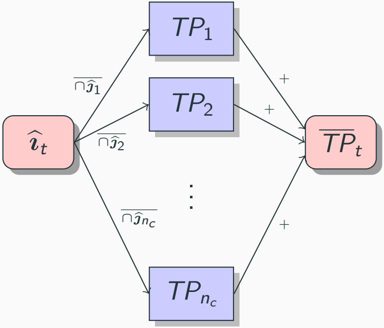


Figure 9: ROC fusion for each t. Similar to $\overline{TN}_t$,$\overline{FP}_t$ and, $\overline{FN}_t$.

- This generates the confusion matrix to calculate the ROC statistic.

Fusion Based in the multi-resolution SVD decomposition – MR-SVD

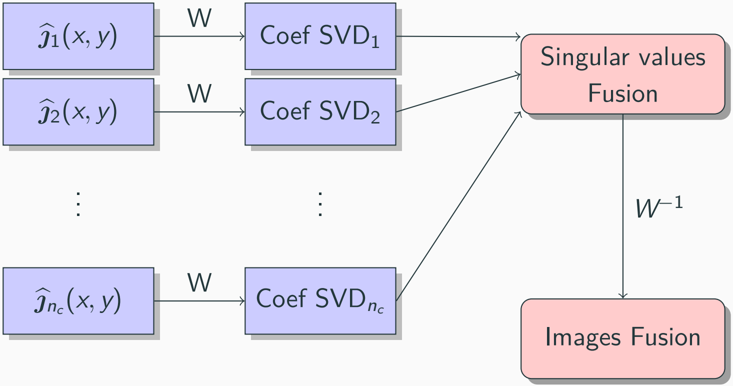


Figure 10: MR–SVD fusion

- W is a SVD decomposition.

Results

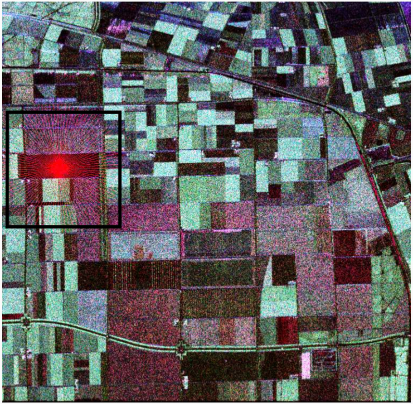
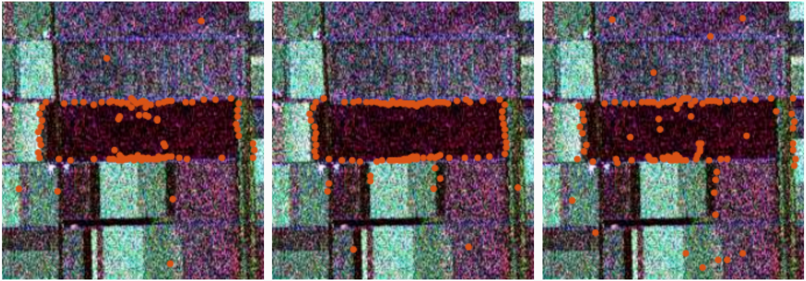


Figure 11: Region of interest (ROI) in the image of Flevoland.

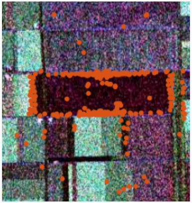
FLEV-ROI-I



(a) Channel hh (b) Channel hv (c) Channel vv

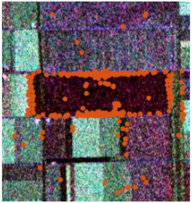
Figure 12: Edge evidence to FLEV-ROI-I

FLEV-ROI-I Fusion

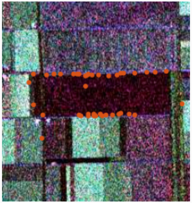


(a) Average

(b) MR-DWT

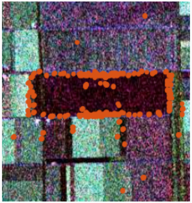


(c) PCA



(d) E-ROC

(e) MR-SWT



(f) MR-SVD

Results

FLEV-ROI-I

Table 3: Processing time for fusion methods

Met.	Average	PCA	MR-DWT	MR-SWT	ROC	MR-SVD
T(s)	0.0095	0.0186	0.109	0.187	0.457	1.168
TR.	1.00	2.05	12.03	20.66	50.31	128.52

Reproducibility and replicability

Platforms, and computational resources

- R Language.
- Matlab Language.
- Computer Intel© Core i7-9750HQ CPU 2.6 GHz with 16 GB of the RAM memory.

Reproducibility and replicability

- https://github.com/anderborba/Code_GRSL_2020_1.

Conclusions, and discussions

Conclusions, and discussions

- Fusion of edge evidence detected in intensity channels is feasible.
- BFGS works very well on flat functions.
- GenSA works very well on non-differentiable functions.
- Empirical definition of the margins to maximize the log-likelihood function
- The diversity of information in each channel justifies the use of fusion methods. Which are the best channels?
- Fusion evidence of detected edges can be extended to more channels or other marginal distributions..
- PCA and MR-SVD fusion methods show good results. (Outliers, time and importance measure for each channel).

Future research

Future research

- Increase the number of channels or density distribution functions to find the edges evidence. This is possible because fully polarimetric data is richer than intensity channels;
- Propose new fusion techniques for edge evidence (Investigate ROC better, insert more channels and PDFs);
- Improve measures for leveraging or discarding channels in the fusion method;
- Verify the fusion methods by inserting texture in the models;
- Classify the PolSAR image regions, and use the proposed ideas to refine edge detection (Machine learning or Pattern recognize);
- Post-processing, both for the partial edge evidence detection methods, and also for the edge evidence fusion methods.

Publications

Publications

- Conference:
  - A. A. de Borba, M. Marengoni, and A. C. Frery, "Fusion of Evidences for Edge Detection in PolSAR Images," in 2019 IEEE Recent Advances in Geoscience and Remote Sensing: Technologies, Standards and Applications (TENGARSS), Kochi, Kerala, India, Oct. 2019, pp. 80–85, `doi:10.1109/TENGARSS48957.2019.8976040`.
- Scientific journals:
  - A. A. de Borba, M. Marengoni, and A. C. Frery, "Fusion of Evidences in Intensities Channels for Edge Detection in PolSAR Images," *IEEE Geoscience and Remote Sensing Letters*, in press, 2020, `doi:10.1109/LGRS.2020.3022511`.

Thanks to everyone!!!!

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