

## AUTHOR QUERIES

### AUTHOR PLEASE ANSWER ALL QUERIES

**PLEASE NOTE:** We cannot accept new source files as corrections for your article. If possible, please annotate the PDF proof we have sent you with your corrections and upload it via the Author Gateway. Alternatively, you may send us your corrections in list format. You may also upload revised graphics via the Author Gateway.

Carefully check the page proofs (and coordinate with all authors); additional changes or updates WILL NOT be accepted after the article is published online/print in its final form. Please check author names and affiliations, funding, as well as the overall article for any errors prior to sending in your author proof corrections.

- 1) Please be aware that authors are required to pay overlength page charges (\$230 per page) if the article is longer than 3 pages. If you cannot pay any or all of these charges please let us know. GRS Society members receive a discounted rate of \$200 per page.
- 2) This pdf contains 2 proofs. The first half is the version that will appear on Xplore. The second half is the version that will appear in print. If you have any figures to print in color, they will be in color in both proofs.
- 3) The “Open Access” option for your article expires when the article is published on Xplore in an issue with page numbers. Articles in “Early Access” may be changed to Open Access. If you have not completed your electronic copyright form (ECF) and payment option please return to Scholar One “Transfer Center.” In the Transfer Center you will click on “Manuscripts with Decisions” link. You will see your article details and under the “Actions” column click “Transfer Copyright.” From the ECF it will direct you to the payment portal to select your payment options and then return to ECF for copyright submission.

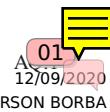
AQ:1 = Please check whether the edit made to the article title is appropriate.

AQ:2 = Please provide the expansions for ROC, BFGS, and AIRSAR.

AQ:3 = Please confirm or add details for any funding or financial support for the research of this article.

AQ:4 = Please confirm whether the corresponding author has been identified correctly.

AQ:5 = Please check and confirm whether the affiliation details of all the authors are correct as set.



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

Anderson A. De Borba<sup>ID</sup>, Maurício Marengoni, and Alejandro C. Frery<sup>ID</sup>, *Senior Member, IEEE*

**Abstract**—Polarimetric synthetic aperture radar (PolSAR) sensors have reached an essential position in remote sensing. The images they provide have speckle noise, making their processing and analysis challenging tasks. We discuss an edge detection method based on the fusion of evidences obtained in the intensity channels hh, hv, and vv of PolSAR multilook images. The method consists of detecting transition points in the thinnest possible range of data that covers two regions using maximum likelihood under the Wishart distribution. The fusion methods used are: simple average, multiresolution discrete wavelet transform (MR-DWT), principal component analysis (PCA), ROC statistics, multiresolution stationary wavelet transform (MR-SWT), and a multiresolution method based on singular value decomposition (MR-SVD). A quantitative analysis suggests that PCA and MR-SVD provide the best results.

**Index Terms**—Edge detection, fusion methods, maximum likelihood estimation, polarimetric synthetic aperture radar (PolSAR).

## I. INTRODUCTION

POLARIMETRIC synthetic aperture radar (PolSAR) has achieved an essential position in remote sensing. The data such sensors provide require specifically tailored signal processing techniques. Among such techniques, edge detection is one of the most important operations for extracting information. Edges are at a higher level of abstraction than mere data and, as such, provide relevant insights about the scene.

Among the available edge detection techniques for SAR and PolSAR images, it is worth mentioning: techniques based on denoising [1]–[4]; Markov random fields [5]; the deep learning approach [6] applied to segmentation and classification; and statistical techniques [7]–[9] applied in edge detection in PolSAR and SAR imagery.

This letter follows the statistical modeling approach using the techniques described in [7]–[9] to find edge evidences, followed by fusion processes [10], [11].

Instead of handling fully polarimetric data, we treat each intensity channel separately, obtain evidence of edges, and

Manuscript received March 24, 2020; revised July 12, 2020; accepted August 31, 2020. (*Corresponding author: Anderson A. De Borba*)

Anderson A. De Borba is with the Department of Engenharia Elétrica e Computação, Universidade Presbiteriana Mackenzie (UPM), São Paulo 01302-907, Brazil, and also with IBMEC-SP, São Paulo 01419-002, Brazil (e-mail: anderson.aborba@professores.ibmec.edu.br).

Maurício Marengoni is with the Department of Engenharia Elétrica e Computação, Universidade Presbiteriana Mackenzie (UPM), São Paulo 01302-907, Brazil (e-mail: mauricio.marengoni@mackenzie.br).

Alejandro C. Frery is with the School of Mathematics and Statistics, Victoria University of Wellington, Wellington 6140, New Zealand (e-mail: alejandro.frery@vuw.ac.nz).

Color versions of one or more of the figures in this letter are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/LGRS.2020.3022511

then produce a single estimator of the edge position. With this, we quantify the contribution each channel provides to the solution of the problem.

The Gambini Algorithm [12] is an attractive edge detection technique. It is local, as it finds evidence of an edge over a thin strip of data; it works with any model, which makes it suitable for SAR data; and it has shown better performance than other approaches. This algorithm consists in casting rays, and then finding the evidence of an edge in the ray by maximizing a value function. We use the total likelihood of two samples: one inside the edge and another outside the edge. Without loss of generality, we assume the complex scaled Wishart distribution for the fully polarimetric observations, from which Gamma laws stem for each intensity channel. The value function depends on the estimates that index such Gamma laws; and we estimate them by maximum likelihood.

The total likelihood function is nondifferentiable at most points, and classical methods have difficulties in finding its maximum. We used the generalized simulated annealing (GenSA) [13] method to solve this problem.

We discuss and compare six fusion methods: Simple average [10], multiresolution discrete wavelet (MR-DWT) [14], principal component analysis (PCA) [10], [14], ROC statistics [15], multiresolution stationary wavelet transform (MR-SWT) [14], [16], and multiresolution singular value decomposition (MR-SVD) [17].

The letter is structured as follows: Section II describes the models, Section III describes the edge detection, Section IV describes the approaches for fusing edge evidences, Section V presents the results, and in Section VI we discuss the results and outline future research directions.

## II. STATISTICAL MODELING FOR POLSAR DATA

Multilooked fully polarimetric data follow the Wishart distribution with probability density function (PDF) defined by:

$$f_{\mathbf{Z}}(\mathbf{z}; \Sigma, L) = \frac{L^{pL} |\mathbf{z}|^{L-p}}{|\Sigma|^L \Gamma_p(L)} \exp(-L \text{tr}(\Sigma^{-1} \mathbf{z})) \quad (1)$$

where  $\mathbf{z}$  is a positive-definite Hermitian matrix,  $L$  is the number of looks,  $\text{tr}(\cdot)$  is the trace operator of a matrix,  $\Gamma_p(L)$  is the multivariate Gamma function defined by  $\Gamma_p(L) = \pi^{1/2p(p-1)} \prod_{i=0}^{p-1} \Gamma(L-i)$ , and  $\Gamma(\cdot)$  is the Gamma function. We used three  $p = 3$  channels in this study. This situation is denoted by  $\mathbf{Z} \sim W(\Sigma, L)$ , which satisfies  $E[\mathbf{Z}] = \Sigma$ . This assumption usually holds for fully developed speckle but, since we will estimate  $L$  locally instead of considering the same number of looks for the whole image, we will in part take into account departures from such hypothesis.

Since we are interested in describing the information conveyed by parts of such matrix under the Wishart model, we assume that the distribution of each intensity channel is a Gamma law with PDF

$$f_Z(z; \mu, L) = \frac{L^L z^{L-1}}{\mu^L \Gamma(L)} \exp\{-Lz/\mu\}, \quad z > 0 \quad (2)$$

where  $L > 0$ , and  $\mu > 0$  is the mean. The log-likelihood of the sample  $z = (z_1, \dots, z_n)$  under this model is

$$\begin{aligned} \mathcal{L}(\mu, L; z) = n[L \ln(L/\mu) - \ln \Gamma(L)] \\ + L \sum_{k=1}^n \ln z_k - \frac{L}{\mu} \sum_{k=1}^n z_k. \end{aligned} \quad (3)$$

We obtain  $(\hat{\mu}, \hat{L})$ , the maximum likelihood estimator (MLE) of  $(\mu, L)$  based on  $z$ , by maximizing (3) with BFGS method [18]. We prefer optimization to solving  $\nabla \mathcal{L} = \mathbf{0}$  for improved numerical stability.

### III. EDGE DETECTION ON A SINGLE DATA STRIP

The Gambini algorithm estimates the point at which the properties of a sample change. It has been used with stochastic distances [9] and with the likelihood function [7], [8] for edge detection in SAR/PolSAR imagery. It can be adapted to any suitable measure of dissimilarity between two samples.

The algorithm starts by casting rays from a point inside the candidate region, e.g., the centroid. Data are collected around each ray to form the sample  $z = (z_1, z_2, \dots, z_n)$ , which is partitioned at position  $j$

$$z = (\underbrace{z_1, z_2, \dots, z_j}_{z_I}, \underbrace{z_{j+1}, z_{j+2}, \dots, z_n}_{z_E}).$$

We assume two (possibly) different models for each partition:  $Z_I \sim \Gamma(\mu_I, L_I)$ , and  $Z_E \sim \Gamma(\mu_E, L_E)$ . We then estimate  $(\mu_I, L_I)$  and  $(\mu_E, L_E)$  with  $z_I$  and  $z_E$ , respectively, by maximizing (3), and obtain  $(\hat{\mu}_I, \hat{L}_I)$  and  $(\hat{\mu}_E, \hat{L}_E)$ .

We then compute the total log-likelihood of  $z_I$  and  $z_E$

$$\begin{aligned} \mathcal{L}(j; \hat{\mu}_I, \hat{L}_I, \hat{\mu}_E, \hat{L}_E) \\ = - \left( \hat{\mu}_I \sum_{k=1}^j z_k + \hat{\mu}_E \sum_{k=j+1}^n z_k \right) \\ + j[\hat{L}_I \ln(\hat{L}_I/\hat{\mu}_I) - \ln \Gamma(\hat{L}_I)] + \hat{L}_I \sum_{k=1}^j \ln z_k \\ + (n-j)[\hat{L}_E \ln(\hat{L}_E/\hat{\mu}_E) - \ln \Gamma(\hat{L}_E)] + \hat{L}_E \sum_{k=j+1}^n \ln z_k. \end{aligned} \quad (4)$$

and the estimate of the edge position on the ray is the coordinate  $\hat{j}$  which maximizes it.

Algorithm 1 is the pseudocode of the basic edge detection with the Gambini Algorithm. We found that 100 rays is a good compromise between spatial continuity and computational load. Also,  $\min_s$  is the minimum sample size.

In our implementation, we replace the exhaustive sequential search (the innermost **for** loop) by GenSA [13].

---

**Algorithm 1** Gambini Algorithm for Intensity Channels

---

**Data:**  $n_c$  intensity channels, interior point, number of rays  
**Result:**  $n_c$  binary images with evidences of edges  
**for** each band  $1 \leq c \leq n_c$  **do**  
  **for** each ray passing through the interior point **do**  
     $z = (z_1, z_2, \dots, z_n) \leftarrow$  data collected around the ray;  
    **for** each  $\min_s \leq j \leq n - \min_s$  **do**  
      Partition the sample as  $z_I = (z_{\min_s}, \dots, z_j)$  and  $z_E = (z_{j+1}, \dots, z_{n-\min_s})$ ;  
      Compute  $(\hat{\mu}_I, \hat{L}_I)$  with  $z_I$ , and  $(\hat{\mu}_E, \hat{L}_E)$  with  $z_E$ ;  
      Compute the total log-likelihood at  $j$  as  $\mathcal{L}(j; \hat{\mu}_I, \hat{L}_I, \hat{\mu}_E, \hat{L}_E)$ ;  
    **end**  
     $\hat{j} \leftarrow$  the value of  $j$  which maximizes the total log-likelihood function;  
    **return**  $(\hat{x}, \hat{y})$ , the coordinates of each  $\hat{j}$ ;  
  **end**  
  **return** the binary image  $\hat{J}_c$  with 1 at every  $(\hat{x}, \hat{y})$ , and 0 otherwise.

---

### IV. FUSION OF EVIDENCES

Assume we have  $n_c$  binary images  $\{\hat{J}_c\}_{1 \leq c \leq n_c}$  in which 1 denotes an estimate of edge and 0 otherwise. They have common size  $m \times n$ ; denote  $\ell = mn$ . These images will be fused to obtain the binary image  $I_F$ .

We compare the results of six fusion techniques: simple average, MR-DWT, PCA, ROC statistics, MR-SWT, and MR-SVD.

#### A. Simple Average

The simple average fusion method proposes the arithmetic mean of the edge evidence in each of the  $n_c$  channels:  $I_F(x, y) = (n_c)^{-1} \sum_{c=1}^{n_c} \hat{J}_c(x, y)$ , where  $1 \leq x \leq m$  indexes the rows, and  $1 \leq y \leq n$  the columns of the image.

#### B. Multiresolution Discrete Wavelet

This section is based on [14]. We apply DWT filters on each binary image  $\hat{J}_c$ : a low-pass filter  $L$  in the vertical direction, and a high-pass filter  $H$  in the horizontal direction, then both are downsampled to create the coefficient matrices  $\hat{J}_{cL}$  and  $\hat{J}_{cH}$ . These operations are repeated on the coefficient matrices, leading to  $\hat{J}_{cLL}$ ,  $\hat{J}_{cLH}$ ,  $\hat{J}_{cHL}$ , and  $\hat{J}_{cHH}$ . We, thus, use two resolution levels.

The DWT fusion method has the following steps.

- 1) Calculate the DWT decomposition  $\hat{J}_{cLL}$ ,  $\hat{J}_{cLH}$ ,  $\hat{J}_{cHL}$ , and  $\hat{J}_{cHH}$ , for each channel.
- 2) Compute  $\bar{J}_{cHH}$ , the pixel-wise mean of all  $\hat{J}_{cHH}$  decompositions.
- 3) Find the pixel-wise maximum of  $\hat{J}_{cLL}$ ,  $\hat{J}_{cLH}$ ,  $\hat{J}_{cHL}$ :  $\bar{J}_{cLL}$ ,  $\bar{J}_{cLH}$ , and  $\bar{J}_{cHL}$ .
- 4) The result of the fusion  $I_F$  is the inverse DWT transform of the coefficient matrices  $\bar{J}_{cHH}$ ,  $\bar{J}_{cLL}$ ,  $\bar{J}_{cLH}$ , and  $\bar{J}_{cHL}$ .

155 C. Principal Component Analysis

This section is based on [10], [14]. The method comprises of the following steps.

- 158 1) Stack the binary images  $\widehat{J}_c$  in column vectors to obtain  
 159 the matrix  $X_{\ell \times n_c}$ .

160 2) Calculate the covariance matrix  $C_{n_c \times n_c}$  of  $X_{\ell \times n_c}$ .

161 3) Compute the matrices of eigenvalues ( $\Lambda$ ) and eigenvectors ( $V$ ) of the covariance matrix, sorted in decreasing  
 162 order by the eigenvalues.

163 4) Compute the vector  $P = (P(1), \dots, P(n_c)) =$   
 164  $(\sum_{c=1}^{n_c} V(c))^{-1}V$ , where  $V$  is eigenvector associated  
 165 with the highest eigenvalue of  $C_{n_c \times n_c}$ ; notice that  
 166  $\sum_{c=1}^{n_c} P(c) = 1$ .

167 5) Fuse  $I_F(x, y) = \sum_{c=1}^{n_c} P(c)\widehat{J}_c(x, y)$ .

169 *D. ROC Statistics*

The ROC method was proposed and described on [15].

- 171 1) Add the binary images  $\widehat{J}_c$  to produce the frequency  
172 matrix ( $V$ ).  
173 2) Use thresholds ranging from  $t = 1, \dots, n_c$  on  $V$  to  
174 generate matrices  $M_t$ .  
175 3) Compare each  $M_t$  with all  $\widehat{J}_c$ , find the confusion matrix  
176 to generate the ROC curve. The optimal threshold cor-  
177 responds to the point of the ROC curve closest (in the  
178 sense of the Euclidean distance) to the diagnostic line.  
179 4) The fusion  $I_F$  is the matrix  $M_t$  which corresponds to  
180 the optimal threshold.

181 *E. Multiresolution Stationary Wavelet Transform*

This section is based on [14], [16]. The difference between MR-DWT and MR-SWT method is the replacement of the DWT by the SWT.

185 *F. Multiresolution Singular Value Decomposition*

MR-SVD fusion [17] works similar to MR-DWT. The MR-SVD fusion method can be summarized as follows.

- 1) Organize the binary image  $\widehat{J}_c$  as nonoverlapping  $2 \times 2$  blocks, and arrange each block as a  $4 \times 1$  vector by stacking columns to form the data matrix  $X_1$  with dimension  $4 \times \ell/4$ .

2) Find the SVD decomposition of  $X_1 = U_1 S_1 V_1^T$ , where  $U_1$  is a  $4 \times 4$  unitary matrix,  $S_1$  is a  $4 \times \ell/4$  rectangular diagonal matrix known as singular values matrix, and  $V_1$  is an  $\ell/4 \times \ell/4$  unitary matrix. The singular values are ordered in a decreasing order.

3) Transform the lines of  $\widehat{X}_1 = U_1^T X_1 = S_1 V_1^T$  into new matrices with dimensions  $m/2 \times n/2$ :  $\{\Phi_1, \Psi_{1V}, \Psi_{1H}, \Psi_{1D}\}$ .

4) Repeat the procedure (1) on  $\Phi_r$  by  $r = 2$  up to the lowest resolution level  $R$ .

5) The MR-SVD decomposition in each channel is

$$\widehat{X}_c \rightarrow \{\Phi_R^c, \{\Psi_{rV}^c, \Psi_{rH}^c, \Psi_{rD}^c\}_{r=1}^R, \{U_r^c\}_{r=1}^R\}.$$

6) Once the decomposition is applied to all channels, compute the average of  $\Phi_R^c$  ( $\Phi_R^f$ ) in the lowest resolution

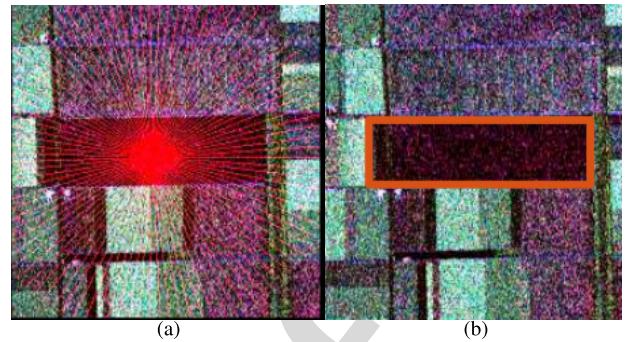


Fig. 1. Flevoland image in Pauli decomposition, and ground reference.  
 (a) Image and rays. (b) Ground reference.

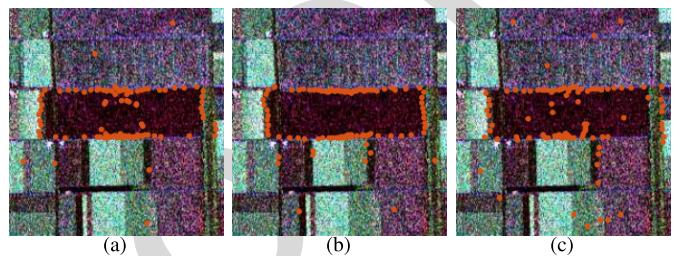


Fig. 2. Edges evidences from the three intensity channels. (a) Channel hh. (b) Channel hv. (c) Channel vv.

level, and the average of  $U_r^c$  ( $U_r^f$ ), for each  $r$ , where  $f$  denotes the fusion among channels.

- 7) Find the pixel-wise maxima of  $\Psi_{rV}^c$ ,  $\Psi_{rH}^c$ , and  $\Psi_{rD}^c$ :  
 $\Psi_{rV}^f$ ,  $\Psi_{rV}^f$ ,  $\Psi_{rH}^f$ , and  $\Psi_{rD}^f$ .

8) The fusion  $I_F$  is the SVD transformation for each level  
 $r = R, \dots, 1$ ,

$$I_F \leftarrow \{ \Phi_R^f, \{ \Psi_{rV}^f, \Psi_{rH}^f, \Psi_{rD}^f \}_{r=R}^1, \{ U_r^f \}_{r=R}^1 \}.$$

We also used two resolution levels.

## V. RESULTS

### *A. Flevoland Images*

Fig. 1(a) shows a  $750 \times 1024$  pixels AIRSAR PolSAR image of Flevoland, L-band, with the radial lines where edges are detected. Fig. 1(b) shows the ground reference in red.

Fig. 2(a)–(c) shows, respectively, the edge evidences in the hh, hv and vv channels as obtained by MLE.

It is worth noting that GenSA has accurately identified the maximum value of  $\mathcal{L}$  [See (4)], even in the presence of multiple local maxima. A visual assessment leads to conclude that the best results are provided by hv, although with a few points far from the actual edge.

Fig. 3(a)–(f) shows the results of fusing these evidences.

Simple average and PCA produce similar results. MR-SVD produces considerably less outliers than the other methods. ROC produces accurate edges, with few outliers, but sparsely. Both wavelet-based methods (DWT and SWT) produce too dense edges and many outliers.

Fig. 4 shows another region in the Flevoland image. In this case, it is a bright target surrounded by darker fields. Fig. 5 shows the edges detected in each intensity channel and, again, the hv data are the one which produce the most accurate results.

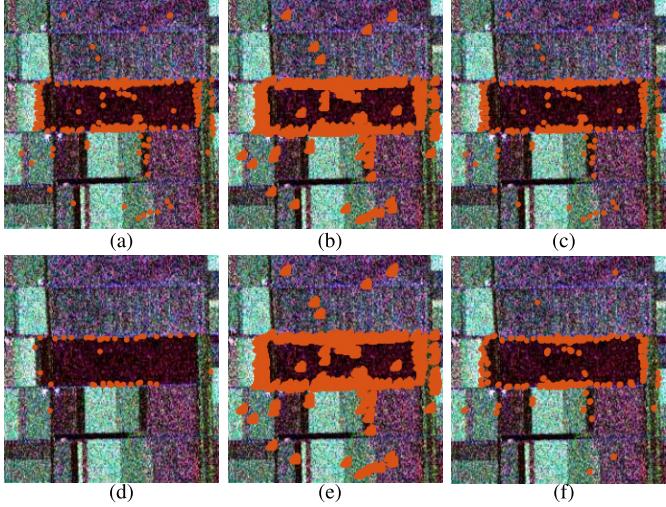


Fig. 3. Results of applying the six fusion methods. (a) Average fusion. (b) MR-DWT fusion. (c) PCA fusion. (d) ROC fusion. (e) MR-SWT fusion. (f) MR-SVD fusion.

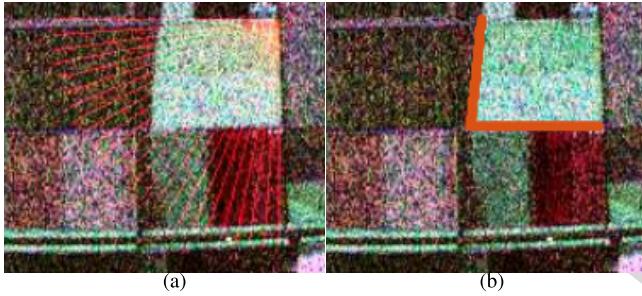


Fig. 4. Flevoland image in Pauli decomposition, and ground reference. (a) Image and rays. (b) Ground reference.

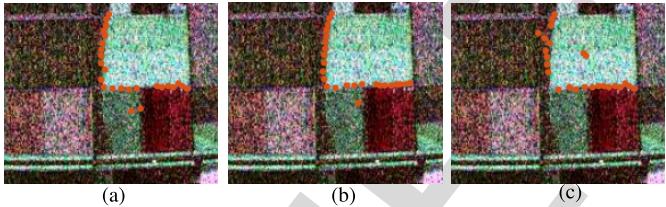


Fig. 5. Edges evidences from the three intensity channels, Flevoland image. (a) Channel hh. (b) Channel hv. (c) Channel vv.

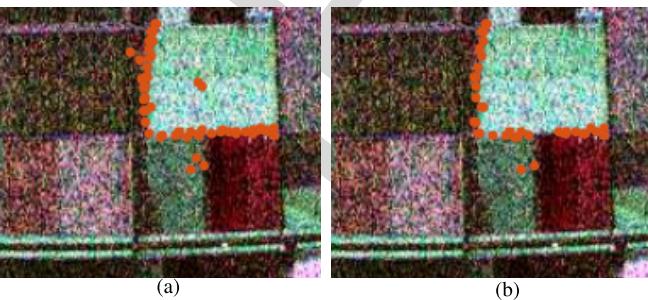


Fig. 6. Two best fusion results in the Flevoland image. (a) PCA fusion. (b) MR-SVD fusion.

237 Fig. 6 shows the two best fusion results: PCA and MR-  
238 SVD. Notice that the latter [Fig. 6(b)] eliminates the wrong  
239 detection close to the center of the area and has fewer wrongly  
240 detected points outside the region of interest.

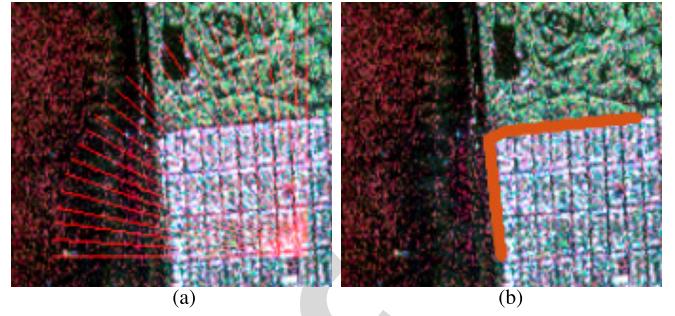


Fig. 7. San Francisco image in Pauli decomposition, and ground reference. (a) Image and rays. (b) Ground reference.

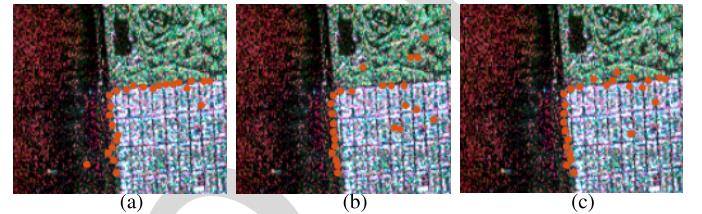


Fig. 8. Edges evidences from the three intensity channels to San Francisco. (a) Channel hh. (b) Channel hv. (c) Channel vv.

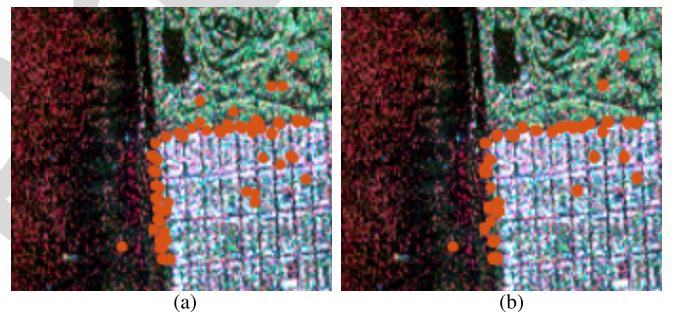


Fig. 9. Two best fusion results in the San Francisco image. (a) PCA fusion. (b) MR-SVD fusion.

### B. San Francisco Image

241 Fig. 7 shows an area of an L-band AIRSAR image over San  
242 Francisco. The distinctive areas are urban, sea, and vegetation.  
243 The aim is finding the edge between the former and the other  
244 two.

245 Fig. 8 shows the evidences of edges found in each of the  
246 three intensity channels. A visual inspection suggests that the  
247 hh channel is the one that produces the best estimation.

248 Fig. 9 shows the two best fusion results: PCA and MR-SVD.  
249 Again, the latter is more resistant to outliers, both inside and  
250 outside the region of interest.

### C. Error Analysis

251 Fig. 10 shows the error of  $\hat{f}$  in finding the true edge shown  
252 in Fig. 1(b), as measured on 100 lines with the minimum  
253 Euclidean distance between the ground truth and the detected  
254 pixel in the fusion methods. We use relative frequencies to  
255 estimate the probability of having an error smaller than a  
256 number of pixels. Denoting  $H(k)$  the number of lines for  
257 which the error is less than  $k$  pixels, an estimate of this  
258 probability is  $f(k) = H(k)/n_r$ , where  $n_r$  is number of lines.

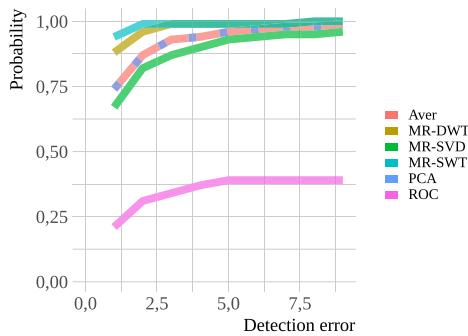


Fig. 10. Probability of detecting the edge by the fusion methods in Fig. 1.

TABLE I  
PROCESSING TIMES (FUSION METHOD)

Method	Aver.	PCA	MR-DWT	MR-SWT	ROC	MR-SVD
Time (s)	0.01	0.02	0.08	0.18	0.40	1.11
Rel. time	1.00	2.19	9.25	21.05	46.59	129.57

In our analysis,  $k$  varies between 1 and 10, and  $n_r = 100$ . The algorithm is described in [8].

We obtained similar results on the images shown in Figs. 4 and 7, which we omit for brevity.

#### 265 D. Implementation Details

266 Table I shows the running times (absolute and relative to the  
267 fastest method). The system presented here was executed on a  
268 Intel Core i7-9750HQ CPU 2.6-GHz 16-GB RAM computer.

269 The method for detecting edge evidence MLE was imple-  
270 mented in the R language. The fusion methods were  
271 implemented in MATLAB. Code and data are available at  
272 [https://github.com/anderborba/Code\\_GRSL\\_2020\\_1](https://github.com/anderborba/Code_GRSL_2020_1).

## VI. CONCLUSION

273 We found evidence of edges using the maximum likelihood  
274 method under the Wishart model for PolSAR data. The evi-  
275 dence was found in each of the three intensity channels of  
276 AIRSAR L-band images over Flevoland and San Francisco.

277 Over the agricultural fields of Flevoland, the best edge  
278 evidence was observed on the hv channel. The hh channel  
279 provided the best estimates of the edges between the urban  
280 and both sea and vegetation areas of San Francisco. Such  
281 diversity of information content justifies the need of fusing  
282 the edge evidences.

283 We applied simple average, MR-DWT, PCA, ROC, MR-  
284 SWT, and MR-SVD fusion methods to aggregate the evidence  
285 obtained in the three channels. The best results were produced  
286 by PCA and by the MR-SVD. Such enhancement comes at  
287 additional computational cost in terms of processing time.

288 We quantitatively assessed the results by checking the  
289 closeness of the fused points to the actual edge, and by the  
290 presence of outliers. Although the average and PCA are similar

291 with respect to the probability of correctly detecting the edge,  
292 the latter provides a more effective weight of the evidences. In  
293 fact, PCA is able to completely discard misleading evidences,  
294 while the average cannot.

295 Two avenues for future improvement of the fusion are:  
296 1) increasing the number of evidences. This is possible, since  
297 fully polarimetric data are richer than mere intensity channels;  
298 and 2) postprocessing of both partial evidences and fusion.

## 300 REFERENCES

- [1] J. Shi, H. Jin, and Z. Xiao, "A novel hybrid edge detection method for polarimetric SAR images," *IEEE Access*, vol. 8, pp. 8974–8991, 2020.
- [2] B. Liu, Z. Zhang, X. Liu, and W. Yu, "Edge extraction for polarimetric SAR images using degenerate filter with weighted maximum likelihood estimation," *IEEE Geosci. Remote Sens. Lett.*, vol. 11, no. 12, pp. 2140–2144, Dec. 2014.
- [3] W. Wang, D. Xiang, Y. Ban, J. Zhang, and J. Wan, "Enhanced edge detection for polarimetric SAR images using a directional span-driven adaptive window," *Int. J. Remote Sens.*, vol. 39, no. 19, pp. 6340–6357, Oct. 2018.
- [4] D. Santana-Cedres, L. Gomez, L. Alvarez, and A. C. Frery, "Despeckling PolSAR images with a structure tensor filter," *IEEE Geosci. Remote Sens. Lett.*, vol. 17, no. 2, pp. 357–361, Feb. 2020.
- [5] F. Baselice and G. Ferraioli, "Statistical edge detection in urban areas exploiting SAR complex data," *IEEE Geosci. Remote Sens. Lett.*, vol. 9, no. 2, pp. 185–189, Mar. 2012.
- [6] X. X. Zhu *et al.*, "Deep learning in remote sensing: A comprehensive review and list of resources," *IEEE Geosci. Remote Sens. Mag.*, vol. 5, no. 4, pp. 8–36, Dec. 2017.
- [7] J. Gambini, M. E. Mejail, J. Jacobo-Berlles, and A. C. Frery, "Feature extraction in speckled imagery using dynamic B-spline deformable contours under the model," *Int. J. Remote Sens.*, vol. 27, no. 22, pp. 5037–5059, Nov. 2006.
- [8] A. C. Frery, J. Jacobo-Berlles, J. Gambini, and M. E. Mejail, "Polarimetric SAR image segmentation with B-splines and a new statistical model," *Multidimensional Syst. Signal Process.*, vol. 21, no. 4, pp. 319–342, Dec. 2010.
- [9] A. D. C. Nascimento, M. M. Horta, A. C. Frery, and R. J. Cintra, "Comparing edge detection methods based on stochastic entropies and distances for PolSAR imagery," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 7, no. 2, pp. 648–663, Feb. 2014.
- [10] H. Mitchell, *Image Fusion: Theories, Techniques and Applications*. Berlin, Germany: Springer, 2010.
- [11] A. A. de Borba, M. Marengoni, and A. C. Frery, "Fusion of evidences for edge detection in PolSAR images," in *Proc. IEEE Recent Adv. Geosci. Remote Sens., Technol., Standards Appl. (TENGARSS)*, Oct. 2019, pp. 80–85.
- [12] J. Gambini, M. E. Mejail, J. Jacobo-Berlles, and A. C. Frery, "Accuracy of edge detection methods with local information in speckled imagery," *Statist. Comput.*, vol. 18, no. 1, pp. 15–26, Mar. 2008.
- [13] Y. Xiang, S. Gubian, B. Suomela, and J. Hoeng, "Generalized simulated annealing for global optimization: The GenSA package," *R J.*, vol. 5, no. 1, pp. 13–28, 2013.
- [14] V. Naidu and J. Raol, "Pixel-level image fusion using wavelets and principal component analysis," *Defence Sci. J.*, vol. 58, no. 3, pp. 338–352, May 2008.
- [15] S. Giannarou and T. Stathaki, "Optimal edge detection using multiple operators for image understanding," *EURASIP J. Adv. Signal Process.*, vol. 2011, no. 1, p. 28, Jul. 2011.
- [16] Q. Jiang, X. Jin, S.-J. Lee, and S. Yao, "A novel multi-focus image fusion method based on stationary wavelet transform and local features of fuzzy sets," *IEEE Access*, vol. 5, pp. 20286–20302, 2017.
- [17] V. P. S. Naidu, "Image fusion technique using multi-resolution singular value decomposition," *Defence Sci. J.*, vol. 61, no. 5, pp. 479–484, Sep. 2011.
- [18] A. Henningsen and O. Toomet, "maxLik: A package for maximum likelihood estimation in R," *Comput. Statist.*, vol. 26, no. 3, pp. 443–458, Sep. 2011.

## AUTHOR QUERIES

### AUTHOR PLEASE ANSWER ALL QUERIES

**PLEASE NOTE:** We cannot accept new source files as corrections for your article. If possible, please annotate the PDF proof we have sent you with your corrections and upload it via the Author Gateway. Alternatively, you may send us your corrections in list format. You may also upload revised graphics via the Author Gateway.

Carefully check the page proofs (and coordinate with all authors); additional changes or updates WILL NOT be accepted after the article is published online/print in its final form. Please check author names and affiliations, funding, as well as the overall article for any errors prior to sending in your author proof corrections.

- 1) Please be aware that authors are required to pay overlength page charges (\$230 per page) if the article is longer than 3 pages. If you cannot pay any or all of these charges please let us know. GRS Society members receive a discounted rate of \$200 per page.
- 2) This pdf contains 2 proofs. The first half is the version that will appear on Xplore. The second half is the version that will appear in print. If you have any figures to print in color, they will be in color in both proofs.
- 3) The “Open Access” option for your article expires when the article is published on Xplore in an issue with page numbers. Articles in “Early Access” may be changed to Open Access. If you have not completed your electronic copyright form (ECF) and payment option please return to Scholar One “Transfer Center.” In the Transfer Center you will click on “Manuscripts with Decisions” link. You will see your article details and under the “Actions” column click “Transfer Copyright.” From the ECF it will direct you to the payment portal to select your payment options and then return to ECF for copyright submission.

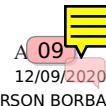
AQ:1 = Please check whether the edit made to the article title is appropriate.

AQ:2 = Please provide the expansions for ROC, BFGS, and AIRSAR.

AQ:3 = Please confirm or add details for any funding or financial support for the research of this article.

AQ:4 = Please confirm whether the corresponding author has been identified correctly.

AQ:5 = Please check and confirm whether the affiliation details of all the authors are correct as set.



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

Anderson A. De Borba<sup>ID</sup>, Maurício Marengoni, and Alejandro C. Frery<sup>ID</sup>, *Senior Member, IEEE*

**Abstract**—Polarimetric synthetic aperture radar (PolSAR) sensors have reached an essential position in remote sensing. The images they provide have speckle noise, making their processing and analysis challenging tasks. We discuss an edge detection method based on the fusion of evidences obtained in the intensity channels hh, hv, and vv of PolSAR multilook images. The method consists of detecting transition points in the thinnest possible range of data that covers two regions using maximum likelihood under the Wishart distribution. The fusion methods used are: simple average, multiresolution discrete wavelet transform (MR-DWT), principal component analysis (PCA), ROC statistics, multiresolution stationary wavelet transform (MR-SWT), and a multiresolution method based on singular value decomposition (MR-SVD). A quantitative analysis suggests that PCA and MR-SVD provide the best results.

**Index Terms**—Edge detection, fusion methods, maximum likelihood estimation, polarimetric synthetic aperture radar (PolSAR).

## I. INTRODUCTION

POLARIMETRIC synthetic aperture radar (PolSAR) has achieved an essential position in remote sensing. The data such sensors provide require specifically tailored signal processing techniques. Among such techniques, edge detection is one of the most important operations for extracting information. Edges are at a higher level of abstraction than mere data and, as such, provide relevant insights about the scene.

Among the available edge detection techniques for SAR and PolSAR images, it is worth mentioning: techniques based on denoising [1]–[4]; Markov random fields [5]; the deep learning approach [6] applied to segmentation and classification; and statistical techniques [7]–[9] applied in edge detection in PolSAR and SAR imagery.

This letter follows the statistical modeling approach using the techniques described in [7]–[9] to find edge evidences, followed by fusion processes [10], [11].

Instead of handling fully polarimetric data, we treat each intensity channel separately, obtain evidence of edges, and

Manuscript received March 24, 2020; revised July 12, 2020; accepted August 31, 2020. (*Corresponding author: Anderson A. De Borba*)

Anderson A. De Borba is with the Department of Engenharia Elétrica e Computação, Universidade Presbiteriana Mackenzie (UPM), São Paulo 01302-907, Brazil, and also with IBMEC-SP, São Paulo 01419-002, Brazil (e-mail: anderson.aborba@professores.ibmec.edu.br).

Maurício Marengoni is with the Department of Engenharia Elétrica e Computação, Universidade Presbiteriana Mackenzie (UPM), São Paulo 01302-907, Brazil (e-mail: mauricio.marengoni@mackenzie.br).

Alejandro C. Frery is with the School of Mathematics and Statistics, Victoria University of Wellington, Wellington 6140, New Zealand (e-mail: alejandro.frery@vuw.ac.nz).

Color versions of one or more of the figures in this letter are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/LGRS.2020.3022511

then produce a single estimator of the edge position. With this, we quantify the contribution each channel provides to the solution of the problem.

The Gambini Algorithm [12] is an attractive edge detection technique. It is local, as it finds evidence of an edge over a thin strip of data; it works with any model, which makes it suitable for SAR data; and it has shown better performance than other approaches. This algorithm consists in casting rays, and then finding the evidence of an edge in the ray by maximizing a value function. We use the total likelihood of two samples: one inside the edge and another outside the edge. Without loss of generality, we assume the complex scaled Wishart distribution for the fully polarimetric observations, from which Gamma laws stem for each intensity channel. The value function depends on the estimates that index such Gamma laws; and we estimate them by maximum likelihood.

The total likelihood function is nondifferentiable at most points, and classical methods have difficulties in finding its maximum. We used the generalized simulated annealing (GenSA) [13] method to solve this problem.

We discuss and compare six fusion methods: Simple average [10], multiresolution discrete wavelet (MR-DWT) [14], principal component analysis (PCA) [10], [14], ROC statistics [15], multiresolution stationary wavelet transform (MR-SWT) [14], [16], and multiresolution singular value decomposition (MR-SVD) [17].

The letter is structured as follows: Section II describes the models, Section III describes the edge detection, Section IV describes the approaches for fusing edge evidences, Section V presents the results, and in Section VI we discuss the results and outline future research directions.

## II. STATISTICAL MODELING FOR POLSAR DATA

Multilooked fully polarimetric data follow the Wishart distribution with probability density function (PDF) defined by:

$$f_{\mathbf{Z}}(\mathbf{z}; \Sigma, L) = \frac{L^{pL} |\mathbf{z}|^{L-p}}{|\Sigma|^L \Gamma_p(L)} \exp(-L \text{tr}(\Sigma^{-1} \mathbf{z})) \quad (1)$$

where  $\mathbf{z}$  is a positive-definite Hermitian matrix,  $L$  is the number of looks,  $\text{tr}(\cdot)$  is the trace operator of a matrix,  $\Gamma_p(L)$  is the multivariate Gamma function defined by  $\Gamma_p(L) = \pi^{1/2p(p-1)} \prod_{i=0}^{p-1} \Gamma(L-i)$ , and  $\Gamma(\cdot)$  is the Gamma function. We used three  $p = 3$  channels in this study. This situation is denoted by  $\mathbf{Z} \sim W(\Sigma, L)$ , which satisfies  $E[\mathbf{Z}] = \Sigma$ . This assumption usually holds for fully developed speckle but, since we will estimate  $L$  locally instead of considering the same number of looks for the whole image, we will in part take into account departures from such hypothesis.

Since we are interested in describing the information conveyed by parts of such matrix under the Wishart model, we assume that the distribution of each intensity channel is a Gamma law with PDF

$$f_Z(z; \mu, L) = \frac{L^L z^{L-1}}{\mu^L \Gamma(L)} \exp\{-Lz/\mu\}, \quad z > 0 \quad (2)$$

where  $L > 0$ , and  $\mu > 0$  is the mean. The log-likelihood of the sample  $z = (z_1, \dots, z_n)$  under this model is

$$\begin{aligned} \mathcal{L}(\mu, L; z) = n[L \ln(L/\mu) - \ln \Gamma(L)] \\ + L \sum_{k=1}^n \ln z_k - \frac{L}{\mu} \sum_{k=1}^n z_k. \end{aligned} \quad (3)$$

We obtain  $(\hat{\mu}, \hat{L})$ , the maximum likelihood estimator (MLE) of  $(\mu, L)$  based on  $z$ , by maximizing (3) with the FGS method [18]. We prefer optimization to solving  $\nabla \ell$  for improved numerical stability.

### III. EDGE DETECTION ON A SINGLE DATA STRIP

The Gambini algorithm estimates the point at which the properties of a sample change. It has been used with stochastic distances [9] and with the likelihood function [7], [8] for edge detection in SAR/PolSAR imagery. It can be adapted to any suitable measure of dissimilarity between two samples.

The algorithm starts by casting rays from a point inside the candidate region, e.g., the centroid. Data are collected around each ray to form the sample  $z = (z_1, z_2, \dots, z_n)$ , which is partitioned at position  $j$

$$z = (\underbrace{z_1, z_2, \dots, z_j}_{z_I}, \underbrace{z_{j+1}, z_{j+2}, \dots, z_n}_{z_E}).$$

We assume two (possibly) different models for each partition:  $Z_I \sim \Gamma(\mu_I, L_I)$ , and  $Z_E \sim \Gamma(\mu_E, L_E)$ . We then estimate  $(\mu_I, L_I)$  and  $(\mu_E, L_E)$  with  $z_I$  and  $z_E$ , respectively, by maximizing (3), and obtain  $(\hat{\mu}_I, \hat{L}_I)$  and  $(\hat{\mu}_E, \hat{L}_E)$ .

We then compute the total log-likelihood of  $z_I$  and  $z_E$

$$\begin{aligned} \mathcal{L}(j; \hat{\mu}_I, \hat{L}_I, \hat{\mu}_E, \hat{L}_E) \\ = - \left( \hat{\mu}_I \sum_{k=1}^j z_k + \hat{\mu}_E \sum_{k=j+1}^n z_k \right) \\ + j[\hat{L}_I \ln(\hat{L}_I/\hat{\mu}_I) - \ln \Gamma(\hat{L}_I)] + \hat{L}_I \sum_{k=1}^j \ln z_k \\ + (n-j)[\hat{L}_E \ln(\hat{L}_E/\hat{\mu}_E) - \ln \Gamma(\hat{L}_E)] + \hat{L}_E \sum_{k=j+1}^n \ln z_k. \end{aligned} \quad (4)$$

and the estimate of the edge position on the ray is the coordinate  $\hat{j}$  which maximizes it.

Algorithm 1 is the pseudocode of the basic edge detection with the Gambini Algorithm. We found that 100 rays is a good compromise between spatial continuity and computational load. Also,  $\min_s$  is the minimum sample size.

In our implementation, we replace the exhaustive sequential search (the innermost **for** loop) by GenSA [13].

---

**Algorithm 1** Gambini Algorithm for Intensity Channels

---

**Data:**  $n_c$  intensity channels, interior point, number of rays  
**Result:**  $n_c$  binary images with evidences of edges  
**for** each band  $1 \leq c \leq n_c$  **do**  
  **for** each ray passing through the interior point **do**  
     $z = (z_1, z_2, \dots, z_n) \leftarrow$  data collected around the ray;  
    **for** each  $\min_s \leq j \leq n - \min_s$  **do**  
      Partition the sample as  $z_I = (z_{\min_s}, \dots, z_j)$  and  $z_E = (z_{j+1}, \dots, z_{n-\min_s})$ ;  
      Compute  $(\hat{\mu}_I, \hat{L}_I)$  with  $z_I$ , and  $(\hat{\mu}_E, \hat{L}_E)$  with  $z_E$ ;  
      Compute the total log-likelihood at  $j$  as  $\mathcal{L}(j; \hat{\mu}_I, \hat{L}_I, \hat{\mu}_E, \hat{L}_E)$ ;  
    **end**  
     $\hat{j} \leftarrow$  the value of  $j$  which maximizes the total log-likelihood function;  
    **return**  $(\hat{x}, \hat{y})$ , the coordinates of each  $\hat{j}$ ;  
  **end**  
  **return** the binary image  $\hat{J}_c$  with 1 at every  $(\hat{x}, \hat{y})$ , and 0 otherwise.

---

### IV. FUSION OF EVIDENCES

Assume we have  $n_c$  binary images  $\{\hat{J}_c\}_{1 \leq c \leq n_c}$  in which 1 denotes an estimate of edge and 0 otherwise. They have common size  $m \times n$ ; denote  $\ell = mn$ . These images will be fused to obtain the binary image  $I_F$ .

We compare the results of six fusion techniques: simple average, MR-DWT, PCA, ROC statistics, MR-SWT, and MR-SVD.

#### A. Simple Average

The simple average fusion method proposes the arithmetic mean of the edge evidence in each of the  $n_c$  channels:  $I_F(x, y) = (n_c)^{-1} \sum_{c=1}^{n_c} \hat{J}_c(x, y)$ , where  $1 \leq x \leq m$  indexes the rows, and  $1 \leq y \leq n$  the columns of the image.

#### B. Multiresolution Discrete Wavelet

This section is based on [14]. We apply DWT filters on each binary image  $\hat{J}_c$ : a low-pass filter  $L$  in the vertical direction, and a high-pass filter  $H$  in the horizontal direction, then both are downsampled to create the coefficient matrices  $\hat{J}_{cL}$  and  $\hat{J}_{cH}$ . These operations are repeated on the coefficient matrices, leading to  $\hat{J}_{cLL}$ ,  $\hat{J}_{cLH}$ ,  $\hat{J}_{cHL}$ , and  $\hat{J}_{cHH}$ . We, thus, use two resolution levels.

The DWT fusion method has the following steps.

- 1) Calculate the DWT decomposition  $\hat{J}_{cLL}$ ,  $\hat{J}_{cLH}$ ,  $\hat{J}_{cHL}$ , and  $\hat{J}_{cHH}$ , for each channel.
- 2) Compute  $\bar{J}_{cHH}$ , the pixel-wise mean of all  $\hat{J}_{cHH}$  decompositions.
- 3) Find the pixel-wise maximum of  $\hat{J}_{cLL}$ ,  $\hat{J}_{cLH}$ ,  $\hat{J}_{cHL}$ :  $\bar{J}_{cLL}$ ,  $\bar{J}_{cLH}$ , and  $\bar{J}_{cHL}$ .
- 4) The result of the fusion  $I_F$  is the inverse DWT transform of the coefficient matrices  $\bar{J}_{cHH}$ ,  $\bar{J}_{cLL}$ ,  $\bar{J}_{cLH}$ , and  $\bar{J}_{cHL}$ .

155 **C. Principal Component Analysis**

156 This section is based on [10], [14]. The method comprises  
157 of the following steps.

- 158 1) Stack the binary images  $\hat{J}_c$  in column vectors to obtain  
159 the matrix  $X_{\ell \times n_c}$ .
- 160 2) Calculate the covariance matrix  $C_{n_c \times n_c}$  of  $X_{\ell \times n_c}$ .
- 161 3) Compute the matrices of eigenvalues ( $\Lambda$ ) and eigenvectors  
162 ( $V$ ) of the covariance matrix, sorted in decreasing  
163 order by the eigenvalues.
- 164 4) Compute the vector  $P = (P(1), \dots, P(n_c)) =$   
165  $(\sum_{c=1}^{n_c} V(c))^{-1}V$ , where  $V$  is eigenvector associated  
166 with the highest eigenvalue of  $C_{n_c \times n_c}$ ; notice that  
167  $\sum_{c=1}^{n_c} P(c) = 1$ .
- 168 5) Fuse  $I_F(x, y) = \sum_{c=1}^{n_c} P(c)\hat{J}_c(x, y)$ .

169 **D. ROC Statistics**

170 The ROC method was proposed and described on [15].

- 171 1) Add the binary images  $\hat{J}_c$  to produce the frequency  
172 matrix ( $V$ ).
- 173 2) Use thresholds ranging from  $t = 1, \dots, n_c$  on  $V$  to  
174 generate matrices  $M_t$ .
- 175 3) Compare each  $M_t$  with all  $\hat{J}_c$ , find the confusion matrix  
176 to generate the ROC curve. The optimal threshold cor-  
177 responds to the point of the ROC curve closest (in the  
178 sense of the Euclidean distance) to the diagnostic line.
- 179 4) The fusion  $I_F$  is the matrix  $M_t$  which corresponds to  
180 the optimal threshold.

181 **E. Multiresolution Stationary Wavelet Transform**

182 This section is based on [14], [16]. The difference between  
183 MR-DWT and MR-SWT method is the replacement of the  
184 DWT by the SWT.

185 **F. Multiresolution Singular Value Decomposition**

186 MR-SVD fusion [17] works similar to MR-DWT. The  
187 MR-SVD fusion method can be summarized as follows.

- 188 1) Organize the binary image  $\hat{J}_c$  as nonoverlapping  $2 \times 2$   
189 blocks, and arrange each block as a  $4 \times 1$  vector by  
190 stacking columns to form the data matrix  $X_1$  with  
191 dimension  $4 \times \ell/4$ .
- 192 2) Find the SVD decomposition of  $X_1 = U_1 S_1 V_1^T$ , where  
193  $U_1$  is a  $4 \times 4$  unitary matrix,  $S_1$  is a  $4 \times \ell/4$  rectangular  
194 diagonal matrix known as singular values matrix, and  $V_1$   
195 is an  $\ell/4 \times \ell/4$  unitary matrix. The singular values are  
196 ordered in a decreasing order.
- 197 3) Transform the lines of  $\hat{X}_1 = U_1^T X_1 = S_1 V_1^T$   
198 into new matrices with dimensions  $m/2 \times n/2$ :  
199  $\{\Phi_1, \Psi_{1V}, \Psi_{1H}, \Psi_{1D}\}$ .
- 200 4) Repeat the procedure (1) on  $\Phi_r$  by  $r = 2$  up to the  
201 lowest resolution level  $R$ .
- 202 5) The MR-SVD decomposition in each channel is

$$203 \hat{X}_c \rightarrow \{\Phi_R^c, \{\Psi_{rV}^c, \Psi_{rH}^c, \Psi_{rD}^c\}_{r=1}^R, \{U_r^c\}_{r=1}^R\}.$$

- 204 6) Once the decomposition is applied to all channels,  
205 compute the average of  $\Phi_R^c (\Phi_R^f)$  in the lowest resolution

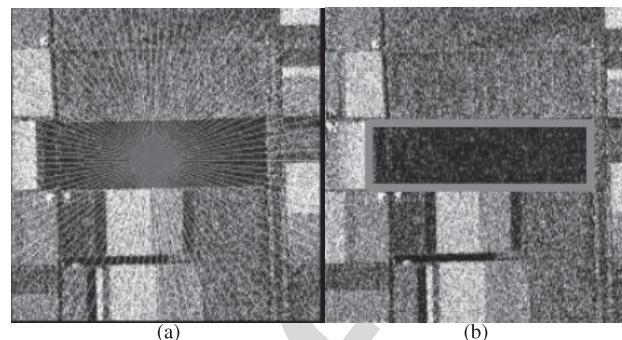


Fig. 1. Flevoland image in Pauli decomposition, and ground reference.  
(a) Image and rays. (b) Ground reference.

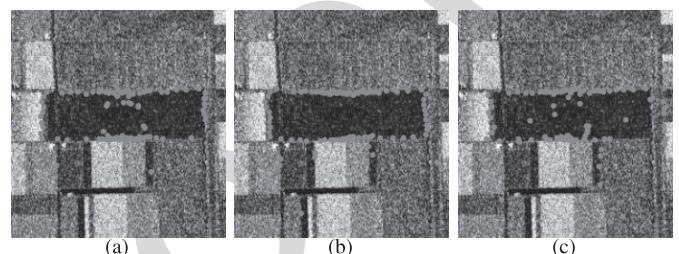


Fig. 2. Edges evidences from the three intensity channels. (a) Channel hh.  
(b) Channel hv. (c) Channel vv.

206 level, and the average of  $U_r^c (U_r^f)$ , for each  $r$ , where  $f$   
207 denotes the fusion among channels.

- 208 7) Find the pixel-wise maxima of  $\Psi_{rV}^c$ ,  $\Psi_{rH}^c$ , and  $\Psi_{rD}^c$ :  
209  $\Psi_{rV}^f$ ,  $\Psi_{rV}^f$ ,  $\Psi_{rH}^f$ , and  $\Psi_{rD}^f$ .
- 210 8) The fusion  $I_F$  is the SVD transformation for each level  
211  $r = R, \dots, 1$ ,

$$212 I_F \leftarrow \{\Phi_R^f, \{\Psi_{rV}^f, \Psi_{rH}^f, \Psi_{rD}^f\}_{r=R}^1, \{U_r^f\}_{r=R}^1\}.$$

We also used two resolution levels.

## V. RESULTS

### A. Flevoland Images

213 Fig. 1(a) shows a  $750 \times 1024$  pixels AIRSAR PolSAR  
214 image of Flevoland, L-band, with the radial lines where edges  
215 are detected. Fig. 1(b) shows the ground reference in red.

216 Fig. 2(a)–(c) shows, respectively, the edge evidences in the  
217 hh, hv and vv channels as obtained by MLE.

218 It is worth noting that GenSA has accurately identified  
219 the maximum value of  $\mathcal{L}$  [See (4)], even in the presence of  
220 multiple local maxima. A visual assessment leads to conclude  
221 that the best results are provided by hv, although with a few  
222 points far from the actual edge.

223 Fig. 3(a)–(f) shows the results of fusing these evidences.

224 Simple average and PCA produce similar results. MR-SVD  
225 produces considerably less outliers than the other methods.  
226 ROC produces accurate edges, with few outliers, but sparsely.  
227 Both wavelet-based methods (DWT and SWT) produce too  
228 dense edges and many outliers.

229 Fig. 4 shows another region in the Flevoland image. In this  
230 case, it is a bright target surrounded by darker fields. Fig. 5  
231 shows the edges detected in each intensity channel and, again,  
232 the hv data are the one which produce the most accurate  
233 results.

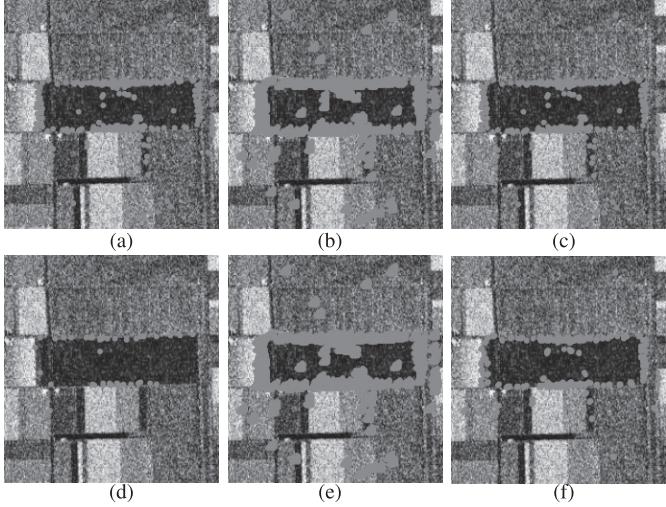


Fig. 3. Results of applying the six fusion methods. (a) Average fusion. (b) MR-DWT fusion. (c) PCA fusion. (d) ROC fusion. (e) MR-SWT fusion. (f) MR-SVD fusion.

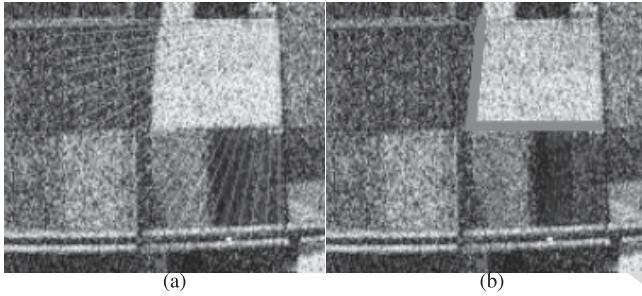


Fig. 4. Flevoland image in Pauli decomposition, and ground reference. (a) Image and rays. (b) Ground reference.

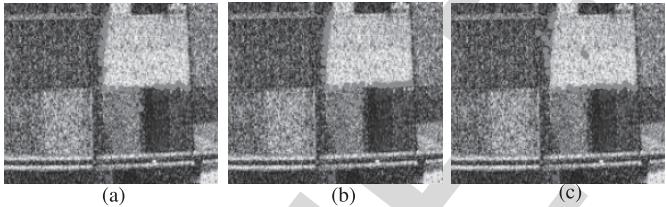


Fig. 5. Edges evidences from the three intensity channels, Flevoland image. (a) Channel hh. (b) Channel hv. (c) Channel vv.

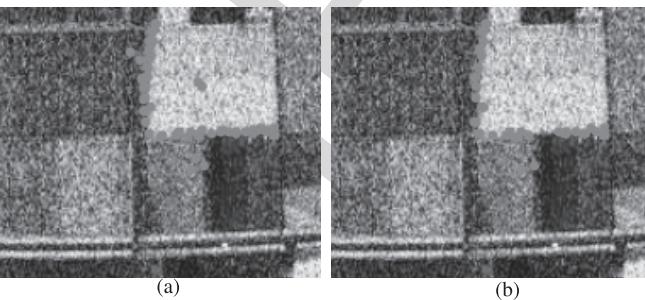


Fig. 6. Two best fusion results in the Flevoland image. (a) PCA fusion. (b) MR-SVD fusion.

237 Fig. 6 shows the two best fusion results: PCA and MR-  
238 SVD. Notice that the latter [Fig. 6(b)] eliminates the wrong  
239 detection close to the center of the area and has fewer wrongly  
240 detected points outside the region of interest.

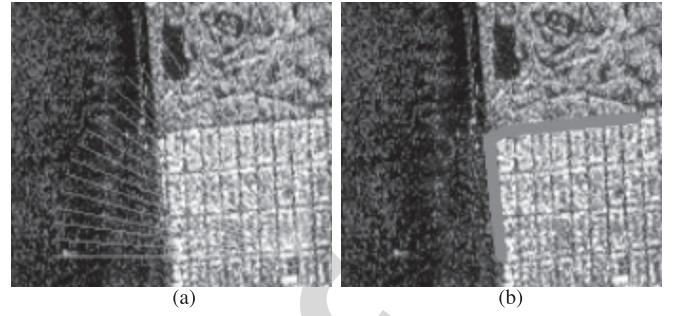


Fig. 7. San Francisco image in Pauli decomposition, and ground reference. (a) Image and rays. (b) Ground reference.

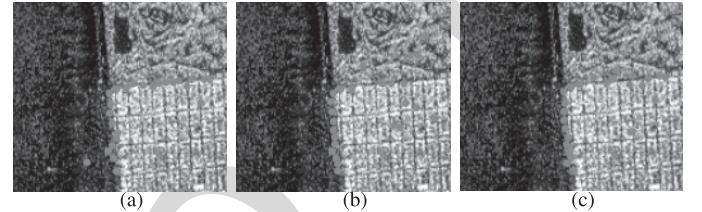


Fig. 8. Edges evidences from the three intensity channels to San Francisco. (a) Channel hh. (b) Channel hv. (c) Channel vv.

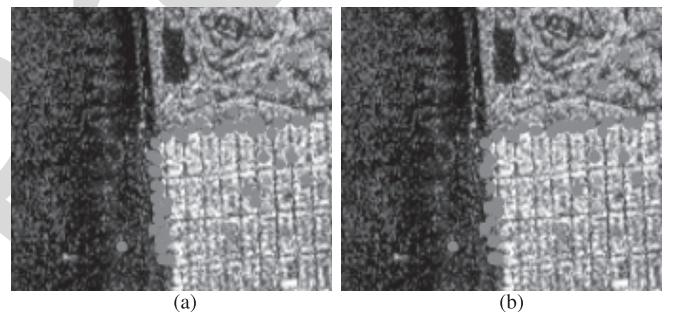


Fig. 9. Two best fusion results in the San Francisco image. (a) PCA fusion. (b) MR-SVD fusion.

### B. San Francisco Image

241 Fig. 7 shows an area of an L-band AIRSAR image over San  
242 Francisco. The distinctive areas are urban, sea, and vegetation.  
243 The aim is finding the edge between the former and the other  
244 two.

245 Fig. 8 shows the evidences of edges found in each of the  
246 three intensity channels. A visual inspection suggests that the  
247 hh channel is the one that produces the best estimation.

248 Fig. 9 shows the two best fusion results: PCA and MR-SVD.  
249 Again, the latter is more resistant to outliers, both inside and  
250 outside the region of interest.

### C. Error Analysis

251 Fig. 10 shows the error of  $\hat{f}$  in finding the true edge shown  
252 in Fig. 1(b), as measured on 100 lines with the minimum  
253 Euclidean distance between the ground truth and the detected  
254 pixel in the fusion methods. We use relative frequencies to  
255 estimate the probability of having an error smaller than a  
256 number of pixels. Denoting  $H(k)$  the number of lines for  
257 which the error is less than  $k$  pixels, an estimate of this  
258 probability is  $f(k) = H(k)/n_r$ , where  $n_r$  is number of lines.

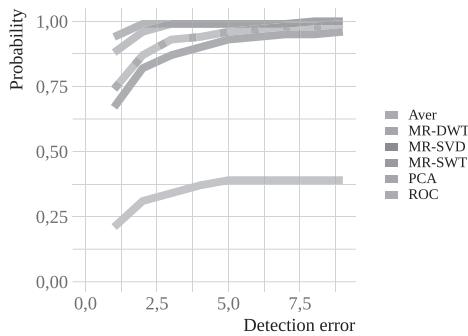


Fig. 10. Probability of detecting the edge by the fusion methods in Fig. 1.

TABLE I  
PROCESSING TIMES (FUSION METHOD)

Method	Aver.	PCA	MR-DWT	MR-SWT	ROC	MR-SVD
Time (s)	0.01	0.02	0.08	0.18	0.40	1.11
Rel. time	1.00	2.19	9.25	21.05	46.59	129.57

In our analysis,  $k$  varies between 1 and 10, and  $n_r = 100$ . The algorithm is described in [8].

We obtained similar results on the images shown in Figs. 4 and 7, which we omit for brevity.

#### 265 D. Implementation Details

266 Table I shows the running times (absolute and relative to the  
267 fastest method). The system presented here was executed on a  
268 Intel Core i7-9750HQ CPU 2.6-GHz 16-GB RAM computer.

269 The method for detecting edge evidence MLE was imple-  
270 mented in the R language. The fusion methods were  
271 implemented in MATLAB. Code and data are available at  
272 [https://github.com/anderborba/Code\\_GRSL\\_2020\\_1](https://github.com/anderborba/Code_GRSL_2020_1).

## VI. CONCLUSION

273 We found evidence of edges using the maximum likelihood  
274 method under the Wishart model for PolSAR data. The evi-  
275 dence was found in each of the three intensity channels of  
276 AIRSAR L-band images over Flevoland and San Francisco.

277 Over the agricultural fields of Flevoland, the best edge  
278 evidence was observed on the hv channel. The hh channel  
279 provided the best estimates of the edges between the urban  
280 and both sea and vegetation areas of San Francisco. Such  
281 diversity of information content justifies the need of fusing  
282 the edge evidences.

283 We applied simple average, MR-DWT, PCA, ROC, MR-  
284 SWT, and MR-SVD fusion methods to aggregate the evidence  
285 obtained in the three channels. The best results were produced  
286 by PCA and by the MR-SVD. Such enhancement comes at  
287 additional computational cost in terms of processing time.

288 We quantitatively assessed the results by checking the  
289 closeness of the fused points to the actual edge, and by the  
290 presence of outliers. Although the average and PCA are similar

291 with respect to the probability of correctly detecting the edge,  
292 the latter provides a more effective weight of the evidences. In  
293 fact, PCA is able to completely discard misleading evidences,  
294 while the average cannot.

295 Two avenues for future improvement of the fusion are:  
296 1) increasing the number of evidences. This is possible, since  
297 fully polarimetric data are richer than mere intensity channels;  
298 and 2) postprocessing of both partial evidences and fusion.

## 300 REFERENCES

- [1] J. Shi, H. Jin, and Z. Xiao, "A novel hybrid edge detection method for polarimetric SAR images," *IEEE Access*, vol. 8, pp. 8974–8991, 2020.
- [2] B. Liu, Z. Zhang, X. Liu, and W. Yu, "Edge extraction for polarimetric SAR images using degenerate filter with weighted maximum likelihood estimation," *IEEE Geosci. Remote Sens. Lett.*, vol. 11, no. 12, pp. 2140–2144, Dec. 2014.
- [3] W. Wang, D. Xiang, Y. Ban, J. Zhang, and J. Wan, "Enhanced edge detection for polarimetric SAR images using a directional span-driven adaptive window," *Int. J. Remote Sens.*, vol. 39, no. 19, pp. 6340–6357, Oct. 2018.
- [4] D. Santana-Cedres, L. Gomez, L. Alvarez, and A. C. Frery, "Despeckling PolSAR images with a structure tensor filter," *IEEE Geosci. Remote Sens. Lett.*, vol. 17, no. 2, pp. 357–361, Feb. 2020.
- [5] F. Baselice and G. Ferraioli, "Statistical edge detection in urban areas exploiting SAR complex data," *IEEE Geosci. Remote Sens. Lett.*, vol. 9, no. 2, pp. 185–189, Mar. 2012.
- [6] X. X. Zhu *et al.*, "Deep learning in remote sensing: A comprehensive review and list of resources," *IEEE Geosci. Remote Sens. Mag.*, vol. 5, no. 4, pp. 8–36, Dec. 2017.
- [7] J. Gambini, M. E. Mejail, J. Jacobo-Berlles, and A. C. Frery, "Feature extraction in speckled imagery using dynamic B-spline deformable contours under the model," *Int. J. Remote Sens.*, vol. 27, no. 22, pp. 5037–5059, Nov. 2006.
- [8] A. C. Frery, J. Jacobo-Berlles, J. Gambini, and M. E. Mejail, "Polarimetric SAR image segmentation with B-splines and a new statistical model," *Multidimensional Syst. Signal Process.*, vol. 21, no. 4, pp. 319–342, Dec. 2010.
- [9] A. D. C. Nascimento, M. M. Horta, A. C. Frery, and R. J. Cintra, "Comparing edge detection methods based on stochastic entropies and distances for PolSAR imagery," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 7, no. 2, pp. 648–663, Feb. 2014.
- [10] H. Mitchell, *Image Fusion: Theories, Techniques and Applications*. Berlin, Germany: Springer, 2010.
- [11] A. A. de Borba, M. Marengoni, and A. C. Frery, "Fusion of evidences for edge detection in PolSAR images," in *Proc. IEEE Recent Adv. Geosci. Remote Sens., Technol., Standards Appl. (TENGARSS)*, Oct. 2019, pp. 80–85.
- [12] J. Gambini, M. E. Mejail, J. Jacobo-Berlles, and A. C. Frery, "Accuracy of edge detection methods with local information in speckled imagery," *Statist. Comput.*, vol. 18, no. 1, pp. 15–26, Mar. 2008.
- [13] Y. Xiang, S. Gubian, B. Suomela, and J. Hoeng, "Generalized simulated annealing for global optimization: The GenSA package," *R J.*, vol. 5, no. 1, pp. 13–28, 2013.
- [14] V. Naidu and J. Raol, "Pixel-level image fusion using wavelets and principal component analysis," *Defence Sci. J.*, vol. 58, no. 3, pp. 338–352, May 2008.
- [15] S. Giannarou and T. Stathaki, "Optimal edge detection using multiple operators for image understanding," *EURASIP J. Adv. Signal Process.*, vol. 2011, no. 1, p. 28, Jul. 2011.
- [16] Q. Jiang, X. Jin, S.-J. Lee, and S. Yao, "A novel multi-focus image fusion method based on stationary wavelet transform and local features of fuzzy sets," *IEEE Access*, vol. 5, pp. 20286–20302, 2017.
- [17] V. P. S. Naidu, "Image fusion technique using multi-resolution singular value decomposition," *Defence Sci. J.*, vol. 61, no. 5, pp. 479–484, Sep. 2011.
- [18] A. Henningsen and O. Toomet, "maxLik: A package for maximum likelihood estimation in R," *Comput. Statist.*, vol. 26, no. 3, pp. 443–458, Sep. 2011.

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

Borba, Anderson Adaime De Borba

- 01 ANDERSON BORBA Page 2  
12/9/2020 18:26  
AQ:1 - OK
- 02 ANDERSON BORBA Page 2  
12/9/2020 18:27  
AQ:2 - Receiver operating characteristic (ROC)
- 03 ANDERSON BORBA Page 2  
12/9/2020 18:28  
AQ:3 - Please insert: "This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001".
- 04 ANDERSON BORBA Page 2  
12/9/2020 18:28  
AQ:4 - Revised
- 05 ANDERSON BORBA Page 2  
12/9/2020 18:29  
AQ:5 - Revised
- 06 ANDERSON BORBA Page 3  
12/9/2020 18:35  
AQ:2 - BFGS (Broyden-Fletcher-Goldfarb-Shanno)
- 07 ANDERSON BORBA Page 3  
12/9/2020 18:36  
Correct please: The authors found an inconsistency in the text; please, could change inline 94 the following latex symbols  $\ell$  for  $\mathcal{L}$ . We highlight in the revised text.

08 ANDERSON BORBA Page 4

12/9/2020 18:38  
AQ:2 - AIRSAR (Airborne Synthetic Aperture Radar)

09 ANDERSON BORBA Page 8

12/9/2020 18:39  
AQ1: ok

10 ANDERSON BORBA Page 8

12/9/2020 18:40  
AQ:2 - ROC (Receiver operating characteristic)

11 ANDERSON BORBA Page 8

12/9/2020 18:40  
AQ:3 - Please insert: "This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001".

12 ANDERSON BORBA Page 8

12/9/2020 18:41  
AQ:4 - Revised

13 ANDERSON BORBA Page 8

12/9/2020 18:41  
AQ: 5 - Revised

14 ANDERSON BORBA Page 9

12/9/2020 18:41  
AQ:2 - BFGS (Broyden-Fletcher-Goldfarb-Shanno)

15 ANDERSON BORBA Page 9

12/9/2020 18:42  
Correct please: The authors found an inconsistency in the text; please, could change inline 94 the following Latex symbols \$\ell\$ for \$\mathcal{L}\$. We highlight in the revised text.

16 ANDERSON BORBA Page 10

12/9/2020 18:43  
AQ:2 - AIRSAR (Airborne Synthetic Aperture Radar)