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Narrow River Extraction from SAR Images Using Exogenous Information

Nicolas Gasnier, *Student Member, IEEE*, Loïc Denis, Roger Fjørtoft, *Member, IEEE*, Frédéric Liège and Florence Tupin, *Senior Member, IEEE*

Abstract—Monitoring of rivers is of major scientific and societal importance, due to the crucial resource they provide to human activities and the threats caused by flood events. Rapid revisit Synthetic Aperture Radar (SAR) sensors such as Sentinel-1 or the future Surface Water and Ocean Topography (SWOT) mission are indispensable tools to achieve all-weather monitoring of water bodies at the global scale. Unfortunately, at the spatial resolution of these sensors, the extraction of narrow rivers is extremely difficult without resorting to exogenous knowledge. This paper introduces an innovative river segmentation method from SAR images using a priori databases such as the Global River Widths from Landsat (GRWL). First, a recently proposed linear structure detector is used to produce a map of likely line structures. Then, a limited number of nodes along the prior river centerline are extracted from the exogenous database, and used to reconstruct the full river centerline from the detection map. Finally, an innovative conditional random field approach is used to delineate accurately the river extent around its centerline. The proposed method is applied on various Sentinel-1 images and on simulated SWOT images. Both visual and qualitative evaluations show the efficiency of the proposed method.

Index Terms—conditional random field, graph cut, hydrology, river extraction, segmentation, Synthetic Aperture Radar

I. INTRODUCTION

IN THE last five years, two major research works have provided comprehensive worldwide maps of continental water surfaces: the Global Surface Water (GSW) masks of Pekel et al. [1] and Global River Widths from Landsat (GRWL) of Allen and Pavelsky [2]). They are based on multi-spectral Landsat optical images over decades. Such optical satellite sensors are not well suited for real-time monitoring of water bodies, as they lack the all-weather capability of Synthetic Aperture Radar (SAR) sensors such as Sentinel-1 that can observe through clouds. The Ka-band Radar Interferometer (KaRIn) of the future Surface Water and Ocean Topography (SWOT) mission [3], scheduled for launch in 2022, is an interferometric SAR system that has the capability to measure water elevation as well. Thanks also to their short revisit time, these freely available SAR data are expected to play a crucial role in river monitoring in the coming years. However,

SAR images have specific characteristics that make their direct exploitation difficult. In addition to their limited number of information channels (one for SWOT, two for Sentinel-1), these images are corrupted by strong multiplicative speckle noise and affected by artifacts that can make their exploitation for water detection difficult. Robust and efficient methods to detect narrow rivers in such images are therefore needed.

Most of the methods previously developed for river detection do not use exogenous information, except for some approaches using digital earth models to account for slope in water detection both with SAR and optical images [4]. Multiple generic water detection algorithms, not specific to rivers, have already been proposed for example by Liu and Jezek [5] or Cazals et al. [6], which applies thresholding on a filtered SAR image, or the baseline method for operational water detection in SWOT images of Lobry et al. [7] that uses Markov Random Fields (MRF). Other methods use active contour approaches such as level sets [8]. These methods use strong regularization priors to avoid speckle-induced false detection, which impairs the detection of narrow rivers. Specific approaches for river detection have also been proposed such as the one developed by Cao et al. [9] for SWOT images. Valero [10] proposes an approach based on mathematical morphology for road detection in high-resolution images. This approach has been adapted for rivers and automated using machine learning by Klemenjak et al. [11]. Sghaier et al. [12] combines it with structural feature sets.

The detection of narrow rivers in SAR images with a limited false detection rate without using any exogenous information is very difficult. Indeed, beyond usual issues associated with speckle noise and low contrast, river detection is more difficult because roads, terrain slope, and various artifacts can create structures resembling rivers. To prevent false detection, prior information about the location and the direction of known rivers can be useful. It allows to distinguish linear structures corresponding to a known river from other visually similar linear features.

In this context, the aforementioned GRWL database provides, on a global scale, information that can be included within new approaches for river detection from SAR images. Before such global databases became available, the use of exogenous information was difficult and often required manual preparation of input and semi-automated approaches, such as [13], [14] for optical images. Nonetheless, direct use of the prior centerline of a river provided by the database to detect and segment the river in a SAR image remains problematic. The actual position shape of the river can change

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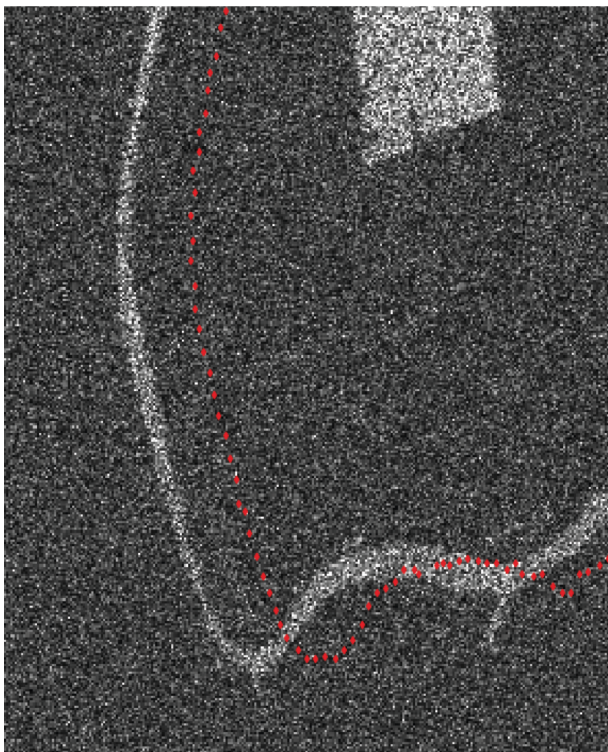


Fig. 1. Illustration of the displacement between the database centerline projected in radar geometry (red dotted line) and the river observed in a simulated SWOT image (where water is bright and land is dark). Such a displacement can be caused by variations in water elevation or inaccuracies in the digital elevation model used for projection: a few meters difference between actual and prior elevation can lead to shifts of hundreds of meters in ground range.

over time [15] and there can be errors in the database itself. Discrepancies in position induced by variations in the water level with respect to the prior knowledge of it can have a major impact on the projected position in the range direction, in particular for near-nadir sensors such as SWOT, as illustrated by Figure 1.

The main contribution of this paper is to propose of a new river detection approach for SAR images, guided by prior information on the approximate river centerline. It can be provided by a database such as GRWL that features several information layers including the river centerline for most rivers wider than 30 m, with a better completeness for rivers above 90 m. The robustness and efficiency of the proposed method are illustrated by several examples for both Sentinel-1 and SWOT data. The paper is organized as follows: The method is presented in section II, the results are presented and discussed in section III, and a conclusion and future work are detailed in section IV.

II. PROPOSED FRAMEWORK

A. Overview

As mentioned in the introduction, our goal is to provide a novel framework for river extraction in SAR images using a database of rivers to overcome the limitations of detection based only on a SAR image. The method needs to be robust to differences between the observed river location and shape and

those in the database. To achieve this, we propose a three-step framework summarized in Figure 2. The first step consists in applying a line detector to the SAR image, as described in the next section. Its response gives the likelihood of the presence of a locally linear structure at each pixel of the image, irrespective of the nature of the linear structure (river, road, artifact, ...). The second step uses the Dijkstra algorithm [16] to find the least-cost curvilinear path between two nodes of the prior river database through a cost array derived from the response of the linear structure detector. These first two steps lead to an estimation of the actual river centerline in the image that is robust to speckle noise and low water/land contrast, and to inaccuracies in the shape and position of the prior centerline projected in radar geometry. The third step consists in segmenting the river reach around the extracted centerline to accurately delineate the river extent (width). An innovative conditional random field (CRF) approach is proposed for this purpose.

B. Detection of linear structures in the SAR image

The first step of our approach computes a map that indicates the likelihood of the presence of a linear structure at each pixel of the image. In our context, a linear structure can be defined as a set of contiguous pixels in a long and thin layout (width of a few pixels) whose radar reflectivity (brightness) is significantly different from that of the background [17]. The relevant linear structures can be dark, as for most sensors such as Sentinel-1 or RADARSAT, or bright for near-nadir sensors such as KaRIn on the future SWOT satellite. The detection of lines on SAR images can be very difficult because of the strong, multiplicative speckle noise and the low contrast of some rivers. Therefore, methods developed for optical images [18]–[22] cannot be directly applied to SAR images, even after log-transformation to make the speckle additive. Methods specific to SAR images have been proposed in the past by Hellwich et al. [23], who use both intensity and coherence images, and by Tupin et al. [24] who combine the results of two detectors: one based on ratios in a neighborhood, the other based on cross-correlation. More recently, the authors have developed a line detector that improved the detection performance compared to [24] and has been described and tested in [17].

As explained in [17], this detector is based on a generalized likelihood ratio test (GLRT) and evaluates at each pixel k the likelihood ratio between two hypotheses on a small square patch $\mathbf{I}_{\square}(k)$ of size $(2N + 1) \times (2N + 1)$ centered on the considered pixel k :

- H_0 : Absence of any linear structure (homogeneous area)
- H_1 : Presence of a linear structure

The GLRT at pixel k can be written:

$$\text{GLRT}(k) = \frac{p(\tilde{\mathbf{I}}(k)|H_1, \hat{\mathbf{P}}(k), \hat{\theta}(k))}{p(\tilde{\mathbf{I}}(k)|H_0, \hat{\mathbf{R}}(k))}. \quad (1)$$

$\tilde{\mathbf{I}}(k)$ is a vector obtained by concatenating the log-transformed intensities of every pixels of the patch $\mathbf{I}_{\square}(k)$.

For both hypotheses, the likelihood depends on unknown parameters that can be estimated by maximum likelihood.

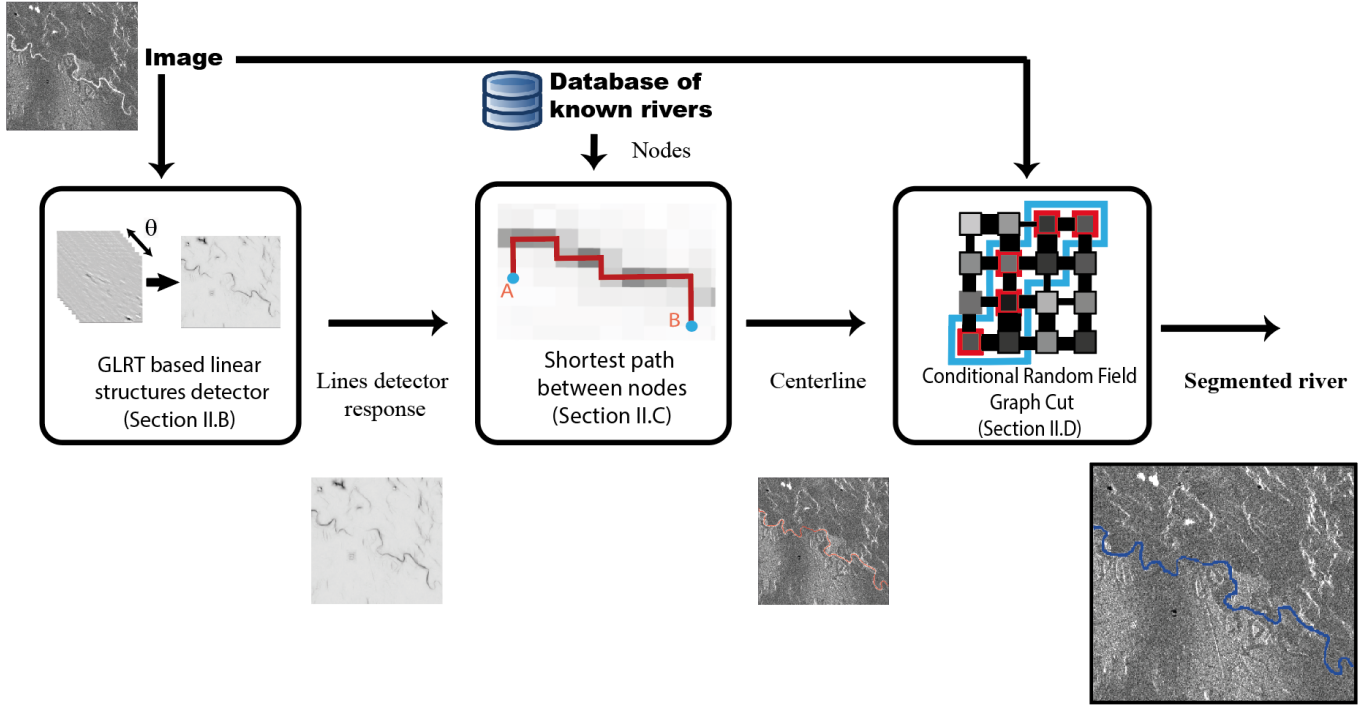


Fig. 2. Global overview of the proposed method: the first step consists in computing the linear structure detector response, used in the second step with the nodes from the a priori database to retrieve the centerline. The river is then segmented around the centerline using a CRF approach in the third step.

Under the H_0 hypothesis, the only parameter is the homogeneous reflectivity $R(k)$ over the patch $I_{\square}(k)$, whose estimator is $\hat{R}(k)$. Under the H_1 hypothesis, there are two parameters: the orientation of the line $\theta(k)$ and the estimated profile $P(k)$, which is a vector containing the intensities along the direction perpendicular to the line. With our model, this profile is symmetric and its extreme value is located in its center (see Figure 3).

The GLRT presented in equation (1) can be simplified by considering a Gaussian approximation of the log-transformed speckle [25] which leads to a quadratic expression:

$$p(\tilde{I}|\tilde{R}_\mu) \simeq f(\tilde{I}) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\tilde{I}-\tilde{R}_\mu}{\sigma}\right)^2}, \quad (2)$$

where $\sigma = \sqrt{\psi(1, L)}$, $\tilde{R}_\mu = \tilde{R} - \log(L) + \psi(L)$, ψ is the polygamma function (or digamma when used with a single parameter), and L is the equivalent number of looks (ENL) of the image.

This Gaussian simplification yields a closed form estimation and permits fast computation. The approximation can be considered fairly accurate for multilook images such as SWOT High Rate (HR) coherent power (L=4) or Sentinel-1 Ground Range Detected (GRD) High Definition data (L=4,4). Under these hypotheses, the log-reflectivity of the patch under the homogeneous hypothesis H_0 can be estimated as the empirical mean of the log-transformed intensities $\tilde{I}(k)$ of the patch $I_{\square}(k)$.

In the following, $\mathbf{1}$ is a vector of ones with the same dimension as $I(k)$ (the number of pixels in a patch). Under

For every pixel k and every orientation θ

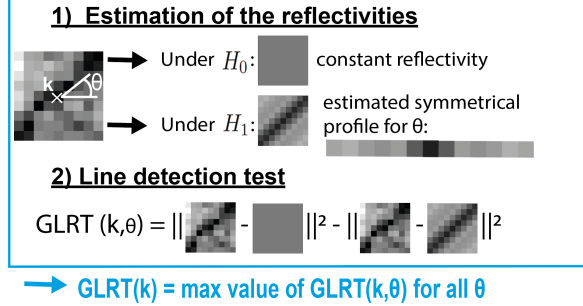


Fig. 3. General presentation of the linear structures detection performed on the log transformed images. Example for a patch centered in k and for dark linear structure detection.

H_0 , we use a uniform patch $\tilde{R}_\mu(k)\mathbf{1}$ with the Gaussian approximation. Under H_1 , the estimated patch $\hat{r}(\hat{\theta}(k), k)$ is computed from the estimated orientation $\hat{\theta}(k)$ and profile $\hat{P}(k, \hat{\theta}(k))$ under H_1 . This way, we get a quadratic expression for the log-transformed GLRT (3). The GLRT boils down to the difference between the reconstruction errors $E_0(k)$ and $E_1(k)$, as presented for one pixel k in Figure 3:

$$\begin{aligned} \log(\text{GLRT}(k)) &= \frac{1}{2} \|\tilde{I}(k) - \hat{r}(k)(\hat{\theta})\|^2 \\ &\quad - \frac{1}{2} \|\tilde{I}(k) - \tilde{R}_\mu(k)\mathbf{1}\|^2 \\ \log(\text{GLRT}(k)) &= E_0(k) - E_1(k) \end{aligned} \quad (3)$$

A more efficient way to compute this GLRT is also pre-

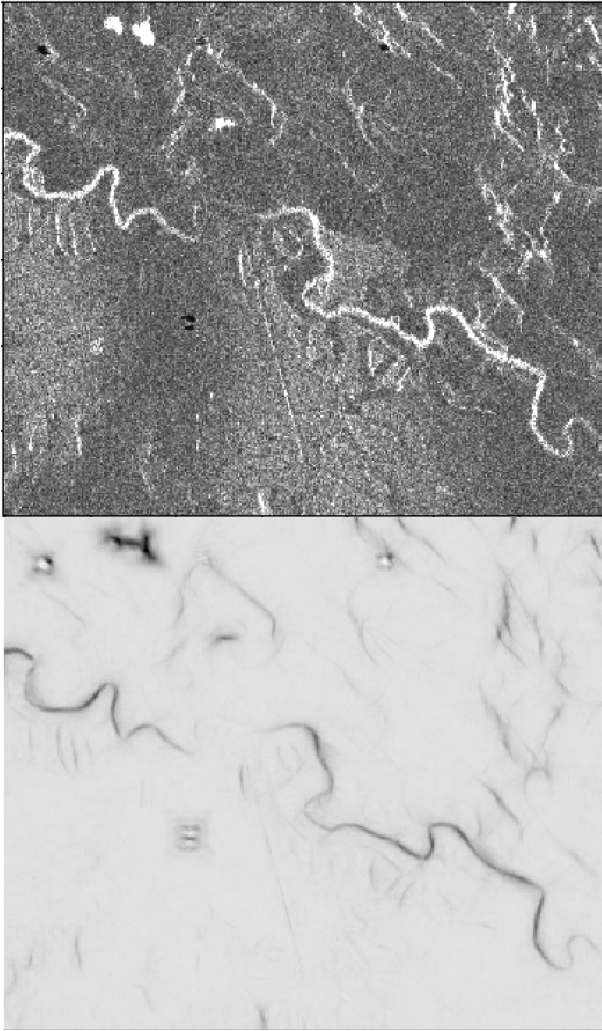


Fig. 4. Simulated SWOT image and linear structure detector response, combining the results for scales 1, 1/2 and 1/3. The response is displayed with inverted gray scale for better visualization.

sented in [17] and used in our framework. It allows to compute the GLRT value at all pixels using Fourier transforms. The detection map can then be improved by combining different scales, in a $[S_{min}, S_{max}]$ range. This allows for the detection of lines larger than a patch and avoids using large patches that would be computationally expensive. An example of the response of the linear structures detector, combining the results for different scales is presented in Figure 4.

C. Accurate centerline determination using least cost path algorithm

The second step of the algorithm is to retrieve the actual centerline of the river reach using both the response of the linear structures detector and prior information on the river position. The external database that we use (GRWL) provides for each river reach (about 10 km long) nodes that are 200 m apart along the centerline. From this approximate centerline, at least two approaches can be considered to obtain the actual centerline:

- To apply an active contour approach such as snake [26] on the entire centerline using the detector response
- To consider only some nodes in the centerline and to compute the minimum cost path between pairs of nodes on a cost image derived from the detector response.

A major issue with the snakes approach for this application is its sensitivity to the initialization and to the parameters that determine the evolution of the active contour. A preliminary study showed the difficulty to choose the right parameters and the lack of stability of the results. The proposed method is based on a minimum path between a subset of nodes of the centerlines using Dijkstra's algorithm. A similar method has been proposed by Dillabaugh et al. [14] for optical images, with user-specified start and end points. We define the cost $C(x, y)$ at every pixel (x, y) based on the line detector response $D(x, y)$:

$$C(x, y) = [1 - D(x, y)/D_{max}]^{N_{pow}} \quad (4)$$

with D_{max} the maximum value of the detector response on the whole image and N_{pow} a tuning parameter. N_{pow} adjusts the cost of crossing a pixel whose detector response is not maximal. It has to be high enough to penalize short paths that cut through a meander but not too high either to prevent the risk of being diverted by a road with a strong line detector response or having numerical computational issues. In the situation where one or both nodes are outside of the river, and provided N_{pow} is high enough, the least-cost path is expected to go from one node to the other through the river via the minimum cost path, as presented in blue between nodes $B1$ and $B2$ in figure 5.

In order to retrieve the whole centerline, we propose to use overlapping pairs of nodes as extremities for the minimum cost path search. Recall that GRWL has a node every 200 m, whereas the pairs of points that we use are in the order of 1 to 10 km apart. By combining the results for each pair of nodes, we obtain the estimated centerline for the whole reach plus one branch between the centerline and every a priori node that does not belong to the centerline, as illustrated for three pairs of nodes in figure 5.

The off-river branches can be easily eliminated using a pruning method. Because of the overlap of the reach nodes, only the pixels on the least-cost path between the end nodes of a reach and the previous reach are kept in the final central line. An example is presented in Figure 6. The centerline for each river is then stored as a boolean raster C_L of the same size as the image that takes the value 1 on the centerline and 0 elsewhere.

D. Segmentation of the reach from the centerline by conditional random field

The last step of the proposed method is to get an accurate segmentation of the river reach using the previously estimated centerline and the SAR image. This can be considered as a region growing problem around the estimated centerline taking into account the intensities in the SAR image. Random walk [27] using the centerline as a seed, morphological approaches or graph-cut approaches [28] with hard constraints could be

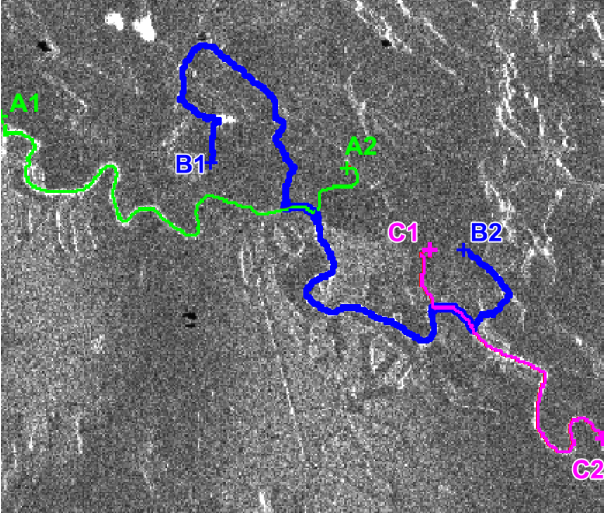


Fig. 5. Visualization on the same image of the result of the least-cost paths for 3 pairs of nodes: $A1 \rightarrow A2$ in green, $B1 \rightarrow B2$ in blue and $C1 \rightarrow C2$ in magenta. The centerlines have been widened for better visualization. In this example, the a priori nodes have been chosen excessively far from the river to illustrate the robustness of the proposed approach.

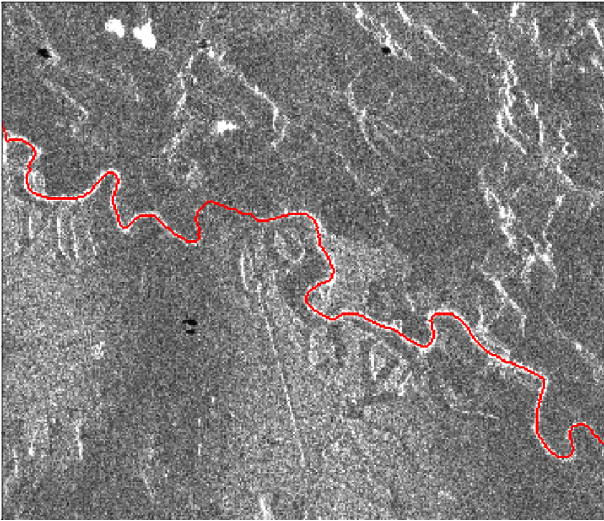


Fig. 6. Centerline obtained after pruning of the previous result. The centerline has been widened for better visualization.

relevant for this problem, but we did not obtain satisfactory results with these.

Instead, we propose an innovative method based on a conditional random field (CRF) [29]. The problem is expressed as the minimization of a global energy function \mathcal{E} that takes both the SAR image and the centerline into account, with an adapted regularization that does not over-penalize narrow rivers. The global energy \mathcal{E} , which depends on the classification ℓ ($\ell = 1$ for water and $\ell = 0$ for land) is the sum of two data terms, a regularization term, and a flux term. The two data terms are U_{data}^I that ensures fidelity with the image intensity I and U_{data}^C that ensures that the centerlines retrieved in the previous step are classified as water. The regularization term U_{reg} is adapted to the segmentation of narrow rivers. Along with this adapted term, we propose a term U_{flux} whose role is

to favor a longer water/land contour despite the regularization U_{reg} if it better fits the gradients of the SAR image.

$$\mathcal{E}(\ell, I) = U_{data}^I(\ell, I) + U_{data}^C(\ell, C_L) + U_{reg}(\ell, I) + U_{flux}(\ell, I) \quad (5)$$

The image data term U_{data}^I is based on a model that considers two likelihoods: a likelihood that depends on the intensity of the image for the water class and a likelihood that is intensity-invariant for the land class. The likelihood for the water class is based on a gamma distribution (6) for the intensity, with two parameters: R_1 for the homogeneous water reflectivity and L for the number of looks. The reflectivity of water R_1 can be estimated using a debiased geometric mean estimator \widehat{R}_1 on the intensity I for every pixel belonging to the centerline. In order to increase robustness, the brightest pixels (for Sentinel 1) that can correspond to bridges or boats can be excluded from the computation of the mean. With these variables, the theoretical distribution of intensity for water is given by:

$$p(I|R_1) = \frac{L^L I^{L-1}}{\Gamma(L) R_1^L} \exp\left(-L \frac{I}{R_1}\right) \quad (6)$$

The neg-log-likelihood \mathcal{L}_1 for the water class ($\ell = 1$) is then given by (7):

$$\mathcal{L}_1(I|R_1) = K(R_1, L) + \frac{LI}{R_1} + (1 - L) \cdot \log(I) \quad (7)$$

where $K(R_1, L) = \log(\Gamma(L)) + L \cdot \log(R_1) - L \cdot \log(L)$

For the land class, in the absence of a model for the distribution of the land class, we consider a uniform likelihood. The constant likelihood value \mathcal{L}_0 is chosen so that the data energy of one well-classified pixel (i.e. its neg-log-likelihood) be equal in expectation for both classes:

$$\mathcal{L}_0 = K(R_1, L) + L + (L - 1) \left(\log\left(\frac{L}{R_1}\right) - \Psi(L) \right). \quad (8)$$

Provided that the estimator for water reflectivity \widehat{R}_1 is accurate enough, the homogeneous log-likelihood $\mathcal{L}_0 = \mathbb{E}_{I|R_1}[\mathcal{L}_1(I, R_1)]$ (8), with the expected value computed over the water pixels, prevents the classification from being biased towards land.

In order to simplify \mathcal{L}_1 and \mathcal{L}_0 , the constant value $K(R_1, L)$ can be subtracted from both neg-log-likelihoods.

For an elementary surface of the image du centered at u , the image data energy is defined by $U_{data}^I(du) = \ell(u) \cdot \mathcal{L}_1(I, R_1, L) \cdot du + (1 - \ell(u)) \cdot \mathcal{L}_0 \cdot du$. Another energy term U_{data}^C ensures that the previously determined centerlines are classified as water. It penalizes by a large value $K_C \cdot du$ the misclassification as land of any elementary surface du that belongs to a centerline ($C_L(du) = 1$). This energy term is given by $U_{data}^C(du) = K_C \cdot (1 - \ell(du)) \cdot C_L(du) \cdot du$.

Finally, a regularization term ensures that the transitions between water and land are compatible with the gradients of the image, by penalizing the transitions that would occur where the gradient magnitude is low, or if the boundaries are not orthogonal to the gradient direction.

We want to minimize over the water boundaries the weighted total variation defined in (9) on the label field ℓ that we assume to be continuous and whose spatial gradient at location u is $\vec{\nabla}\ell(u)$. The total variation is weighted with a weight $w(u)$ defined in (10).

$$U_{reg}(\ell) = \beta \int_{u \in \mathbb{R}^2} w(u) \|\vec{\nabla}\ell(u)\| \cdot du \quad (9)$$

$$\text{with } w(u) = \exp(-[\vec{\nabla}\ell(u) \cdot \vec{\nabla}I(u)]_+ / \lambda). \quad (10)$$

This weighting w favors localizations of the boundaries that are aligned with the strong gradients of the image. The notation $[x]_+$ returns x if $x > 0$ and 0 otherwise. The variable λ and β are parameters that allow adjusting the regularization and its sensitivity to the gradients.

It can be noted that for sensors with dark rivers on a bright background such as Sentinel-1 or TerraSAR-X, the negative of the gradient $-\vec{\nabla}I(u)$ should be used instead to segment the rivers.

To prevent transitions from being encouraged by gradient artifacts caused by speckle noise, we use a gradient adapted to SAR images called Gradient by Ratio (GR) proposed by Dellinger et al. [30], which is an adaptation of ROEWA (Ratio of Exponentially Weighted Average) proposed by Fjörtoft et al. [31]. It computes at each pixel the gradients in the horizontal and vertical direction, as presented in Figure 7.

The former regularization term U_{reg} can cause excessive regularization especially in low contrast situations and lead to false positives and false negatives in detection. For example in SWOT images, a bright sand river inner bank in a meander, also called a point bar (visible in Figure 8) can be erroneously classified as water. Conversely, in the case of a river with an irregular width, the regularization can lead to an incorrect estimation of the width. To cope with these problems that are caused by the regularization that favors shorter water-land boundaries over longer ones despite the weaker gradient, we introduce an additional term that favors longer boundaries co-located with strong gradients.

The boundaries of the river are expected to be located where the gradient of the SAR image is the strongest within a small neighborhood and to be oriented orthogonally to the gradient. Over the boundary $\partial\{\ell = 1\}$ between land ($\ell = 0$) and water ($\ell = 1$), this criterion locally corresponds to maximizing the dot product between the gradient $\vec{\nabla}I(u)$ and the unit normal vector of the segmentation $\{\ell = 1\}$. Over the whole river, the criterion can be expressed as the outward flux Φ of the gradient through the boundary $\partial\{\ell = 1\}$:

$$\begin{aligned} \Phi &= \oint_{u \in \partial\{\ell=1\}} \vec{\nabla}I(u) \cdot \vec{n}(u) \cdot dl \\ &= \iint_{\{\ell=1\}} \vec{\nabla} \cdot \vec{\nabla}I(u) \, du, \end{aligned} \quad (11)$$

where the second line comes from Ostrogradsky's divergence theorem.

Here, the Laplacian of the image can be approximated with a Laplacian of Gaussian (LoG) operator of parameter σ_L that can be computed using a convolution.

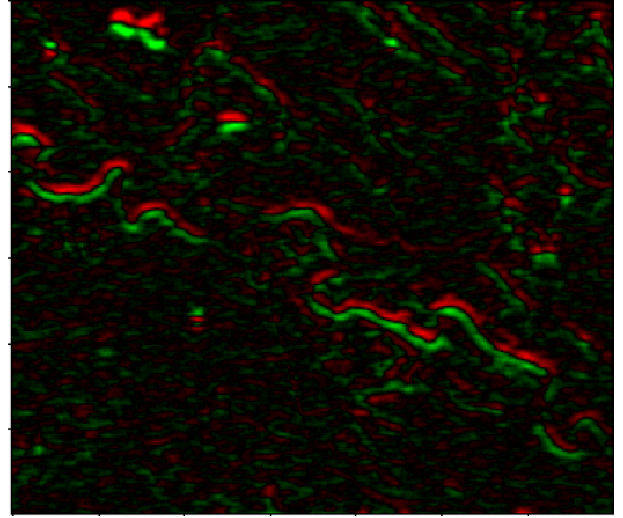
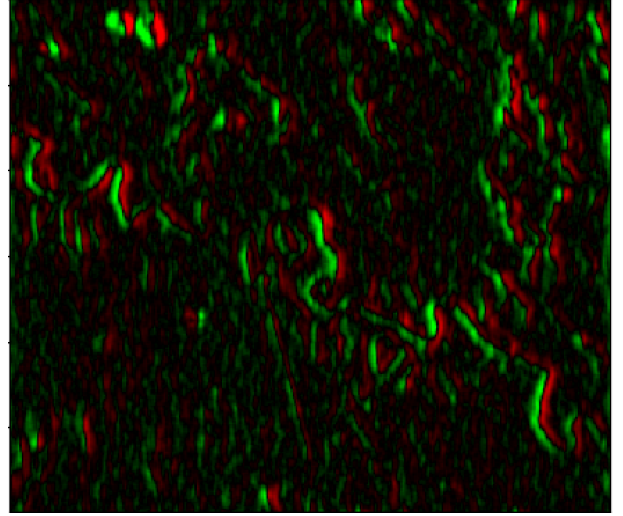


Fig. 7. Gradient for the simulated SWOT image. The positive values are displayed in green, the negative values are displayed in red. Above: horizontal gradient, below: vertical gradient. The gradients have been computed with the GR approach with a weighting parameter $\alpha = 2.4$ which is a good compromise between smoothing and location for $L = 4$.

$$\vec{\nabla} \cdot \vec{\nabla}I \approx \text{LoG}(I, \sigma_L) \quad (12)$$

The influence of the flux energy $U_{flux}(\ell)$ can be balanced with a multiplicative parameter η that adjusts its effect. The sign of η depends on the sensor: $\eta < 0$ for SWOT (water generally brighter than land) and $\eta > 0$ for Sentinel 1 (land mostly brighter than water):

$$U_{flux}(\ell) = \int_{u \in \mathbb{R}^2, \ell(u)=1} \eta \cdot \text{LoG}(I, \sigma_L) \, du. \quad (13)$$

By combining the four terms: U_{data}^I , U_{data}^C , U_{reg} , U_{flux} of \mathcal{E} , we can write the segmentation problem as a minimization

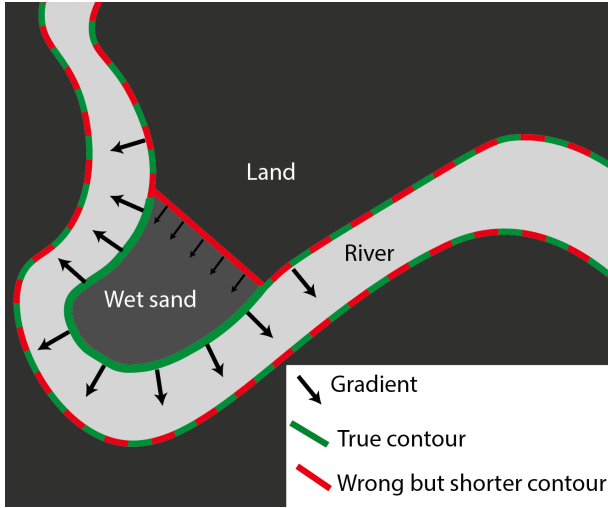


Fig. 8. Illustration of a situation in which using solely the total variation regularization may lead to an erroneous contour detection.

problem:

$$\begin{aligned} \arg \min_{\ell} \int_{u \in \mathbb{R}^2, \ell(u)=1} \mathcal{L}_1(I, R_1, L) + \eta \cdot \text{LoG}(I, \sigma_L) du \\ + \int_{u \in \mathbb{R}^2, \ell(u)=0} \mathcal{L}_0 + C_L(u) \cdot K_C du \\ + \beta \int_{u \in \mathbb{R}^2} w(u) \cdot \|\vec{\nabla} \ell(u)\| \cdot du. \end{aligned} \quad (14)$$

This equation can be discretized:

$$\begin{aligned} \arg \min_{\ell} \sum_i \ell(i) \cdot (\mathcal{L}_1(I, R_1, L) + \eta \cdot \text{LoG}(I, \sigma)) \\ + (1 - \ell(i)) \cdot (\mathcal{L}_0 + C_L(i)) \\ + \beta \sum_{i \sim j} w(i, j) \cdot |\ell(j) - \ell(i)| \end{aligned} \quad (15)$$

with $w(i, j) = \exp(-[(\ell(j) - \ell(i)) \cdot (I(j) - I(i))]_+ / \lambda)$. $i \sim j$ means that j is an 8-neighbor of i . In the case of pixels that are 8-neighbors of i but not 4-neighbors, λ is multiplied by $\sqrt{2}$.

The minimization problem presented in (15) can be solved using a minimal cut approach such as the one proposed by Boykov et al. [28], with asymmetric edges on a directed graph.

III. EXPERIMENTAL RESULTS

In this section we evaluate the interest and characterize the performances of our method in segmenting small rivers in SAR images using a prior database, both for SWOT and Sentinel-1 images. Even if the images from the experimental dataset have been chosen to be as representative as possible of various situations, the comprehensive calibration of the algorithm on a specific sensor is beyond the scope of our experiments.

The results presented below have been obtained using our published code ¹ that uses the PyMaxFlow ² wrapper to Vladimir Kolmogorov's graph cut solver presented in [32].

¹The code is not yet available for public distribution on our gitlab but the reviewers can download it: <https://www.dropbox.com/s/xzps72g6uj7zlmu/RiverDetectionReviewersVersion.zip?dl=1>

²<http://pmneila.github.io/PyMaxflow/>

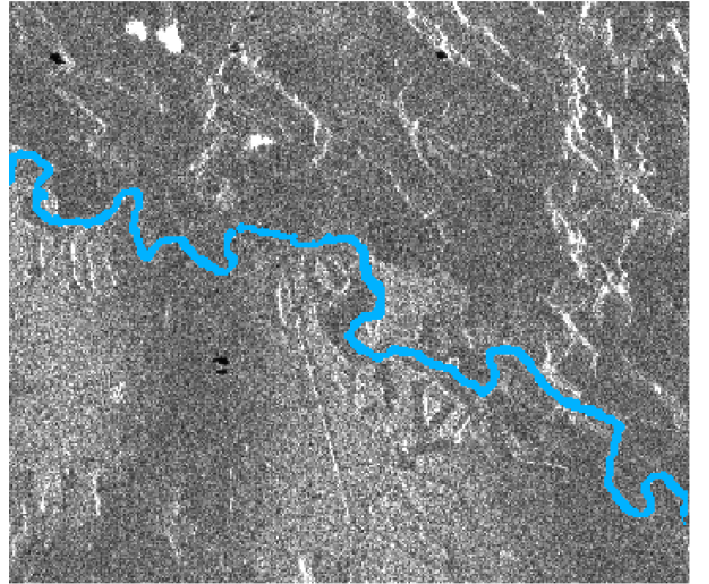


Fig. 9. Result of the CRF segmentation for the same SAR image as in Figures 4 and 6

A. Dataset

Our method has been tested on Sentinel-1 GRD images and on simulated SWOT HR images.

a) *Sentinel-1*: We used Sentinel-1 GRD images (more specifically Interferometric Wide Ground Range Detected High Definition images) in VV or VH polarization that have been downloaded from a Copernicus Open-Access mirror and cropped around the study area without orthorectification or calibration.

These images have been multilooked by a factor of five in the range direction from the Single Look Complex images and have an ENL of about 4.4. Their spatial resolution is about 20.5m az \times 22.m rg and each pixel corresponds to a 10m \times 10m square on the ground.

We use 7 images in our Sentinel-1 dataset, presented in table I, corresponding to various examples of small rivers with different kinds of environments.

These images are associated with a ground truth that has been manually drawn on the SAR image using GIMP software, with the help of Open Street Map and Bing aerial view data displayed over the SAR images with QGIS software to help to distinguish between actual rivers and other dark linear structures. This ground truth is not binary but classifies the pixels of the images into three classes: Land, Water, Uncertain classification. The Uncertain class corresponds to pixels for which it was not possible to determine whether or not it should belong to the river. We used it for our ground truth in four situations:

- 1) Isolated strong reflectors in rivers (most likely boats).
- 2) Bridges over rivers.
- 3) Small anabranches (diverging branches of a river, separated by an island, that re-enter the main stream downstream).
- 4) Flooded areas or small lakes that are only partially connected to a river.

TABLE I
SENTINEL-1 GRD IMAGES USED FOR OUR EXPERIMENTS

Image #-name	River name	Location	Date	Polarization	River width	Size (pixels)
1 - Des Moines	Raccoon	Des Moines, Iowa, USA	2018-08-02	VH	40m - 120m	1313×1750
2 - Sunar	Sunar	Garhakota, Madhya Pradesh, India	2018-06-22	VH	40m - 150m	1026 × 923
3 - Gaoual	Tomine Koumba	Near Gaoual, Guinea	2018-07-15	VH	30m - 130m 30m - 130m	927×1854
4 - Angers	Maine Loire Louet anabranh	Angers, Pays de la Loire, France	2019-12-02	VV	100m - 150m 200m - 1000m 25m-120m	927×1854
5 - Garonne	Garonne	North of Toulouse, France	2020-02-09	VV	80m - 200m	1109×1704
6 - Redon	Oust Vilaine	Redon, Brittany France	2018-07-04	VH	15m - 60m 40m - 160m	618×773
7 - Régina	Arataï Approuague	Régina, French Guiana, France	2017-10-11	VH	25m - 100m 100m - 150m	553×1216

All Sentinel-1 image extracts and associated ground truth are made available in the same repository as our published code.

b) *SWOT*: Concerning SWOT images, as the SWOT satellite has not yet been launched, all test images have been simulated with the Jet Propulsion Laboratory (JPL) HR science simulator [33]. These images are associated with the water mask that has been used for the simulation as ground truth.

We used three simulated images for our experiments. All images have been simulated considering pessimistic assumptions about the performances of the sensor (worst case scenario). The first image has been simulated from Lidar and high-resolution landcover data on the Saline River, Lincoln County, Kansas, USA, and presented in the previous part. This image has been simulated with the so-called dark water phenomenon. Dark water is water with a very low contrast compared to land and is caused by very low water surface roughness at low wind speed. This dark water phenomenon, and numerous bright land structures, make river detection especially difficult on this image. The two other images have been simulated using Lidar data on the Rhône delta, France. Unlike the Saline River image, these two images have been simulated without dark water: the contrast between water and land is more homogeneous. Image 9 corresponds to the downstream Petit Rhône river, whereas image 10 corresponds to the upstream Petit Rhone river with two small channels.

The SWOT images are summarized in Table II. The river widths are here given in pixels and not in meters as the pixel ground range spacing in SWOT depends on the position in the swath.

B. Metrics

In order to quantitatively assess the performance of the water detection compared to our ground truth, we use the same six metrics as Lobry et al. [7]. These metrics are based on the number of pixels considered as true positives (TP) for adequately classified water, true negatives (TN) for adequately classified land, false negatives (FN) for water classified as land

and false positives (FP) for land classified as water:

$$\begin{aligned} \text{Recall} &= \frac{\text{TP}}{\text{TP} + \text{FN}} \\ \text{FPR} &= \frac{\text{FP}}{\text{FP} + \text{TN}} \\ \text{Precision} &= \frac{\text{TP}}{\text{TP} + \text{FP}} \\ \text{F-score} &= 2 \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \\ \text{ER} &= \frac{\text{FP} + \text{FN}}{\text{TP} + \text{FN}} \\ \text{MCC} &= \frac{\text{TP} \times \text{TN} - \text{FP} \times \text{FN}}{\sqrt{(\text{TP} + \text{FN})(\text{FP} + \text{TN})(\text{TP} + \text{FP})(\text{TN} + \text{FN})}} \end{aligned}$$

The recall is the proportion of actual water pixels that are classified as water. The FPR is the proportion of land pixels that are classified as water. The precision is the proportion of actual water among all the pixels classified as water. The F-score is the harmonic mean of precision and recall and will be our main metrics. ER is the ratio between the number of incorrectly classified pixels and the number of actual water pixels. This metric is similar to the metric of the SWOT mission science requirements [34], but computed in radar geometry instead of ground geometry. The Matthews correlation coefficient (MCC) [35] is another metric that takes into account the over-representation of land in the context of river detection.

C. Implementation

For each image, we extract the rivers using our method by choosing a very limited number of prior centerline nodes, in order to highlight the robustness of the proposed approach. For single rivers (except for image 8, used as an example in the previous part), we use only two nodes: one for each endpoint. When two rivers are joining in a confluence, we locate one node on the confluence and one node at each endpoint of the two upstream rivers and of the downstream river. In the case of an anabranh (e.g. in Angers image), a node is added in the anabranh in order to prevent its centerline from going through the main stream. The nodes that have been used are plotted on the images.

We used the parameters presented in Table III. These parameters have been chosen empirically by testing multiple

TABLE II
SIMULATED SWOT IMAGES USED FOR OUR EXPERIMENTS

Image # - name	River name	Location	Hypothesis on sensor performances	Simulated dark water	River width (pixels)	Size (pixels)
8 - Saline	Saline	Lincoln County, Kansas, USA	Worst Case	Yes	2-5	301×351
9 - Petit Rhône downstream	Petit Rhône	Camargue France	Worst Case	No	3-14	700×800
10 - Petit Rhône Upstream and channels	Petit Rhône Chanel Bas-Rhône Languedoc Channel of Rhône in Sète	Camargue France	Worst Case	No	2-8	800×730

TABLE III
PARAMETERS USED FOR THE EXPERIMENTS

SWOT Sentinel-1 GRD	Line detection			Centerline detection	River segmentation			
	Patch size N	Scale Range [S_{min}, S_{max}]	Angular step θ_{step}	Linear detector power N_{pow}	Regularization		Flux	
					β	λ	σ_L	η
	9	[1,3]	3°	70	4	0.2	3	20
	9	[1,4]	3°	10	4	0.2	3	20

values on the SWOT simulated image Saline. We manually increased the maximum scale S_{max} of the detection of the linear structures from 3 to 4 to account for the wider range of river width in our use of Sentinel-1 images and decreased the N_{pow} parameter from 70 to 10 in order to be more robust to dark roads.

The results could have been improved by fitting the parameters to the type of image (SWOT, Sentinel-1 VV, Sentinel-1 VH) or even to the environment (urban area, rain-forest, desert...), but our main goal for these experiments was to show satisfactory performances without fine-tuning of the parameters.

D. Results

Table IV gives the metrics for each image in our dataset. The metrics are computed only for river detection (the detection of surrounding lakes is considered to be a separate task, already addressed by [7]). Three images are presented in detail below, with their associated detection maps: image 1 (Des Moines) is representative of the results obtained with our method for typical Sentinel-1 images in urban areas, image 2 (Sunar) to present an example where the centerline detection is not successful, and image 9 (Petit Rhône Downstream) as an example for SWOT images. All ten images of our dataset and the corresponding segmentation results are presented in the supplementary materials and for Sentinel-1 images the results can be reproduced using our published code.

a) Example 1: Image 1 (Des Moines), displayed in Figure 10, shows that our method leads to a correct detection of the whole river, despite using only two nodes as prior information, and although the river is meandering. The centerline (b) has been correctly classified with the proposed approach based on the response of the linear feature detector. The segmentation of the river from the centerline using our conditional random field approach also gives good results in this example. The river contour is relatively well respected. It can be noted that, despite a reflectivity similar to the reflectivity of the river, the lake (which is not connected to the river) and two large roads

(Figure 10 (a)) are not misclassified as river. Our approach avoids two typical pitfalls of river detection on SAR images that are lakes close to rivers and highways.

b) Example 2: Image 2 (Sunar) presented in Figure 11 illustrates a possible issue with the proposed approach when using insufficient exogeneous information about the location of the river. If a dark linear structure in a river meander in a Sentinel-1 image creates a shorter path between two a priori nodes of the centerline and if the actual river is not identifiable, the detected centerline will be incorrect. This leads to false positives on the dark linear structure and false negatives in the part of the river that has been bypassed, such as in Figure 12. The resulting classification is erroneous for this part of the river. However, this does not significantly affect the classification of the remainder of the river, as the estimation of the parameters is robust enough.

A possible improvement would be to use more centerline nodes as exogenous information and to use a post-processing step to flag as uncertain the river parts where the reflectivity is too high (possibly sand, mud or flooded vegetation) and remove them if appropriate.

c) Example 3: Image 9 (Petit Rhone downstream), presented in Figure 13, illustrates the behavior of the proposed method applied to simulated SWOT HR images. In this example, the river centerline has been correctly detected and the river segmentation is relatively accurate except for some false positives caused by speckle noise, and a very small connected channel that has not been detected. In comparison with the baseline method [7] that only detects a small part of the narrow river, the proposed approach shows an improved detection. Because our approach does not detect other water surfaces, but only rivers that would have been missed by the generic method, both approaches are complementary.

It can be noted that for SWOT images, the bright area corresponding to the river response might be slightly larger than the river itself in the azimuth direction because water is moving and does not necessarily remain coherent during the entire SAR integration time. This issue could be addressed by

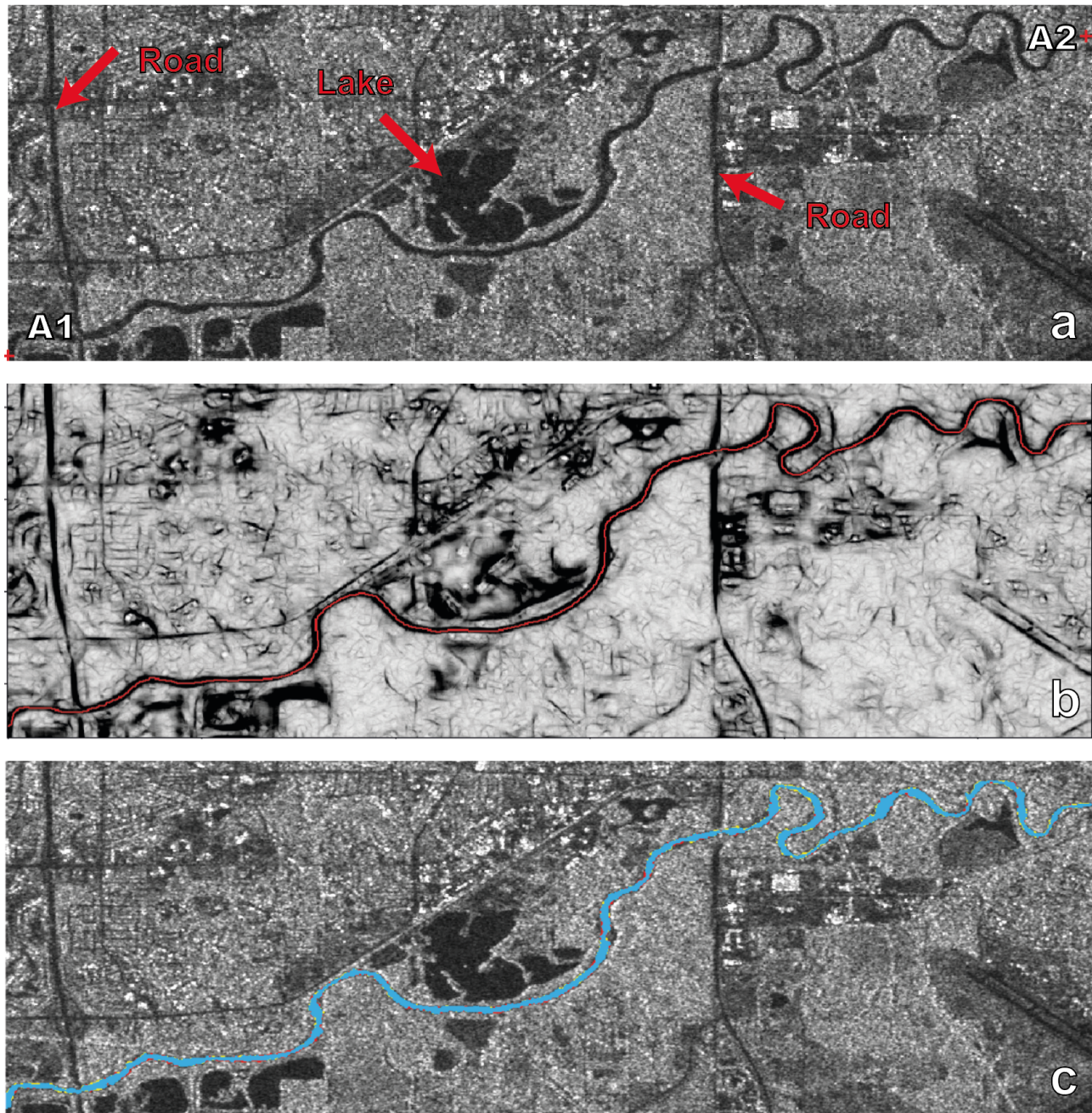


Fig. 10. Image 1 (Des Moines): (a) SAR image with annotations, (b) centerline (in red) on the linear features detector and (c) final segmentation. A1 and A2 mark the two nodes used as prior information. The color map of the line detector has been inverted and the centerline has been widened for better visualization. In (c) the true positives are displayed in blue, the false positives in yellow and the false negatives in red. True negatives are displayed as the actual SAR image pixels.

a morphological post-processing in order to erase such false positive pixels and thereby improve the precision.

IV. CONCLUSION

In this article, an innovative river extraction method is proposed and evaluated. The originality of our approach is that it uses an exogenous river database in order to guide the river detection. The proposed technique consists of three phases: First, computing the response of a linear feature detector, then detecting the centerline using the response and the prior river nodes, and finally segmenting the river around the previously

detected centerline using a CRF approach. Experiments performed on both Sentinel-1 and simulated SWOT HR images have shown that our method performs well including in low contrast situations and for very narrow rivers of only a few pixels.

The proposed method has been developed in the context of the SWOT mission to process SWOT HR images that are single-polarization and cannot easily be combined with images from other sensors. This leads us to design a resilient method for river segmentation in such images. While the proposed method achieves good results in detecting river in single-

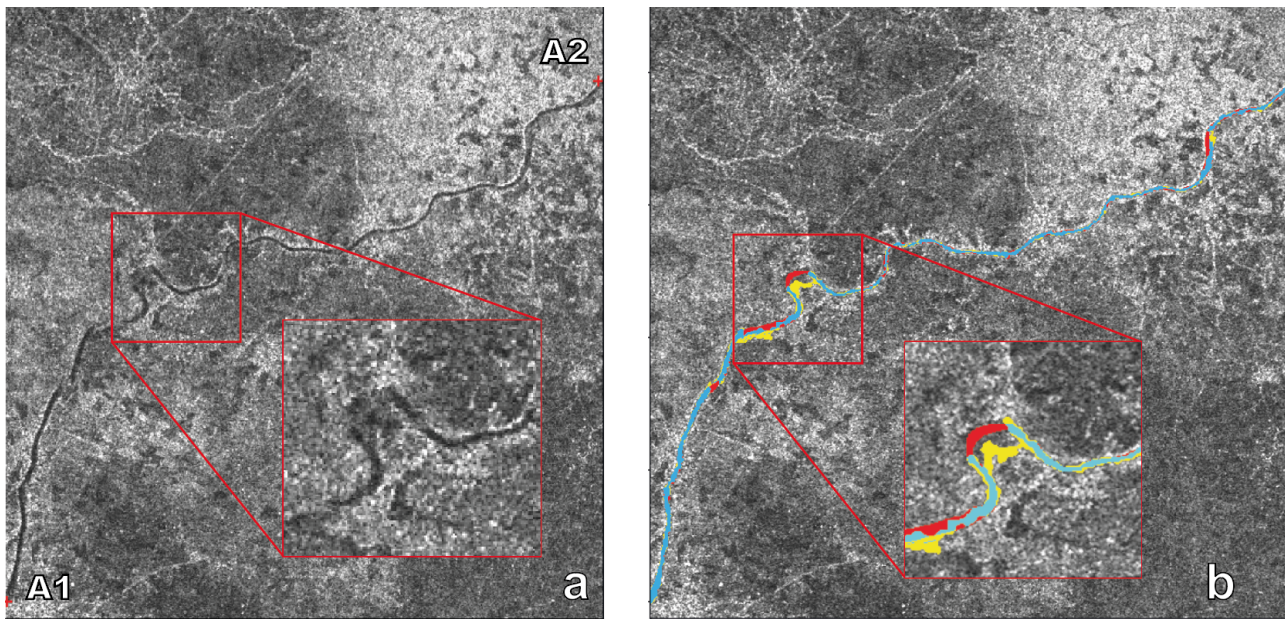


Fig. 11. Image 2 (Sunar): (a) SAR image with annotations and (b) final segmentation. A1 and A2 mark the two nodes used as prior information. The close up squared in red in both images show a meander in which the segmentation is unsuccessful as the centerline bypasses the meander. A1 and A2 mark the two nodes used as prior information. In (b) the true positives are displayed in blue, the false positives in yellow and the false negatives in red. True negatives are displayed as the actual SAR image pixels.

TABLE IV
SUMMARY OF THE METRICS FOR EACH RESULT

Number	Name (sensor)	Method	Precision (%)	Recall (%)	FPR (%)	F-Score (%)	ER (%)	MCC (%)	Execution time (s)
1	Des Moines (S1)	Proposed	92.44	93.35	0.13	92.89	14.29	92.78	57.73s
2	Sunar (S1)	Proposed	82.36	81.71	0.15	82.03	35.79	81.88	89.32s
3	Gaoual (S1)	Proposed	92.51	89.09	0.12	90.77	18.12	90.64	212.96s
4	Angers (S1)	Proposed	98.90	94.04	0.05	96.40	7.01	96.28	160.96s
5	Garonne (S1)	Proposed	97.60	82.44	0.02	89.38	19.59	89.60	166.01s
6	Redon (S1)	Proposed	90.71	92.34	0.14	91.52	17.12	91.40	47.48s
7	Régina (S1)	Proposed	89.33	82.95	0.18	86.02	26.96	85.83	62.86s
8	Saline (SWOT)	Proposed	63.24	94.45	1.02	75.76	60.45	76.81	10.45s
		Baseline	5.30	87.58	33.87	10.00	1576.64	65.92	/
9	Petit Rhône downstream (SWOT)	Proposed	80.71	89.46	0.57	84.86	31.92	84.56	47.23s
		Baseline	91.00	9.80	0.03	17.69	91.17	9.66	/
10	Petit Rhône upstream and channels (SWOT)	Proposed	73.07	87.45	0.58	79.62	44.78	79.55	57.17s
		Baseline	87.32	8.89	0.02	16.14	92.40	8.80	/

polarization (VV or VH) Sentinel 1 images, these results might be further improved by using jointly the two polarizations or even by merging information from optical images when available. The two polarizations of Sentinel-1 images could be combined by simply multiplying pixel-wise the VV and VH amplitude images as it has been proposed by Nunziata et al. [36] for coastal line segmentation, or as used in Ferrentino et al. [37] for segmenting a lake. This would require a minor adaptation of the last step of the proposed method (as the product is not Gamma-distributed), but could improve the discrimination between dark river banks and water.

The direct application of the proposed framework has an obvious potential for monitoring rivers included in the GRWL database, but it may also be adapted to the detection of rivers unknown to the database. For example, if other hydrological

information or a digital elevation model (DEM) indicate that a small tributary is missing from the database, our approach can help to retrieve it by using two inputs: one node in the main river and one node placed further up in the expected tributary.

Other interesting research tracks concern the adaptation of the proposed approach to other applications than river monitoring, for example, road extraction in SAR images.

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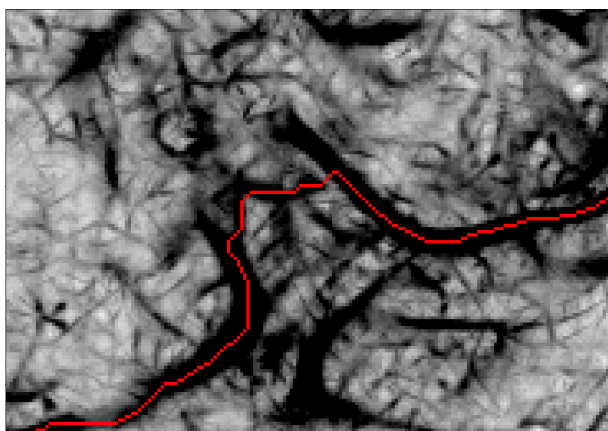


Fig. 12. Image 2 (Sunar): Zoom on the red square area in Figure 11, with the response of the linear structure detector (inverted grayscale) and the detected centerline (red, widened for better visualization).

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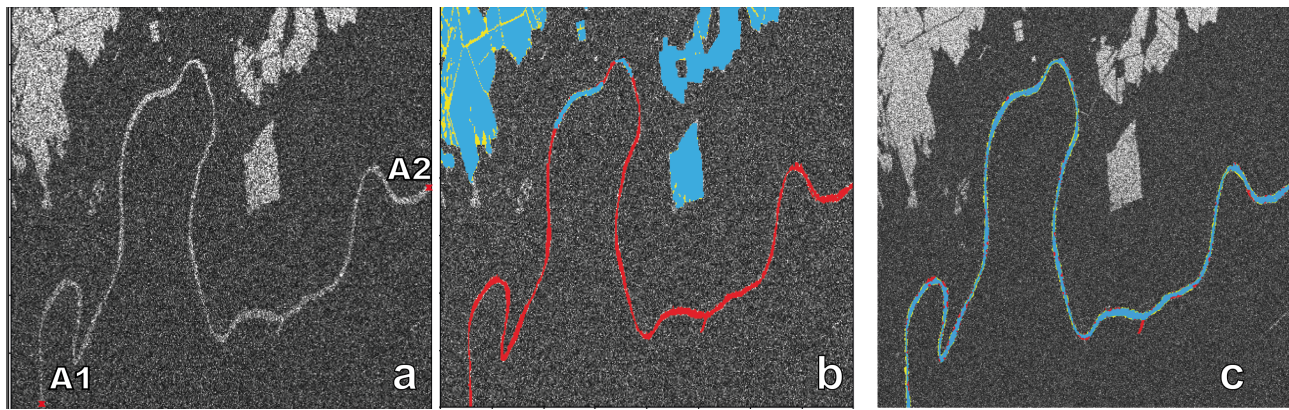


Fig. 13. Image 9 (Petit Rhône downstream): (a) SAR image with a priori nodes, (b) segmentation with the baseline MRF method and (c) proposed method segmentation. A1 and A2 mark the two nodes used as prior information. In (b) and (c) the true positives are displayed in blue, the false positives in yellow, and the false negatives in red. True negatives are displayed as the actual SAR image pixels.

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