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River channel segmentation in polarimetric SAR images: Watershed transform combined with average contrast maximisation

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ABSTRACT

This publication presents a computer method allowing river channels to be segmented based on SAR polarimetric images. Solutions have been proposed which are based on a morphological approach using the watershed segmentation and combining regions by maximising the average contrast. The image processing methods were developed so that their computational complexity is as low as possible, which is of particular importance in analysing high resolution SAR/polarimetric SAR images, where it has a measurable impact on the total segmentation time. What is more, compared to the existing solutions known from the literature review: (1) in the proposed approach, there is no need to execute further steps necessary to eliminate objects (i.e. background components) located outside the river channel from the image as a result of the segmentation carried out, (2) there is no need to sample the entire image and carry out a pixel–wise classification to prepare the segmentation process. If the steps listed in items (1) – (2) are performed, they can, unfortunately, extend the segmentation time. The experiments completed on images acquired from the ALOS PALSAR satellite for different regions of the world have shown a high quality of the segmentations carried out and a high computational efficiency compared to state–of–the art methods. Consequently, the proposed method can be used as a useful tool for monitoring changes in river courses and adopted in expert and intelligent systems used for analysing remote sensing data.

1. Introduction

The Synthetic Aperture Radar (SAR) produces high-resolution images throughout its operation and regardless of weather conditions. Because of these advantages, the SAR technology is widely used in remote sensing applications for Earth observations. SAR images are monochromatic and only contain information about the reflectance of the observed area. These images can be enhanced using more complex processing methods, i.e. polarisation techniques with the use of variable polarisation antennas (Hamazaki, 1999; Ito, Hamazaki, & Tomioka, 2001). Polarimetric SAR provide more data than conventional, monopolarized SAR, producing preclassified–like images (e.g. forest/nonforest discrimination) (Rosenqvist, Shimada, Ito, & Watanabe, 2007; Santoro, Eriksson, & Fransson, 2015). The images used in this study came from a variable resolution instrument, namely a polarimetric Phased Array L–band Synthetic Aperture Radar (PALSAR) installed on board the Advanced Land Observing Satellite (ALOS) (Rosenqvist et al., 2007). The acquisition of images from ALOS PALSAR was adjusted, among others, for the purpose of providing repeated dual–polarized (Horizontal–Horizontal, HH, and Horizontal–Vertical, HV) data in the Fine Beam Dual (FBD) mode (Rosenqvist et al., 2007).

In the analysis of SAR images, image segmentation (Ersahin, Cumming, & Ward, 2010; Morio, Goudail, Dupuis, Dubois-Fernandez, & Réfrégier, 2007; Yin & Yang, 2014; Yu, Qin, & Clausi, 2012) and land classification (Dickinson, Siqueira, Clewley, & Lucas, 2013; Egorov, Hansen, Roy, Kommareddy, & Potapov, 2015; Lee, Grunes, Pottier, & Ferro-Famil, 2004; Liu et al., 2013; Shi, Zhang, Yang, Zhang, & Li, 2013) are significant. The data obtained can be used for various applications, and allows the following to be monitored, among others:

- drought or flood (Schlaffer, Matgen, Hollaus, & Wagner, 2015; Seitz, Hedman, Meyer, & Lee, 2014; Syvitski, Overeem, Brakenridge, & Hannon, 2012)
- deforestation (Liesenberg & Gloaguen, 2013)
- urban areas growing (Ince, Kiranyaz, & Gabbouj, 2012; Salehi, Sahebi, & Maghsoudi, 2014; Tuia, Pacifici, Kanevski, & Emery, 2009)
- agricultural crop areas (Jiao et al., 2014; Skriver, 2012)
- sea and lake shorelines (Silveira & Heleno, 2009; Yang & Lu, 2013; Yu & Acton, 2004)

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- river channels (Klemenjak, Waske, Valero, & Chanussot, 2012; Li et al., 2014; Sghaier, Foucher, & Lepage, 2017; Silveira & Heleno, 2009; Sui, Xu, Liu, Sun, & Wen, 2012)
- oil spills (Fustes et al., 2014; Salberg, Rudjord, & Solberg, 2014)

Among classification algorithms used for polarimetric SAR images, three main classes can be listed based on literature (Ince et al., 2012): (1) classification based on physical scattering mechanisms inherent in data (Bielecka, Porzycka-Strzelczyk, & Strzelczyk, 2014; Van Zyl, 1989), (2) a classification based on the statistical data analysis (Lee, Grunes, & De Grandi, 1999b; Wu, Ji, Yu, & Su, 2008) and (3) classification based on image processing methods (Ince, 2010; Tan, Lim, & Ewe, 2007). What is more, there are also approaches which combine the techniques listed (Lee et al., 1999a; Pottier & Lee, 2000).

This publication focuses on the subject of river channel segmentation which allows changes of river courses to be monitored. In SAR images, the grey level of pixels in the area covered by water is relatively low and contrasts with the higher values of the rougher land surrounding it. Consequently, the grey level is generally considered to be a significant function for identifying the river channel and then segmenting it. However, in the analysed images of river channels, these may adjoin other bodies of water, arable fields with a contrast very similar to that of water, which may be wrongly identified as areas of the river. In addition, in urbanised regions, man–made infrastructure is portrayed (e.g. bridges, docks as well as anchored and sailing vessels), which interferes with the identification of natural, continuous sections of rivers. In addition, speckle noise occurs widely in SAR images, producing a very grainy appearance and hence making the segmentation and classification difficult (Parrilli, Poderico, Angelino, & Verdoliva, 2012; Yahya, Kamel, & Malik, 2014; Yu & Acton, 2002).

The method of river channel segmentation proposed in this paper can be classified as a global approach making use of local image features, whereas the global segmentation is a method of watershed by immersion segmentation (with a linear time complexity relative to the pixel number) (Roerdink & Meijster, 2000; Soille, 2013), and the process of merging output regions is controlled by maximising the average contrast for the neighbouring regions (the average contrast is calculated 'locally') starting with the selected initial one. The number of regions is significantly reduced using the appropriate pre–processing methods. The solutions presented in this article made it possible to produce high segmentation results while all operation steps are very fast during the processing of the analysed images, also compared to other, existing solutions taken from literature. This is discussed further down in the publication. In the experimental part of the publication, the proposed approach was compared to three well–known segmentation methods: Multilevel image thresholding using Otsu's method (Liao, Chen, Chung et al., 2001), Fast Random Walker (Grady, 2006), Active Contour Without Edges (Chan & Vese, 2001).

This article is structured as follows. Section 2 contains a brief review of the existing methods that allow river channels to be segmented. Section 3 discusses the experiments conducted and the research results. Section 4 contains conclusions from the research carried out, while the Section 5 is an acknowledgement of Japan Aerospace Exploration Agency (JAXA), which provided ALOS PALSAR images.

2. Related works

A literature review reveals three main approaches to segmenting river channels, namely:

- global methods (Silveira & Heleno, 2009; Song, Wu, & Dai, 2016; Sui et al., 2012)
- global methods with manual user interaction during the segmentation (Zhu, Li, Zhang, & Shen, 2015)
- mixed methods: global methods with the use of local image features (Klemenjak et al., 2012; Li et al., 2014; Sghaier et al., 2017)

Silveira and Heleno (2009) presented an approach making use of a region–based active contour and an expectation-maximization (EM) algorithm, which makes it possible to identify water regions. The solution presented makes it possible to identify the river channel as well as isolated bodies of water present in the entire processed image, for example formed as a result of floods. This study also analyses situations in which the global segmentation completed extracted, apart from the river channel, also isolated area as which are not bodies of water, i.e. false positive signals. This problem can then be solved using postprocessing operations and the morphological closing filter (Soille, 2013), followed by the selection of the largest region. In the experimental part it is stated that the classification error amounted to 36.7%.

Sui et al. (2012) proposed a segmentation method which integrates the multi–scale level set and the Gamma statistical model. The gamma distribution is one of widely used models for the statistical representation of speckle noise in SAR images. Sui et al. used the threshold segmentation method to initialize the level set function. In the experimental part, for an example SAR image for analysis, with the resolution of 2522×2122 pixels, acquired in a non–built–up area, the river channel segmentation took 24.9 s. with the accuracy of 98%.

Song et al. (2016) proposed an active contour method allowing a global segmentation and using an entropy–based image thresholding algorithm. However, it should be noted that for the global segmentations executed using the methods applied, all the analysed examples contain not only the extracted river channels, but also background elements: the area of land including the features present in it, such as arable fields or man–made buildings.

Zhu et al. (2015) applied a solution allowing river channels to be segmented and employing a global segmentation method (Otsu, 1975) with one threshold for the source SAR image. Then, based on several manually traced, rectangular ROIs approximating subsequent fragments of the river channel, further morphological operations are executed and then the image is once again threshold using the Otsu method (Otsu, 1975). Finally, the image is processed using morphological dilation and erosion to remove the artefacts that have appeared. Unfortunately, the publication by Zhu et al. (2015) does not specify the resolution of several example SAR images analysed.

Li et al. (2014) presented a solution enabling river boundaries extraction using several image processing techniques. Once noise is removed from the image, the latter is thresholded using the Otsu method (Otsu, 1975). Then, the morphological operations of opening and closing are executed, followed by the local connectivity–based regions of interest (ROI) extraction. At the end, region–based active contour driven by local image fitting (LIF) (Zhang, Song, & Zhang, 2010) is used to produce the river boundaries. Li et al. (2014) stated that the average computational time of all processing steps amounts to 21 min for a 4000×4000 pixel image, while the average values of the measured commission error and omission error amount, respectively to: 6.5% and 3.3%.

Klemenjak et al. (2012) introduced a method operating in three subsequent phases: 1 – Generating morphological profiles by applying a series of closing paths; 2 – Output pixels classification as follows: "Confident non–water–pixels", "potential non–water–training–pixels" and "potential water–training–pixels"; 3 – at this phase of the supervised classification, two classes are identified: "water" and "non–water" using One–class Support Vector Machines (One–class SVM). During the training phase, "potential water–