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Optical images-based edge detection in Synthetic Aperture Radar images

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ABSTRACT

We address the issue of adapting optical images-based edge detection techniques for use in Polarimetric Synthetic Aperture Radar (PolSAR) imagery. We modify the gravitational edge detection technique (inspired by the Law of Universal Gravity) proposed by Lopez-Molina et al., using the non-standard neighbourhood configuration proposed by Fu et al., to reduce the speckle noise in polarimetric SAR imagery. We compare the modified and unmodified versions of the gravitational edge detection technique with the well-established one proposed by Canny, as well as with a recent multiscale fuzzy-based technique proposed by Lopez-Molina et al. We also address the issues of aggregation of gray level images before and after edge detection and of filtering. All techniques addressed here are applied to a mosaic built using class distributions obtained from a real scene, as well as to the true PolSAR image; the mosaic results are assessed using Baddeley's Delta Metric. Our experiments show that modifying the gravitational edge detection technique with a non-standard neighbourhood configuration produces better results than the original technique, as well as the other techniques used for comparison. The experiments show that adapting edge detection methods from Computational Intelligence for use in PolSAR imagery is a new field worthy of exploration.

1. Introduction

Edge detection seeks to identify sharp differences automatically in the information associated with adjacent pixels in an image [1]. Edge detection for optical images is nowadays quite an established field. It is traditionally carried out using gradient-based techniques, such as the well-known Canny algorithm [2]. Techniques based on Computational Intelligence have also been proposed in the recent literature. Sun et al. [3] proposed the gravitational edge detection method, inspired by Newton's Universal Law of Gravity. Lopez-Molina et al. [4] proposed a fuzzy extension for this technique, allowing the use of T-norms, a large class of fuzzy operators; they also proposed small modifications in the basic formalism (see Section 3). Danková et al [5] proposed the use of a fuzzy-based function, the F-transform; the original universe of functions is transformed into a universe of their skeleton models (vectors of F-transform components), making further computations easier to perform. Barrenechea et al. [6] proposed the use of interval-valued fuzzy relations for edge detection, using a T-norm and a T-conorm to produce a fuzzy edge image, that is then binarized. This approach was extended by Chang and Chang [7]. First of all, two new images are created—one rather dark and the other rather bright—by applying two different parameters on the linear combinations of the images obtained using min and max operators, respectively. Then, the fuzzy edge image is created by the difference between these two new images. Another recent approach from Computational Intelligence is the multiscale edge detection method proposed by Lopez-Molina et al. [8], using Sobel operators for edge extraction and the concept of Gaussian scale-space.

SAR sensors are not as adversely affected by atmospheric conditions and the presence of clouds as optical sensors. Moreover, unlike the optical counterparts, SAR sensors can be used at any time of day or night. For these reasons, remote sensing applications using SAR imagery have been growing over the years [9]. SAR images, however, contain a great amount of noise, known as *speckle*, that degrades the visual quality of the images. Caused by inherent characteristics of radar technology, this multiplicative

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non-Gaussian noise is proportional to the intensity of the received signal.

Contrary to what happens with optical images, there are still few algorithms specifically dedicated to SAR images [10]. One interesting means to create edge detection algorithms for SAR images is to modify those created for optical images. However, the use of these methods on SAR images is not straightforward, due to speckle. One can either adapt optical image techniques to meet SAR data properties, or first preprocess the images using filters and then apply the original optical techniques.

The main purpose of our study is to investigate the application of the gravitational edge detection, Here we modify the original 3×3 window: the value in each cell in the window is no longer the original one, but the aggregation of a set of neighbouring pixels, according to the larger 9×9 neighbourhood configuration proposed by Fu et al. [10]. We propose a typology of experiments to study the behaviour of the modified edge detection method, considering polarization, image aggregation, and image binarization. We focus on the use of the following processes: DAB (edge Detection on non-binary images, Aggregation of the resulting non-binary images, Binarization) and ADB (Aggregation of non-binary images, edge Detection on the resulting non-binary image, Binarization).

We also investigate the use of noise-reduction filters in preprocessing the images, by making use of the well-known Enhanced Lee filter [11] and a filter recently proposed by Torres et al. [12].

da Silva et al. [13] describe a classification experiment, based on a full polarimetric image from an agricultural area in the Amazon region in Brazil. In that study, the authors estimated the parameters for probability distributions associated to each of the classes of interest, such as water and different types of vegetation and their phenology. They assessed their results in an image formed by a mosaic of the classes, with pixel values generated using the parameters found for each class. We apply all techniques addressed in this study on twenty simulated mosaics, using the parameters estimated in [13], considering amplitude images derived from different polarizations. We assess the quality of the results, according to Baddeley's Delta Metric (BDM) [14].

We also apply the methods on the real images, but assessment is only visual. We compare our results with those produced by the use of Canny's algorithm [2] and the recently proposed multiscale method by Lopez-Molina et al. [8].

The present study is an extended version of [15], in which some of the main ideas of this paper were first delineated. However, the present study and [15] differ in the scope of the proposed approach as well as in the reliability of the results. Indeed, in [15], only one simulated image was used in the experiments and only Canny's technique was compared to its results. Moreover, in the previous paper we only addressed the edge detection of the image resulting from the aggregation of the three simulated polarization images. In our first paper only ADB was addressed; edge detection on the individual polarization images as well as DAB strategy were not considered.

The results from our current study show that adapting edge detection methods from Computational Intelligence to use in radar imagery is a new field worthy of exploration. In particular, our experiments show that modifying the gravitational method with Fu's 9×9 neighbourhood produces better results than the unmodified method. They also show the importance of filtering when adapting edge detection techniques from optical to radar images.

2. Basic concepts on SAR images

Optical and SAR sensors measure the amount of energy reflected by a target in various bands of the electromagnetic spectrum. The bands employed in most imaging radars use frequencies in the 2 MHz to 12.5 GHz range, with wavelengths ranging from 2.4 cm to 1 m. In this study, we used only the L-band with wavelengths of [30 cm, 1 m] and frequencies of [1 MHz, 2 GHz].

SAR systems generate the image of a target area by moving along a usually linear trajectory, and transmitting pulses in lateral looks towards the ground, in either horizontal (H) or vertical (V) polarizations [16], respectively denoted as H and V (see Fig. 1). In the past, the reception of the transmitted energy was made solely on the same polarization of the transmission, generating images in the HH and VV polarizations. Currently, with the advent of polarized and fully polarimetric radars (PolSAR – *Polarimetric Synthetic Aperture Radar*), information about intensity and phase of the cross signals are also obtained, generating images relating to HV and VH polarizations. Usually, applications only consider the HH, VV, and HV polarizations.

The imaging can be obtained by gathering all the intensity and phase information data from the electromagnetic signal after it has been backscattered by the target in a given polarization [18]. Each polarization in a given a scene generates a complex image, which can be thought of as two images, containing the real and imaginary values for the pixels, respectively.

We denote the complex images from HH, VV, and HV polarizations as S_{HH}, S_{HV}, and S_{VV}. Multiplying the vector $[S_{HH}\ S_{HV}\ S_{VV}]$ by its transposed conjugated vector $\left[S^*_{HH}\ S^*_{HV}\ S^*_{VV}\right]^t$, we obtain a 3×3 covariance matrix. The main diagonal contains intensity values; taking their square root, we obtain amplitude values. We denote the intensity images by I_{HH}, I_{HV}, and I_{VV} and their corresponding amplitude counterparts by A_{HH}, A_{HV}, and A_{VV}. In this paper, we only considered the amplitude images, such as those depicted in Fig. 2.

Speckle noise is multiplicative, non-Gaussian, and is proportional to the intensity of the received signal. Speckle degrades the visual quality of the displayed image by sudden variations in image intensity with a salt and pepper pattern, as can be seen in Fig. 2. It can be reduced with multiple looks in the generation of the complex images, causing degradation in spatial resolution. Another way to reduce noise is to employ filters, as will be discussed in the next section.

In SAR image classification, one often uses samples from the classes in order to estimate the parameters of the distribution believed to underlie each class. Synthetic images can then be created using Monte Carlo simulation by taking the realization of the random variable associated to the class of each classified pixel. This artifice is useful to choose the most apt classifier for a given application: instead of relying solely on the original image, one takes the classifier that obtains the best average accuracy on the set of synthetic images. This methodology can also be used in other tasks, such as edge detection.

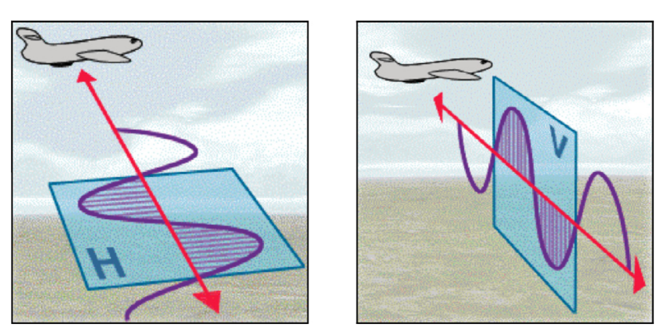

Fig. 1. Horizontal and vertical signal polarizations transmitted by an antenna. *Source:* [17].