Neural Network Based Edge Detection in Two-Look and Dual-Polarization Radar Images

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Abstract—**Edge detection is a standard operation in image processing. It becomes problematic if noise is not additive, not Gaussian and not i.i.d. as this happens in images acquired by synthetic aperture radar (SAR). To perform edge detection better, it has been recently proposed to apply a trained neural network (NN) and SAR image pre-filtering for single-look mode. In this paper, we demonstrate that the proposed detector is, after certain modifications, applicable for edge detection in two-look and dual-polarization SAR images with and without pre-filtering. Moreover, we show that a recently introduced parameter AUC (Area Under the Curve) can be helpful in optimization of parameters for elementary edge detectors used as inputs of the NN edge detector. Quantitative analysis results confirming efficiency of the proposed detector are presented. Its performance is also studied for real-life TerraSAR-X data.**

Index Terms—**Synthetic aperture radar; speckle; edge detection; neural network; polarimetric and two-look images**

I. Introduction

Synthetic aperture radar (SAR) imaging has become a useful remote sensing tool for numerous applications [1-3]. This is due to several advantages of modern SAR systems as ability to acquire data in all-weather conditions during day and night, rather high spatial resolution, etc. Meanwhile, acquired images suffer from noise-like phenomenon called speckle and its presence makes problems at different stages of image processing as interpreting, object detection, classification, segmentation, filtering.

The latter two operations often presume edge detection as a particular step [2, 4]. For example, detected edges, alongside with other heterogeneities, are exploited in locally adaptive filtering [4-6]. While detecting edges for the considered case, one has to take into account several peculiarities of the noise (speckle). First, it possesses non-Gaussian probability density function (PDF) especially if a number of looks for a given SAR image is small [2, 6]. Second, speckle is a specific type of multiplicative noise [2, 4]. Third, usually speckle is spatially correlated [2, 5]. These peculiarities, taken together, sufficiently limit a set of conventional edge detectors that can be effectively applied to SAR images directly or after certain pre-processing of data [4].

Certainly, there are edge detectors specially designed to cope with speckle noise [7, 8]. However, if speckle is intensive (as this happens in single-look SAR images) and edge contrast is not high, then efficient edge detection is problematic. Recall that for most edge detectors there are some thresholds and edge is assumed detected if output value of a considered elementary edge detector (EED) exceeds this threshold. Then, the use of a larger threshold leads to missing true edges (with low contrasts) and to breaks in edge contours. In turn, the use of a smaller threshold results in a larger number of falsely detected pixels that are wrongly recognized as belonging to edges.

One idea put forward recently [9-11] is that a trained neural network (NN) can be used to provide an improved performance compared to EEDs the outputs of which are used as NN inputs. All these papers address a question of NN-based edge detection in single-look SAR images which are the most complicated practical case due to fully developed speckle.

The main outcomes of the studies carried out are the following. First, there is no need to use a large number of EEDs in NN edge detector. It is enough to use 4…5 EEDs where these EEDs are efficient enough and are based on different operation principles. These properties allow NN to aggregate advantages of the used EEDs and to diminish influence of EED negative features [9]. Second, pre-filtering of single-look SAR images by the local statistic Lee filter [6] allows improving edge detectability. Certainly, NN edge detector should be trained with taking into account is an image pre-processed or not [10]. Third, NN edge detectors have been trained for spatially uncorrelated simulated speckle. Because of this, before applying them to detect edges in real-life images these images have been down-sampled to remove spatial correlation [9-11]. Fourth, usually a detector performance is characterized by the so-called ROC (receiver operation curve). In [11], it has been proposed to use Area Under the Curve (AUC) parameter [12] to characterize performance of any detector by a single value. This has allowed to easily compare performance of different detectors (both EEDs and NN ones) and, moreover, to optimize parameters of some EEDs [11].

The positive results reached for the case of single-look SAR images have inspired us to pay attention to other complex situations. They are two-look and dual-polarization SAR images [2, 13-15]. The use of multi-look mode makes speckle less intensive [2, 6, 7]. Similarly, availability of two components (usually HH and VV) in dual-polarization data simplifies the task of edge detection [13] (recall that many modern SAR systems exploit polarimetric mode in collecting data). However, it still remains quite complex. Thus, performance of edge detectors is worth improving and this can be done by means of trained NN with optimized EEDs.

II. Image-Noise Model and Elementary Edge Detectors

The image/noise model can be expressed as

$$I_{ij}^{n} = I_{ij}^{true}\mu_{ij}\,, \qquad (1)$$

where I_{ij}^{true} denotes the true image value in *ij*-th pixel and μ_{ij} stands for the multiplicative noise. This factor has unity mean and its distribution depends upon several factors as (equivalent) number of looks (ENL) and how a given SAR image is formed – as amplitude or intensity of received and processed backscattered signals. As it is known, speckle variance $\sigma_{\mu}^{2} = 0.273$ if a single-look amplitude image is acquired. Then, speckle obeys Rayleigh distribution [2]. Speckle variance is inversely proportional to ENL and, for amplitude SAR images, $\sigma_{\mu}^{2} = 0.273 / ENL$.

The model (1) does not directly take into account that speckle is usually spatially correlated. To solve this problem and to simplify the task, we assume that speckle is i.i.d. for test images. For real-life images, as said above, we carry out preliminary down-sampling to come to validity of assumption.

All NN edge detectors analyzed below employ four EEDs as input data. A first EED is a relative local variance calculated as

$$\sigma_{ij}^{2} = \sum_{k=i-2}^{i+2}\sum_{l=j-2}^{j+2}(I_{kl} - I_{ij}^{mean})^{2} / (24(I_{ij}^{mean})^{2}\sigma_{\mu 0}^{2})\,, \qquad (2)$$

where I_{ij}^{mean} is the local mean in *ij*-th pixel, $\sigma_{\mu 0}^{2}$ equals to σ_{μ}^{2} if pre-filtering is not applied or to residual speckle variance if a pre-filtering is applied.

Another local parameter, quasirange, is determined as

$$QR_{ij} = I_{ij}^{(q)} / I_{ij}^{(p)}\,, \qquad (3)$$

where $I_{ij}^{(q)}, I_{ij}^{(p)}$ denote *q*-th and *p*-th order statistics, respectively, for the scanning window (SW) having its center on *ij*-th image pixel. A third local parameter is a ratio-based Harris EED output [12]. This detector uses geometric information and sub-windows. A fourth local parameter deals with a number of DCT coefficients that have absolute values exceeding a threshold $\beta\sigma_{\mu 0}I_{ij}^{mean}$ where β is the parameter set equal to 3.5

Note that all four local parameters are determined in 5x5 pixel SW and can be calculated quite quickly. It is also worth recalling the following. For four considered EEDs applied to single-look test SAR images without pre-filtering, the values of AUC are from 0.729 to 0.798 (larger AUC corresponds to better edge detection, the ideal, potentially reachable, value equals to unity).

The NN based detector provides AUC=0.810. If pre-filtering is applied, AUC values for EEDs are from 0.767 to 0.838 and 0.860 for the trained NN based edge detector [11]. Thus, we expect better values for the case of two-look speckle and dual-polarization data.

III. NN Based Detector Training and Input Parameter Optimization

First of all, we have decided to use a perceptron NN [16]. This deals with several factors. First, there exist well established efficient methods and algorithms for perceptron training in a supervised manner [16]. Second, we have taken into account experience of solving similar tasks [16].

The used NN is of forward propagation type and contains three layers. The first, input, layer has four neurons according to the number of EEDs. A hidden layer has 7 neurons (this is determined by empirical rules of NN training). Finally, output layer contains only two neurons that correspond to two output classes, namely, “edge” and “non-edge”. Neurons in all layers have sigmoid activation function. Training error for a current epoch is passed to input for modifying weights of connection matrix before the next epoch using a factor α that determines a speed and an accuracy of training

$$w_{t}^{m} = w_{t}^{m-1} + \alpha\left(Y_{g} - H_{g}\right) f\left(X_{g}\right), \qquad (4)$$

where w_{t}^{m}, w_{t}^{m-1} are the weights for next and current epochs, respectively; $f\left(X_{g}\right)$ is an input weighted by the neuron activation function; $\left(Y_{g} - H_{g}\right)$ is an error for a current training epoch determined as a difference between a current result (H_g) and a desired value for a training data sample (Y_g). Training is, thus, intended to minimize $\left(Y_{g} - H_{g}\right)$ and is considered completed when the error becomes less than 1%.

Training has been carried out using standard error back-propagation approach for two test images. An example of the test images is presented in Fig. 1 (for the case of two-look speckle). The test images have edges of different contrast of vertical and horizontal orientation. Training samples (4-element vectors) are collected in such a manner that they either contain EED output values (vectors) for SWs positioned on edges or on homogeneous regions with full overlapping. Number of such SWs in this case is equal to 30000. Test images are created and training samples are formed in such a manner that there are quite many “edge” samples for low contrast edges. This is done “to force” NN to better recognize just low contrast edges detection of which is more complex than for high contrast edges. Meanwhile, high contrast edge SWs are also used in training data to provided NN based detector ability to perform its function in any situation that might happen in practice and to prevent overfitting.

AUC is determined as

$$A = \frac{S_{0} - n_{0}(n_{0} - 1)/2}{n_{0}n_{1}}\,, \qquad (5)$$

where n_0 and n_1 denote the numbers of elements in the first and second classes, respectively, $S_{0} = \sum r_{m}$, r_{m} is the rank of *m*-th element that belongs to the first class. To calculate it for the test images, we considered SWs positioned exactly on edges (SW central pixel is on edge strip) or exactly on homogeneous region (all SW pixels belong to the same homogeneous region). Then, a given edge detector is applied, its values (“decision”) are determined and AUC is calculated.

Number of SWs used in AUC calculation is equal to the NN training set size (30000).

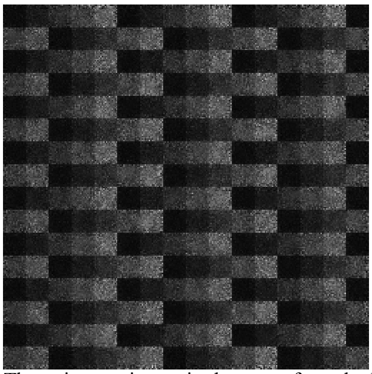

Figure 1. The noisy test image in the case of two-look speckle

Availability of the test images allows measuring AUC for the EEDs and trained NN-based edge detector. Moreover, it is possible to optimize EED parameters. Let us start from considering this opportunity. One EED for which there are parameters to be chosen (set) is the quasirange (2) where for indices q and p of order statistics the condition $q+p$=5x5+1 has to be satisfied for 5x5 pixel SW. So, let us analyze dependence of AUC on q and p. The data are presented in Table 1 for two-look test images (we consider the case of NN training for un-filtered test image). The best result is provided for q=23 and p=3. There is a small improvement compared to the set q=20 and p=6 recommended earlier [9, 10].

TABLE I. COMPARATIVE RESULTS OF SEPARATED AND DUAL-CHANNEL FILTERING METHODS FOR TEST IMAGES

q, p	20, 6	21, 5	22, 4	23, 3	24, 2
AUC	0.820	0.826	0.827	0.828	0.821

AUC values for other EEDs are from 0.835 for relative local variance (2) to 0.80 for the DCT-based EED. All these values are better than for single-look case.

Consider now what happens if pre-filtering by the local statistic Lee filter [6] is applied. First of all, AUC values increase for all employed EED. They become equal to 0.870 for the relative local variance (2), 0.864 for the optimized quasirange, 0.857 for the Harris EED, and 0.840 for the DCT-based EED. Second, q=23 and p=3 are the best parameters again for the quasirange EED. Optimization has been also carried out for the Harris and DCT-based EEDs. However, the earlier recommended values of their parameters occurred to be optimal. In other words, only for the quasirange EED its parameters (performance) should be optimized depending upon speckle distribution determined by number of looks and by the fact is pre-filtering used or not.

The NN edge detector produces AUC equal to 0.871 for un-processed test two-look SAR images and equal to 0.889 for pre-filtered ones. As it can be seen, the result is better than for any EED applied in the corresponding situation and better than for single-look test images. Again, the use of pre-filtering is expedient.

One way to carry out edge detection in dual-polarization SAR images has been recently proposed in [11]. Suppose we have two noisy images $I_{1ij}, I_{2ij}, i=1,..,I_{IM}, j=1,..,J_{IM}$ where sub-indices 1 and 2 relate to a used polarization and I_{IM}, J_{IM} define the processed image size. Then, it has been proposed to obtain a composite image $I_{ij}^{C}=(I_{1ij}I_{2ij})^{1/2}$, $i=1,..,I_{IM}, j=1,..,J_{IM}$ where speckle variance for this image is of the order $\sigma_{\mu}^{2}\approx 0.15$. For the test images, AUC is from 0.820 to 0.889 without pre-filtering and from 0.826 to 0.896 after-pre-filtering. Interestingly, the optimal q=19 and p=7 in this case. For the NN-based edge detector, AUC equal to 0.911 if pre-filtering is not applied and to 0.915 if pre-filtering is used. These values are better than the corresponding ones reported in [11] due to exploiting quasi-range with optimized parameters.

IV. EXPERIMENTAL RESULTS

EEDs and the trained NN-based edge detectors have been applied to several real-life images. In particular, we have used dual-polarization SAR images produced by TerraSAR-X (http://www.astrium-geo.com/en/23-sample-imagery). Several images with both HH (horizontal-horizontal) and VV (vertical-vertical) components are available where efficient number of looks ENL≈2.2, i.e. practically as in our simulated case. These images exhibit sufficient spatial correlation of speckle. Speckle is, in fact, correlated only for two neighboring pixels in both directions. Because of this, downsampling by two has been carried out before processing (pre-filtering if applied and edge detection). After edge detection, inverse up-sampling of edge maps was performed.

Fig. 2 presents examples of the obtained results. Original (HH component) image with ENL≈2.2 is shown in Fig. 2a ($\sigma_{\mu}^{2}\approx 0.11$). Its despeckled version is given in Fig. 2b where it is seen that speckle is sufficiently suppressed whilst important information is not lost ($\sigma_{\mu 0}^{2}\approx 0.03$). The edge map obtained by the optimized quasirange is represented in Fig. 2c. The edge map for the trained NN-based edge detector is presented in Fig. 2d. Their comparison shows that there are less false detections in homogeneous image regions for the latter edge detector. This is its main advantage.

V. SUMMARY AND CONCLUSIONS

Several conventional edge detectors and the NN edge detector designed on their basis are considered. It is shown that the NN edge detector allows improving detection performance. This happens for both un-processed and pre-filtered images. Moreover, this holds for different types of SAR images including multi-look and dual-polarization ones presented in the special form. Improvement of EED performance (that can be done using AUC parameter) leads to better performance of the NN edge detector that has to be re-trained for the new set of input EEDs. In future we plan to consider the cases of full polarimetric SAR images with different number of looks.

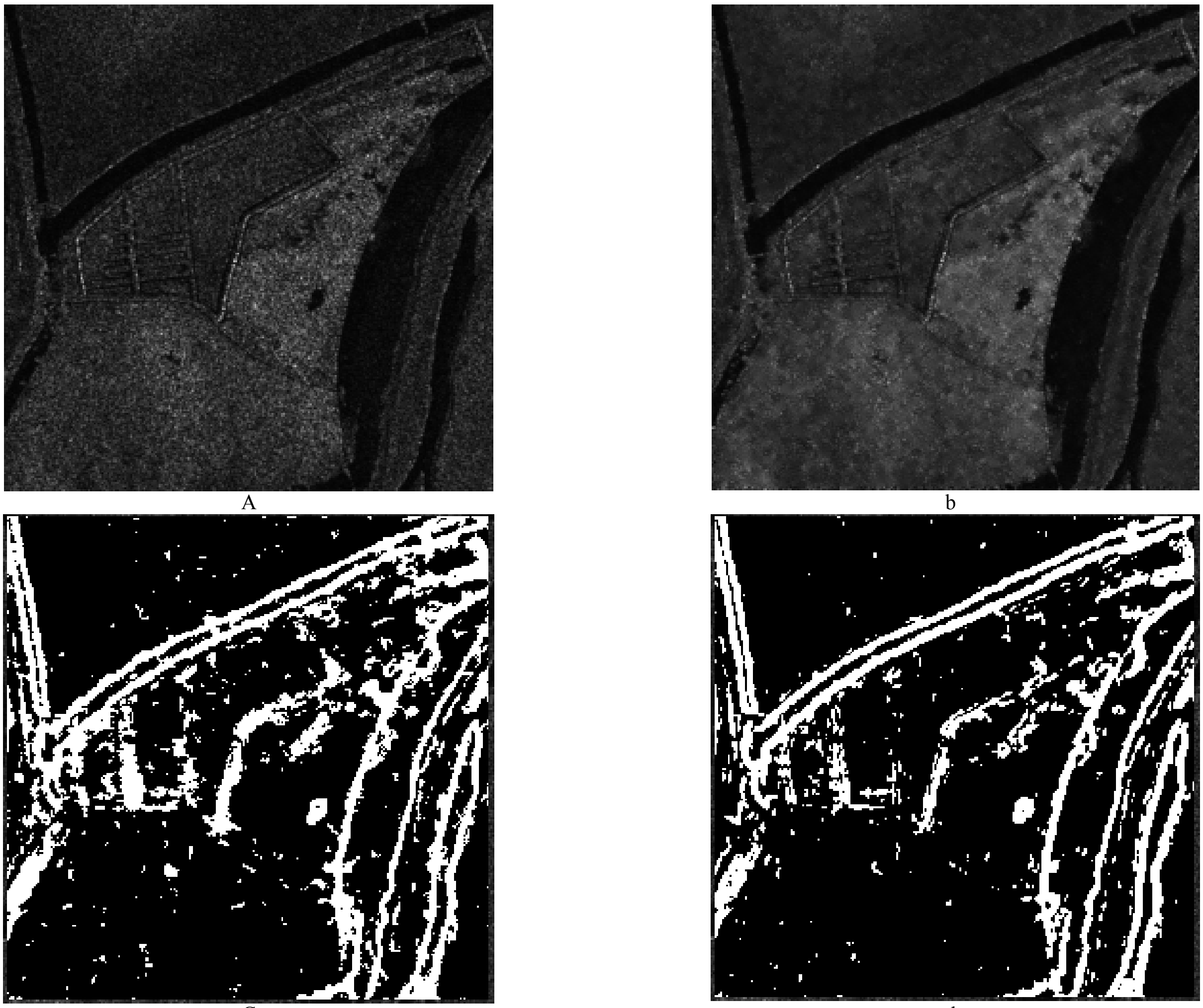

Figure 2. Noisy (a) and pre-filtered (b) images and the quasirange (c) and NN-edge detector (d) maps obtained for pre-filtered image

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