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Training CNNs on speckled optical dataset for edge detection in SAR images

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Abstract

Edge detection in SAR images is a difficult task due to the strong multiplicative noise. Many researches have been dedicated to edge detection in SAR images but very few try to address the most challenging 1-look situations. Motivated by the success of CNNs for the analysis of natural images, we develop a CNN edge detector for 1-look SAR images. We propose to simulate a SAR dataset using the optical dataset BSDS500 to avoid the tedious job of edge labeling, and we propose a framework, a hand-crafted layer followed by learnable layers, to enable the model trained on simulated SAR images to work in real SAR images. The hypothesis behind these two propositions is that both optical and SAR images can be divided into piecewise constant areas and edges are boundaries between two homogeneous areas. The hand-crafted layer, which is defined by a ratio based gradient computation method, helps to tackle the gap between training and testing images, because the gradient distribution will not be influenced by the mean intensity values of homogeneous areas. The gradient computation step is done by Gradient by Ratio (GR) and the learnable layers are identical to those in HED. The proposed edge detector, GRHED, outperforms concurrent approaches in all our simulations especially in two 1-look real SAR images.

Keywords:

edge detection, 1-look SAR image, optical dataset, CNNs, hand-crafted layer, GRHED

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1. Introduction

Edges are important features in Synthetic Aperture Radar (SAR) images. They can be used as low level features for many applications like line segment detection [1, 2], SAR image segmentation [3, 4], coastline detection [5, 6], image registration [7, 8] and even SAR image despeckling [9]. Due to the strong multiplicative speckle noise in SAR images, methods developed for optical images, which are usually based on pixel value differences, produce more false edges in brighter areas and thus are not suitable for SAR images. Many researches have been dedicated to edge detection in SAR images in the past years. In [10], the Ratio of Average (ROA) was proved to have a constant false alarm rate for SAR images (CFAR property). The ratio operator is applied along four directions and the minimum normalized ratio is used to compute the gradient magnitude. The direction corresponding to the minimum normalized ratio is regarded as the edge orientation. A threshold determined by a given probability of false alarms and a morphological operator are then applied to obtain a binary thin edge map. However, ROA is optimal only for isolated step edges. An efficient multiedge detector, ROEWA, was proposed afterwards in [11]. The Ratio of Exponentially Weighted Average was shown to be optimal in terms of minimum mean square error (MMSE) under the hypothesis of a stochastic multi-edge model. The method is based on ROA, but averages are weighted by a decreasing exponential function, allowing a better detection of multiple edges close to each other. Besides, instead of computing the ratio along four directions, the ratio is computed along the horizontal and vertical directions and the normalized ratios are considered as the horizontal and vertical components of the gradient magnitude. A modified watershed algorithm is then used to threshold the Edge Strength Map and a region merging algorithm is used to eliminate the false edge pixels. Edge detectors using different shape of window functions were introduced later in [12] and [13]. Non-maxima suppression [14] and hysteresis thresholding are applied to obtain the binary thin edge map. An edge compensation strategy was also introduced in [13] to extract weak edge pixels. To reduce the influence of isolated strong bright points in real SAR images, an Anisotropic Morphological Directional Ratio (AMDR) [15] was proposed by replacing the weighted average filter with the weighted median filter. The edge localization accuracy in the Edge Strength Map (ESM) and the Edge Direction Map (EDM) was then improved by a multiplicative spatial and directional matching filter. By introducing the improved ESM and EDM into the routine of Canny edge detector [14], the resulting edge detector is able to obtain a binary thin edge map. The connectivity of edges is finally im-

proved by an edge remedy strategy. However, the performances of the edge detectors developed for SAR images are still not fully satisfying, especially in the very noisy 1-look situation.

On the other hand, convolutional neural networks (CNNs) have proven to be very successful for edge detection in natural images, with approaches such as Deepedge [16], DeepContour [17], HED [18, 19], CEDN [20], AMH-Net [21] or RCF [22, 23], which have permitted to improve significantly the performances of traditional edge detectors like Sobel [24], Canny [14], Statistical Edge [25], Pb [26], gPb [27] and Structured Edge [28], at least on databases similar to the training sets. Motivated by this fact, we propose to develop a CNN based edge detector for SAR images.

One crucial factor that contributes to the success of CNNs is the availability of training datasets with ground truth, but there is still no training dataset for edge detection in SAR images. Under the hypothesis that both optical and SAR images can be divided into piecewise constant areas. we propose to simulate a SAR dataset using optical dataset. Only if we can ensure that all homogeneous areas in the simulated SAR dataset follow similar distributions as those in real SAR images, the models trained using the simulated dataset should be applicable to real SAR images. The simulated dataset can be obtained by multiplying images in the optical dataset with speckle noise. The simulated SAR images are called speckled optical images in the following.

Even though the homogeneous areas in simulated SAR images are modified to follow similar distributions as those in real SAR images, the distributions of homogeneous areas depend on their mean intensity values. Due to the existence of some bright homogeneous areas in real SAR images which are not contained in the simulated dataset. CNN models directly trained on the images are not applicable to real SAR images as can be seen in Figure 1-(c), where we train a classical CNN edge detector HED [18, 19] using the simulated dataset and apply the trained model to the 1-look real SAR images. HED produces spurious detections since it does not learn the way to process those areas.

To cope with this problem, we propose in this paper to add a hand-crafted layer before the learnable layers. The hand-crafted layer is defined by a ratio based gradient computation method. Since the parameters in the hand-crafted layer are fixed, we train learnable layers on the feature maps computed by the hand-crafted layer in images, and apply the trained layers to the (gradient) feature maps of testing images. The motivation is that, with the ratio operation, the gradient distribution in each pixel depends only on the ratio of the mean intensity values of two homogeneous areas in the

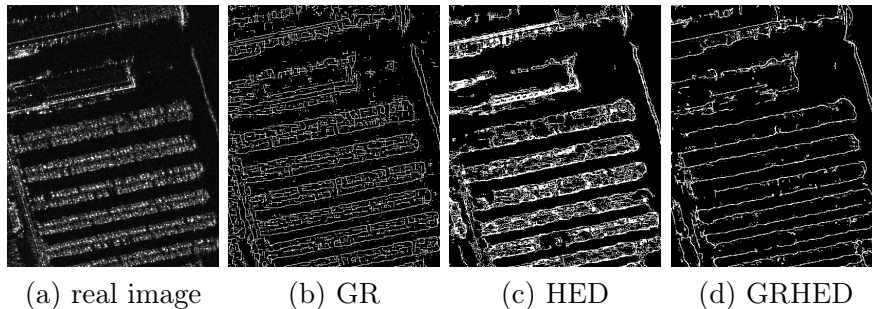


Figure 1: Edge maps produced by different methods in a 1-look real image (a subpart of the TerraSAR-X image, San Francisco). (a) 1-look real image of size 512×512 pixels; (b) edge map computed by GR [29]; (c) edge map computed by HED; (d) edge map computed by GRHED (proposed method).

opposite side windows (ratio being 1 for pixels in homogeneous areas) [10]. In this paper, the hand-crafted layer is chosen as Gradient by Ratio (GR) proposed in [29]. The learnable layers are identical to those in HED [18, 19]. We train HED layers on the gradient feature maps of training images and apply the trained model to the gradient feature maps of testing images. The proposed edge detector will thus be called GRHED. It can be seen in Figure 1-(d) that GRHED is performing efficient edge detection in 1-look real SAR images. The contributions of this paper can be summarized as follows:

- we propose to simulate a SAR dataset using the optical dataset, since there is still no dataset for edge detection in SAR images;
- we propose a framework, which is composed of a hand-crafted layer and learnable layers, to tackle the gap between training and testing images. The hand-crafted layer defined by a ratio based method, ensures the similarity of computed feature maps in simulated SAR and real SAR images;
- the proposed edge detector GRHED, largely outperforms existing edge detectors in the most challenging situations (complex scenes, 1-look real SAR images).

This paper is organized as follows: in Section 2 we give details about the building of the speckled optical dataset and explain the gap between simulated SAR and real SAR images. In section 3, we describe the proposed framework, a hand-crafted layer defined by a ratio based gradient computation method, followed by learnable fully convolutional layers. We will also

explain why the proposed strategy is able to tackle the gap between training and testing images. In section 4, we demonstrate the efficiency of the proposed edge detector, GRHED, with experiments on several 1-look simulated edge images, 200 speckled optical images simulated from BSDS500 [27], one 1-look realistically simulated SAR image, and two 1-look real SAR images.

2. Simulated SAR dataset and the gap between simulated SAR and real SAR images

2.1. Speckled optical dataset

Since the aim of this paper is to train CNNs for edge detection in SAR images, the training dataset is of crucial importance for the performances of the edge detector. In order to avoid the tedious job of manual edge labeling, we simulated a SAR dataset using optical dataset for edge detection in natural images, under the hypothesis that both optical and SAR images are composed of piecewise constant areas and edges are boundaries between two homogeneous areas. If we can ensure that all homogeneous areas in the simulated dataset follow similar distributions as those in real SAR images, the simulated dataset should be usable for edge detection in real SAR images.

Due to the coherent imaging system, SAR data present the well known speckle phenomenon. Following Goodman model [30] of fully developed speckle, it can be shown that the amplitude of the backscattered electromagnetic field of a homogeneous area with mean intensity $\langle I \rangle$ follows a Nakagami distribution :

$$f(t|\langle I \rangle) = \frac{2}{\Gamma(L)} \left(\frac{L}{\langle I \rangle} \right)^L t^{2L-1} e^{-(Lt^2/\langle I \rangle)}, \quad (1)$$

L being the number of looks of the image. For images with the best resolution, $L = 1$ and the amplitude of a physically homogeneous area follows a Rayleigh distribution. Another way of modeling 1-look data is the multiplicative model : $t = \sqrt{\langle I \rangle} s$, s representing the speckle noise and following the Rayleigh distribution given in eq. (1) with $\langle I \rangle = 1$ and $L = 1$.

Using the multiplicative noise model it is therefore easy to generate speckled data by multiplying an image by s . In this paper, we use the Berkeley Segmentation Data Set 500 (BSDS500) [27] with the same data augmentation as in HED [19] for training and validation, to simulate a SAR dataset. Specifically, each image in the training and validation set is rotated by 16 angles, flipped horizontally, and rescaled to 50%, 100% and 150% of its original size. There is no data augmentation for the testing set. The resulting

speckled optical dataset, which we will call BSDS500-speckled in the following, is obtained by multiplying the grayscale intensity channel of each color image with 1-look speckle noise. It contains $300 \times 16 \times 2 \times 3 = 28800$ images for training (80%) and validation (20%) and 200 images for testing.

2.2. The differences between speckled optical images and real SAR images

In order to compare the differences between speckled optical images and real SAR images, we plot the histograms for both of them. We display the histograms of five speckled optical images which are randomly selected from the training dataset in Figure 2-(a), the histogram of the entire training dataset in Figure 2-(b) and compare them with the histograms of two 1-look real SAR images (a Sentinel-1 image of Lelystad and a TerraSAR-X image of San Francisco) as shown in Figure 3. From Figure 2 and Figure 3 we can see that the main differences between speckled optical images and real SAR images are the range of pixel values. The values of some pixels in real SAR images are much larger than those of pixels in the speckled optical images.

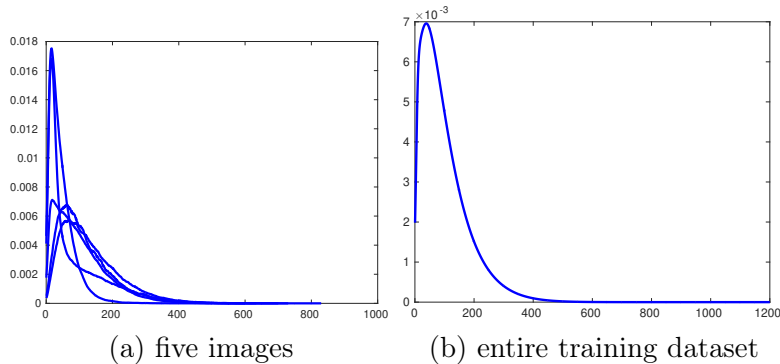


Figure 2: (a) histograms of five speckled optical images which are randomly chosen from the training dataset; (b) the histogram of the entire training dataset. The size of the bin is 1.0.

Formula (1) is the most usual way to describe the statistics of real SAR images, which gives the way of modelling the homogeneous areas in real SAR images. In addition, most existing gradient computation methods for SAR images, such as ROA [10], ROEWA [11] and other ratio based methods, are justified under the hypothesis of piecewise constant areas so all images can be considered as a mixture of homogeneous areas (the ratio operator was shown to be more suitable for SAR images in [10] with the hypothesis that in each (of the two) windows used to compute the ratio, pixel values are independently, identically and Gamma distributed, and in [11], the exponentially

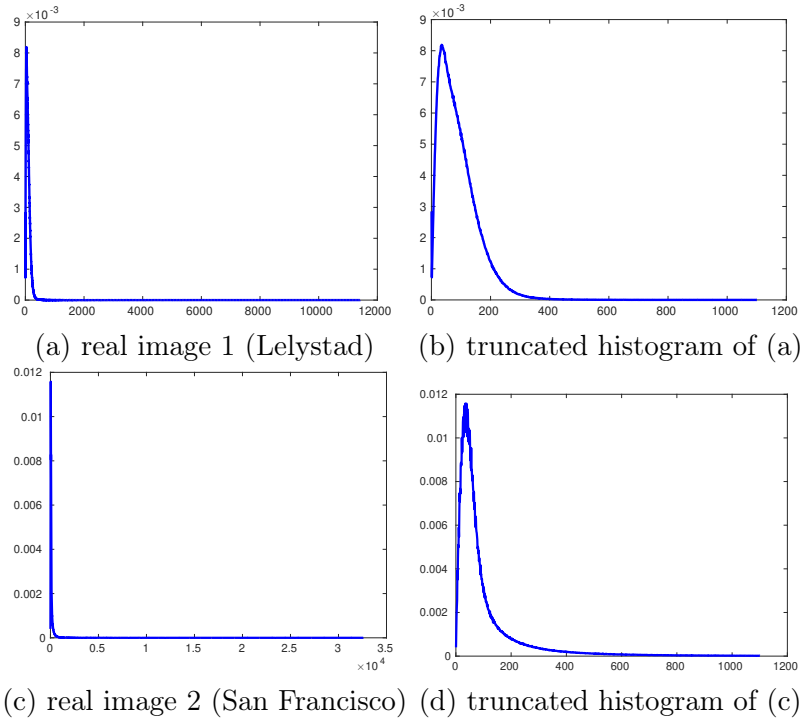


Figure 3: Histograms of two 1-look real SAR images and the truncated histogram for each image. The size of the bin is 1.0.

weighted average was shown to be optimal to estimate the local mean of the homogeneous areas under the hypothesis of a multi-edge model). In this work, we proceed in the same way and assume that both speckled optical images and real SAR images can be divided into homogeneous areas with many different mean intensity values. The edges are defined as boundaries between any two homogeneous areas.

Under the hypothesis that both speckled optical images and real SAR images are composed of piecewise constant areas, we assume that the differences in the range of pixel values are caused by the differences in the mean intensity values of homogeneous areas. We try to evaluate the possible underlying mean intensity values for both speckled optical images and real SAR images. We use windows of size 20×20 pixels to estimate the underlying mean intensity values for areas whose size is equal to the size of the windows, in both speckled optical images and real SAR images. The curves of the square root of the mean intensity values (in ascending order) estimated from two randomly selected speckled optical images and two 1-look

real SAR images can be found in Figure 4. For the estimation in speckled optical images, we use the maximum likelihood estimator to estimate the square root of the mean intensity values, while for real SAR images, we use the mode (the most frequent pixel value after digitizing the pixel values) to estimate the mean intensity values in order to reduce the influence of strong bright points in real SAR images (the square root of the mean intensity value is obtained by multiplying the mode with $\sqrt{2}$). It should be pointed out that both maximum likelihood estimator and mode estimator are under the hypothesis that samples in the windows follow a Rayleigh distribution.

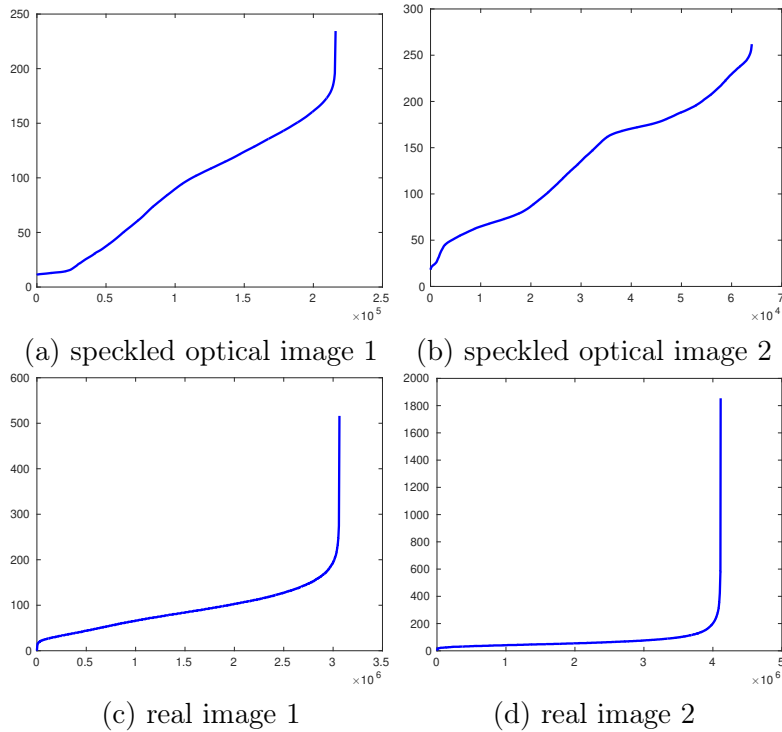


Figure 4: The curves for square root of mean intensity values estimated from two speckled optical images and two real SAR images, using windows of size 20×20 pixels. (a) speckled optical image 1; (b) speckled optical image 2; (c) real image 1 (Leystad); (d) real image 2 (San Francisco).

From Figure 4 we can see that the underlying mean intensity values in homogeneous areas of real SAR images can be much larger than those in speckled optical images (it should be noted that the underlying mean intensity values for all homogeneous areas in the training dataset will not be larger than 255^2 because the maximum possible value in natural images

before multiplying the speckle noise is 255). Therefore, the main differences between speckled optical and real SAR images are that some areas with high mean intensity values exist in real SAR images but not in speckled optical images.

After creating a simulated dataset for training and knowing the gap between simulated SAR and real SAR images, the next question is how to train CNNs using this dataset and how to enable the trained model to work in real SAR images. We will describe the way to tackle the gap between the training and testing data in the next section.

3. GRHED, a CNN based edge detector for SAR images

In order to deal with the differences in the mean intensity values of homogeneous areas between speckled optical images and real SAR images, we propose to add a hand-crafted layer before the learnable layers. The learnable layers are trained on the feature maps computed by the hand-crafted layer. The hand-crafted layer is defined by a ratio based gradient computation method GR [29] and it aims to tackle the gap between training and testing images. The convolutional layers are identical to those in HED [18, 19]. We therefore call GRHED the resulting architecture. In the following we will describe the details about GR, the benefits of adding the hand-crafted layer defined by GR, HED network architecture and the proposed edge detector GRHED.

3.1. Gradient by Ratio (GR)

For a given pixel located at position (x, y) in the image u , the horizontal and vertical gradient components (GR) are defined as

$$G^h(x, y) = \log(R^h(x, y)),$$

$$G^v(x, y) = \log(R^v(x, y)).$$

where $R^h(x, y)$ and $R^v(x, y)$ is the ratio of exponentially weighted average in the opposite side windows of pixel located at (x, y) , along the horizontal and vertical directions. In the horizontal direction, $R^h(x, y)$ can be computed as

$$R^h(x, y) = \frac{m_1^h(x, y)}{m_2^h(x, y)},$$

where

$$\begin{aligned}
m_1^h(x, y) &= \sum_{x'=-W}^W \sum_{y'=1}^W u(x+x', y+y') \times e^{-\frac{|x'|+|y'|}{\alpha}}, \\
m_2^h(x, y) &= \sum_{x'=-W}^W \sum_{y'=-W}^{-1} u(x+x', y+y') \times e^{-\frac{|x'|+|y'|}{\alpha}},
\end{aligned}$$

and where W is the upper integer part of $\log(10) \times \alpha$. $R^v(x, y)$ can be computed in a similar way.

The magnitude $G_{gr}(x, y)$ and orientation $ang_{gr}(x, y)$ of GR at position (x, y) are defined by

$$\begin{aligned}
G_{gr}(x, y) &= \sqrt{G^h(x, y)^2 + G^v(x, y)^2}, \\
ang_{gr}(x, y) &= \arctan \frac{G^v(x, y)}{G^h(x, y)}.
\end{aligned}$$

3.2. Interest of adding a hand-crafted layer before learnable layers

Under the hypothesis that both optical and SAR images are composed of piecewise constant areas, they can be divided into two kinds of regions: homogeneous areas and boundaries (boundaries exist between two homogeneous areas).

If we train CNN models directly on the images, the aim of training can be summarized as follows: 1) the model should learn to suppress all pixels in homogeneous areas; 2) the model should learn to highlight the boundaries between any two homogeneous areas. In this case, CNNs are trained to process samples drawn from many different distributions and the way of the model to process those samples depends on their corresponding distributions. In 1-look SAR images, the amplitude of all homogeneous areas follows a Rayleigh distribution depending on their mean intensity values. For two homogeneous areas across boundaries, the total distribution of them depends on the mean intensity values of both two homogeneous areas. Adding a hand-crafted layer defined by a ratio based gradient computation method before CNN models helps to deal with the gap between training and testing images because for all homogeneous areas, their gradient magnitude fields follow the same distribution, regardless of their mean intensity values, and the gradient distribution computed over two homogeneous areas across boundaries depends only on the ratio of the mean intensity values. The feature maps computed by the hand-crafted layer (GR) in simulated SAR and real SAR images are similar. Adding the hand-crafted layer enables the network trained on speckled optical dataset to work in real SAR images. In addition, computing GR can

be considered as a form of data augmentation since we have much less kinds of distributions to learn while the total amount of data remains unchanged. Besides, the ratio operation contributes to an edge detector having constant false alarm rate for SAR images.

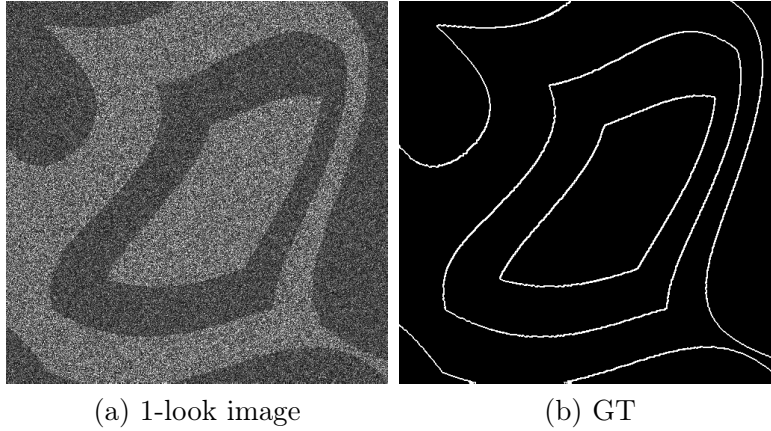


Figure 5: A 1-look edge image with ratio contrast 1.5 and the associated ground truth. The size of the image are 512×512 pixels.

In order to give a better explanation on the benefits of computing GR, we compare the distribution of the data before and after computing the gradient for both homogeneous areas and two homogeneous areas across boundaries. We simulate eight 1-look pure noise images of size 4096×4096 pixels and eight 1-look synthetic images of size 512×512 pixels with amplitude ratio contrast 1.5. The square root of the mean intensity values of the homogeneous images (proportional to an amplitude value) are 60, 90, 120, 150, 180, 210, 240 and 270. For two homogeneous areas across boundaries, the amplitude ratio is chosen as 1.5 for mean values (for the smallest value along the edge) of 20, 50, 70, 90, 110, 130, 150, 200. One example of the synthetic edge image can be found in Figure 5-(a).

The histograms of the eight 1-look pure noise images and the histograms of their gradient magnitude fields computed by GR with weighting parameter $\alpha = 4$ can be found in Figure 6. The histograms of eight 1-look synthetic edge images as well as the histograms of their gradient magnitude fields can be found in Figure 7. From Figure 6 and Figure 7 we can see that the gradient distribution computed by GR depends only on the ratio of the mean intensity values of homogeneous areas (ratio being 1 for homogeneous areas) and will not be influenced by the mean intensity values. The bright homogeneous areas in real SAR images which are not contained in the training dataset will

not be a problem because: 1) the gradient distribution of those homogeneous areas will be the same as that of homogeneous areas with low mean intensity values; 2) the gradient distribution for those homogeneous areas and their neighbouring ones depends only on the ratio of the mean intensity values, which can be the same as the gradient distribution of two homogeneous areas, whose mean intensity values are both contained in the training dataset. In addition, it can be deduced that the number of distributions that has to be learned by CNNs when trained on the gradient magnitude fields is much smaller than that of a direct training on the images. Since the amount of data is unchanged, the amount of training data for each distribution is therefore increased.

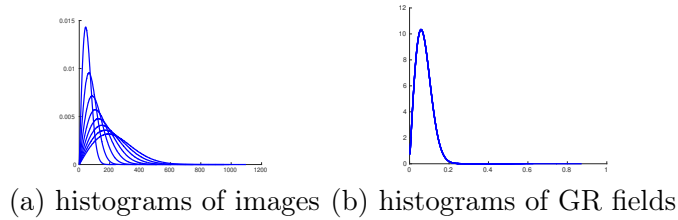


Figure 6: Histograms of the eight 1-look pure noise images and histograms of their gradient magnitude fields computed by GR with $\alpha = 4$.

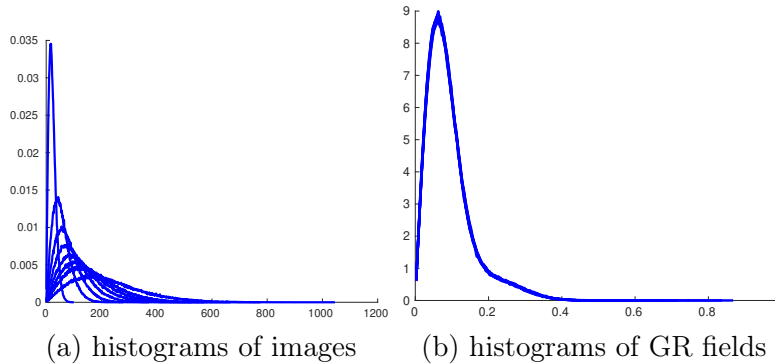


Figure 7: Histograms of the eight 1-look synthetic edge images and histograms of their gradient magnitude fields computed by GR with $\alpha = 4$.

A further illustration of the interest to compute GR can be done by comparing the histograms of GR fields in both speckled optical images and real SAR images. The histograms of the gradient magnitude fields computed by GR in 5 randomly selected speckled optical images and the histograms of the GR field computed in the entire training dataset can be found in

Figure 8. The histograms of the gradient magnitude fields computed by GR in two 1-look real SAR images can be found in Figure 9. The weighting parameter α is set to 4.0. The size of the bin is 0.01. From Figure 8 and Figure 9 we can see that even though the range of pixel values in the GR fields of those two 1-look real SAR images may be larger than that of some speckled optical images, nearly all pixel values in the GR fields of real SAR images are within the range of GR field computed in the entire training dataset (The maximum value in the GR field of the TerraSAR-X image (San Francisco) is 3.7, the maximum pixel value in the GR field of the Sentinel-1 image (Lelystad) is 5.66, and the maximum pixel value in the GR field of the entire training dataset is 5.36). Compared to the huge differences in the range of pixel values of images shown in Figure 2 and Figure 3, this observation illustrates the benefits of computing GR.

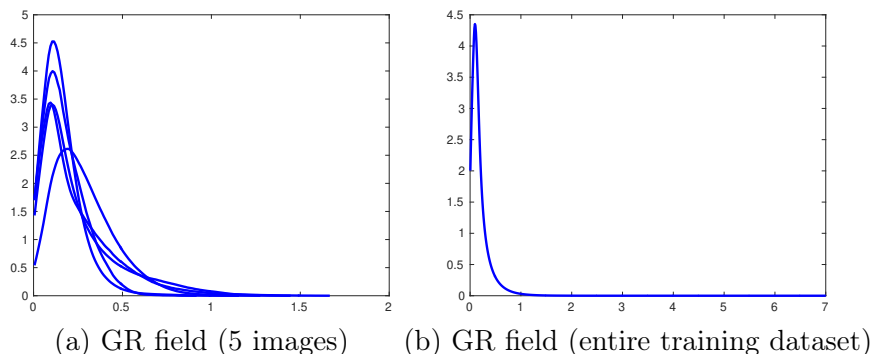


Figure 8: (a) histograms of the gradient magnitude fields computed by GR in five speckled optical images which are randomly chosen from the training dataset; (b) the histogram of the gradient magnitude field computed by GR in the entire training dataset. The weighting parameter α is set to 4.0. The size of the bin is 0.01. The maximum pixel value in the GR field of the entire training dataset is 5.36. The tail of the histogram in (b) goes up to 7.0 because we set the maximum value to be 7.0 when we plot the histogram.

3.3. HED layers

In this work, we choose to use the convolutional layers of HED, and we train HED layers on the gradient feature maps computed by GR. The HED method, introduced in [18, 19], relies on a fully convolutional network [31, 32], which is trained end-to-end to perform image-to-image prediction. The network architecture of HED is shown in table 1. The HED network is trimmed from the VGG-16 [33] net by discarding the last max-pooling layer and the 3 fully connected layers. Motivated by the deeply-supervised nets [34], five

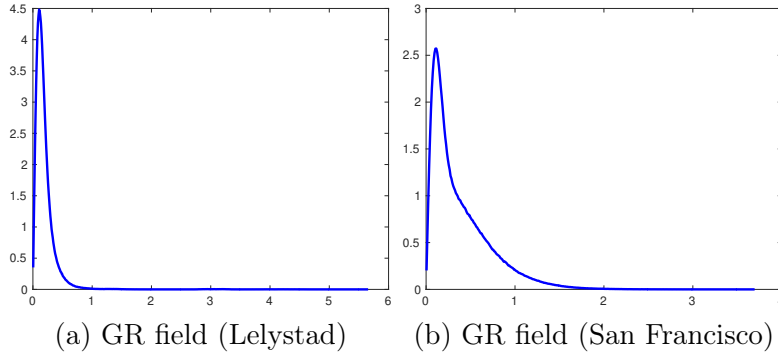


Figure 9: Histograms of the gradient magnitude fields computed by GR in two 1-look real SAR images. The weighting parameter α is set to 4.0. The size of the bin is 0.01. The maximum pixel value in the GR field of the Sentinel-1 image (Lelystad) is 5.66 and the maximum pixel value in the GR field of the TerraSAR-X image (San Francisco) is 3.7.

side outputs are added to the convolutional layers just before the five max-pooling layers in the original VGG-16 net. The loss function of the HED network is composed of the loss function from the side layers and the loss function from the fused output. The final output of HED is an average of the side outputs and the fused output. In-network bilinear interpolation [31, 32] is used to upsample the side outputs so that they all have the same size as the edge ground truth.

3.4. GRHED, the proposed framework for edge detection in real SAR images

Since the gradient distribution of GR is the same for homogeneous areas with all possible mean intensity values, and the gradient distribution in two homogeneous areas across boundaries is influenced by the ratio and not by their mean intensity values, we assume that the possible distributions in the gradient feature space of real SAR images are included in those of the training dataset. Therefore, we propose to train HED on the gradient magnitude field computed by GR in training images and apply the trained model to the gradient features of testing images. This can be seen as the addition of a hand-crafted layer before the usual HED layers. The resulting GRHED has the following advantages:

- the distribution of feature map values obtained by GR depends only on the ratio of the mean intensity values on the opposite side windows of each pixel (ratio being 1 for pixels located in homogeneous areas), therefore, homogeneous areas with high mean intensity values in real SAR images will not impair the performances of GRHED;

Table 1: The network architecture of HED. The convolutional layers are denoted as "conv(receptive field size)-(number of channels)". For brevity, we do not show the ReLU activation function following the convolutional filters in each convolutional layer.

conv3-64	
conv3-64	→ side output 1
MAX-POOLING	
conv3-128	
conv3-128	→ side output 2
MAX-POOLING	
conv3-256	
conv3-256	
conv3-256	→ side output 3
MAX-POOLING	
conv3-512	
conv3-512	
conv3-512	→ side output 4
MAX-POOLING	
conv3-512	
conv3-512	
conv3-512	→ side output 5

- constant false alarm rate (CFAR) is ensured for SAR images because of the ratio operation;
- by using multiple weighting parameter α values in GR [29] we can combine diverse informations from the image by concatenating together gradient magnitude fields produced by GR with different α values (the input of HED will have multiple channels with each channel being the gradient magnitude field computed by GR with a certain value of α). It has been studied in [35] that GR with different α values can capture complementary informations.

4. Experiments

In this section we demonstrate the efficiency of the method we propose, GRHED, using several 1-look synthetic edge images, two hundred 1-look

speckled optical images in BSDS500-speckled, one 1-look realistically simulated SAR image and two 1-look real SAR images. In order to show the efficiency of GRHED, we compare it with the original HED algorithm and to the result of training HED on the logarithm of images, as defined below, an algorithm that we will call HED-log. Observe that for GRHED, HED and HED-log, the convolutional layers that need to be trained are the same, the difference between these methods being the input of the network: gradient magnitude fields of images for GRHED, plain images for HED and logarithm of these for HED-log. The training strategy for those convolutional layers is as follows: we use Adam optimizer to train the network from scratch on the speckled optical dataset BSDS500-speckled. The number of iterations for training is 10000 and the learning rate is 0.001. The size of the batch is 10. The preprocessing step before feeding the data into the learnable layers is global mean subtraction, as done in VGG. Since the outputs of all methods are probability edge maps, they should be processed further to obtain the binary edge maps. In order to obtain the binary edge map, we use the same Non-maxima Suppression procedure as the one in Structured Edge [28] and use a threshold to discard pixels with low values in the probability edge map.

The following methods will be used in the comparison of the next sections:

- GR with $\alpha = 4$ (this choice of $\alpha = 4$ being adapted to GR in 1-look situations, as discussed in [35]). For the GR magnitude field, we use the same postprocessing steps as for the magnitude field produced by HED, HED-log and GRHED;
- HED: HED is trained on the original speckled images and tested on normalized images (see ??);
- HED-log: HED is trained on the logarithm of the images in BSDS500-speckled, and is applied to the logarithm of testing images after normalization (see ??);
- GRHED with multiple α values, $\alpha = 2, 3, 4, 5$: HED is trained on the gradient feature maps which are obtained by concatenating the gradient magnitude fields produced by GR with different α values.

4.1. Comparison in 1-look synthetic edge images

In order to give a fair comparison between the different methods, we compare them in terms of ROC curves and F1-score curves in 1-look synthetic edge images with different ratio contrasts.

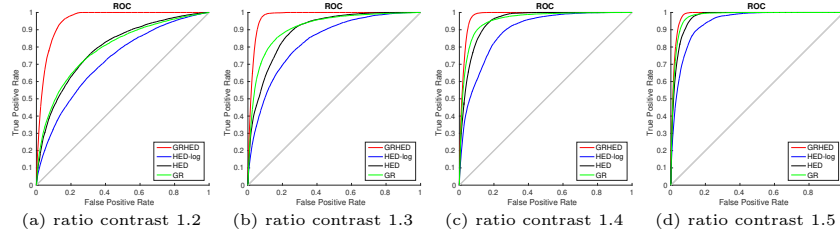


Figure 10: ROC curves computed from the magnitude field produced by GR, HED, HED-log and GRHED in 1-look simulated images with contrast 1.2, 1.3, 1.4 and 1.5. The size of the images is 512×512 pixels.

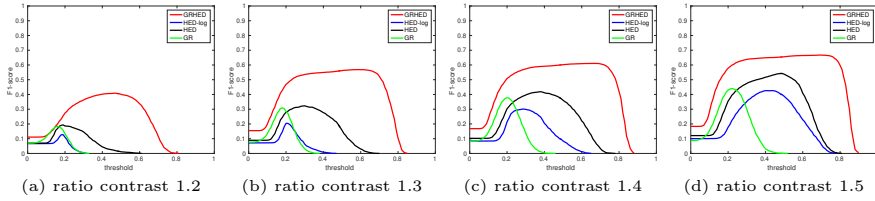


Figure 11: F1-score curves obtained by GR, HED, HED-log and GRHED in synthetic edge images with ratio contrast 1.2, 1.3, 1.4 and 1.5. The F1-score curves are obtained by varying the threshold from 0.0 to 0.9 with step 0.01.

One example of the simulated 1-look edge images with contrast 1.5 and the corresponding ground truth can be found in Figure 5. The ROC curves computed in the magnitude fields produced by GR, HED, HED-log and GRHED in 1-look simulated images with ratio contrast 1.2, 1.3, 1.4 and 1.5 can be found in Figure 10. It can be seen from Figure 10 that GRHED yields the best performances in all situations, especially in 1-look and low contrast situations. The performances of GR and HED appear comparable in terms of ROC curves, and both are better than HED-log.

In order to give a clearer comparison between the different methods, we apply the same Non-maxima suppression step for all methods and vary the threshold from 0.0 to 0.9 with step 0.01 for each method. The F1-score is computed for each threshold and the corresponding F1-score curves for each method in the 4 simulated edge images can be found in Figure 11. From Figure 11 we can see that the F1-score curves of GRHED are above the F1-score curves of the other methods. In addition, flat areas of F1-score curves of GRHED indicate greater stability regarding the threshold choice than with other approaches. Although the best F1-scores that can be obtained by GR and HED are comparable, the performances of HED are less sensitive to the choice of the threshold.

The optimal edge maps obtained by GR, HED, HED-log and GRHED in those synthetic images with contrast 1.2 and 1.4 (using the threshold which gives the best F1-score) can be found in Figure 12 and Figure 13. From Figure 12 and Figure 13 we can see that the ability of GRHED to preserve true edge pixels and suppress noise pixels is clearly greater on these images than when using the other methods; the GRHED method detects most true edge pixels while having the least number of false detections. It should be noted that although these edge maps are obtained using the optimal threshold, the edge maps obtained by HED and GRHED will remain reasonable with the threshold in a relatively large range, as can be deduced from Figure 11, especially for GRHED.

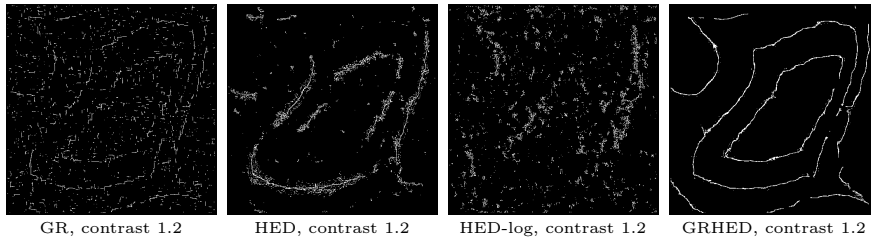


Figure 12: Optimal edge maps obtained by GR, HED, HED-log and GRHED in 1-look simulated edge images with contrast 1.2. For each method, the chosen threshold gives the best F1-score in this image. The size of the images is 512×512 pixels.

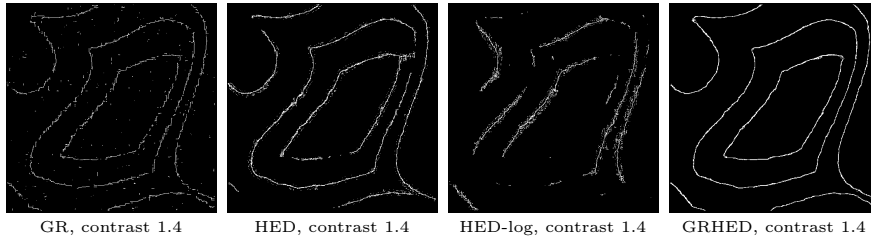


Figure 13: Optimal edge maps obtained by GR, HED, HED-log and GRHED in 1-look simulated edge images with contrast 1.4. For each method, the chosen threshold gives the best F1-score in this image. The size of the images is 512×512 pixels.

4.2. Comparison of different algorithms on the speckled optical images in *BSDS500-speckled*

In order to give a more comprehensive comparison in more general situations between different methods, we compare GR, HED, HED-log and

GRHED in the two hundred 1-look speckled optical images in BSDS500-speckled. For GR, we use $\alpha = 2$ and $\alpha = 4$. For GRHED, GRHED with a single α value and GRHED combining multiple α values are all provided. Three criterions are used to compare different algorithms: ODS F1 (fixed contour threshold for 200 images), OIS F1 (best threshold for each image), and average precision (AP). The quantitative comparison can be found in table 2. From table 2 we can see that compared to GR, the CNN-based methods give much higher values for all three criterions. In addition, GRHED gives at least comparable or even better performances than HED and HED-log in the 200 1-look images, especially when combining multiple α values. We also notice that GRHED combining multiple α values yields better performances than GRHED using a single α value, which is probably due to the richer information which is provided to HED convolutional layers.

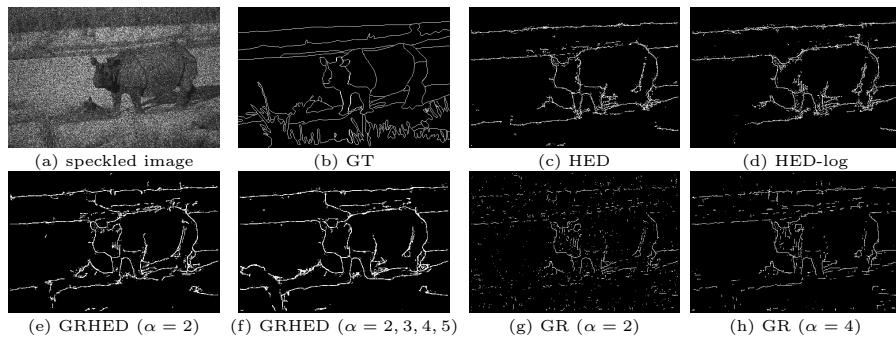


Figure 14: Comparison of different edge detectors on 1-look speckled optical images.

The edge maps obtained by GR (with $\alpha = 2$), GR (with $\alpha = 4$), HED, HED-log, GRHED (with $\alpha = 2$) and GRHED (combining $\alpha = 2, 3, 4, 5$) on one speckled optical image can be found in Figure 14. For each method, the threshold is chosen to be the one corresponding to the ODS F1, which gives the best results in the 200 images. Specifically, the threshold used for each method can be found in table 3. It should be noted that using the threshold corresponding to the ODS F1, GRHED (combining $\alpha = 2, 3, 4, 5$) will obtain near-optimal edge maps in the simulated edge images as shown in Figure 11. The ground truth of this image is the one provided by 1 labeler (there are usually five labelers for each image in BSDS500). From Figure 14 we can see that GRHED detects more true edge pixels than HED, and that both preserve more true edge pixels while detecting less false detections than GR. Using HED layers to postprocess the feature maps computed by GR, the GRHED is able to strengthen true edge pixels and suppress false detections.

Table 2: The performances of different methods over the 200 speckled optical images in BSDS500-speckled.

methods	ODS (F1)	OIS (F1)	AP
GR ($\alpha = 2$)	0.5658	0.5852	0.5094
GR ($\alpha = 4$)	0.5894	0.6151	0.5286
HED	0.6461	0.6671	0.6981
HED-log	0.6258	0.6466	0.6838
GRHED ($\alpha = 1$)	0.6427	0.6523	0.6949
GRHED ($\alpha = 2$)	0.6603	0.6762	0.7208
GRHED ($\alpha = 3$)	0.6570	0.6783	0.7018
GRHED ($\alpha = 4$)	0.6552	0.6729	0.7050
GRHED ($\alpha = 5$)	0.6492	0.6687	0.6897
GRHED ($\alpha = 6$)	0.6463	0.6660	0.6893
GRHED ($\alpha = 2, 3, 4, 5$)	0.6643	0.6826	0.7109
GRHED ($\alpha = 1, 2, 3, 4, 5, 6$)	0.6643	0.6832	0.7070

4.3. Comparison of different methods in 1-look SAR images

Though the efficiency of GRHED has been demonstrated in both simulated edge images and speckled optical images, demonstrating its ability to detect edges in real SAR images is the most important point in practice.

4.3.1. Setting thresholds according to a given probability of false alarms

Usually, detection thresholds for SAR images are set according to a chosen probability of false alarms (pfa). This is only possible when the detectors have a constant false alarm rate (CFAR). Therefore, it is important to study whether HED, HED-log and GRHED have CFAR for SAR images. The CFAR property can be checked experimentally by plotting the histograms of their gradient magnitude fields computed in noise images having different mean values. A method is considered to have CFAR if the histograms of its gradient magnitude fields computed in all images overlap well. We plot the histograms of the magnitude fields produced by GR, HED, HED-log and GRHED in 160 1-look noise images of size 1024×1024 pixels in Figure 15. The square root of the mean intensity values (proportional to the amplitude)

Table 3: The threshold corresponding to the ODS F1-score for each method.

methods	HED	HED-log	GRHED ($\alpha = 2$)	GRHED ($\alpha = 2, 3, 4, 5$)	GR ($\alpha = 2$)	GR ($\alpha = 4$)
threshold (ODS F1)	0.5666	0.5306	0.5686	0.5516	0.3137	0.2745

Table 4: The threshold corresponding to a given pfa for each method.

pfa	10^{-2}	10^{-3}	10^{-4}	10^{-5}	10^{-6}
threshold (GR)	0.18	0.22	0.26	0.29	0.31
threshold (HED)	0.3	0.38	0.48	0.57	0.63
threshold (HED-log)	0.23	0.27	0.3	0.34	0.39
threshold (GRHED)	0.17	0.26	0.37	0.45	0.52

of these noise images can take the following 8 values: 50, 80, 120, 150, 180, 200, 230 and 250. For each possible mean value, there are 20 random realizations. From Figure 15 we can see that GR and GRHED both hold CFAR, but HED and HED-log do not.

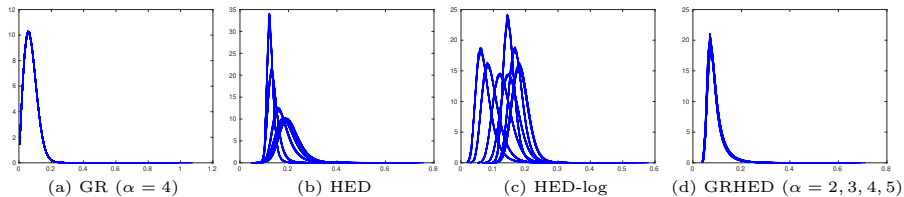
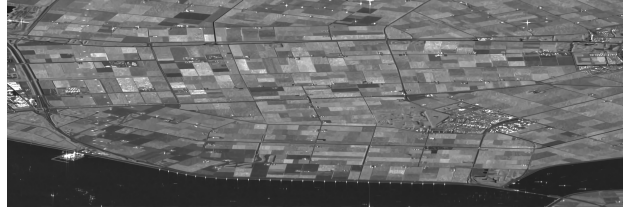
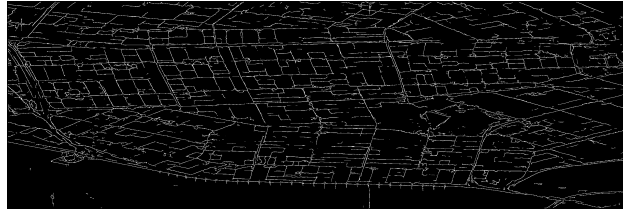


Figure 15: The histograms of the gradient magnitude fields produced by GR, HED, HED-log and GRHED in 160 1-look pure noise images of size 1024×1024 pixels. There are 8 possibilities for the square root of the mean intensity values of these images, namely, 50, 80, 120, 150, 180, 200, 230 and 250. For noise images with each mean intensity value, there are 20 random realizations.

Next, we set the detection thresholds according to a given pfa (en- vethough HED and HED-log do not have CFAR for SAR images). The threshold corresponding to a given probability of false alarms for GR, HED, HED-log and GRHED is estimated from 160 noise images as shown in table 4. Notice that for different methods, we will use the testing threshold corresponding to the pfa (10^{-5} , fifth column in table 4).



(a) clean image



(b) GT

Figure 16: A denoised multi-look image (Leystad, Sentinel 1) and its ground truth. The size of the image is 1024×3072 pixels.

4.3.2. Comparison of different algorithms in synthetic realistic SAR images

It is usually difficult to annotate the edges in real SAR images due to very strong multiplicative noise. In order to give a quantitative evaluation on the performances of HED, HED-log, GRHED, and GR in images with targets similar to those in real SAR images, we use the ground truth which is obtained by applying HED-clean (HED trained on the grayscale images converted from clean natural images in BSDS500) to a SAR image with very little speckle noise. This SAR image with reduced speckle is obtained by averaging a large amount of well registered Sentinel-1 images (equivalent to temporal multi-looking). Although not justified in changing areas, this temporal multi-looking allows a strong reduction of the speckle in stable ones like roads, urban areas, etc. To overcome the varying residual noise, a final despeckling step is applied [36]. The image is then converted to an 8-bits image using a clipping between $[0, 255]$ with a threshold given by the mean value of the image plus three times its standard deviation. This image is a natural image, but contains targets similar to those in real SAR images. The multi-temporal despeckled SAR image and its associated ground truth can be found in Figure 16.

F1-score curves computed for GR, HED, HED-log and GRHED for the synthetic realistic 1-look SAR image can be found in Figure 17, where the 1-look SAR image is obtained by multiplying the clean SAR image with 1-look speckle noise. What can be seen from Figure 17 is that the F1-score

curve of GRHED is above the F1-score curves of all the other methods. We observe also that the performances of GRHED are relatively robust to the choice of the threshold. In addition, both HED and HED-log are shown to be more powerful than GR to detect edges in complex situations. The edge maps obtained with the threshold corresponding to pfa (10^{-5}) for different methods (for GR, the threshold is corresponding to pfa 10^{-3} in order to preserve more true edges) can be found in Figure 18. From Figure 18 we can see that GRHED detects more true edge pixels than the other methods and the F1-scores of GRHED is higher than with other methods. In addition, HED also provides competitive edge detection results. GR detects more false detections probably because of the threshold chosen from a higher pfa, but it should be noted that the F1-score of GR is close to its optimal value, according to Figure 17. The method HED-log yields significantly more false detection, probably as a result of not having CFAR. Due to the poor performances of HED-log, we do not use it for comparison in the following.

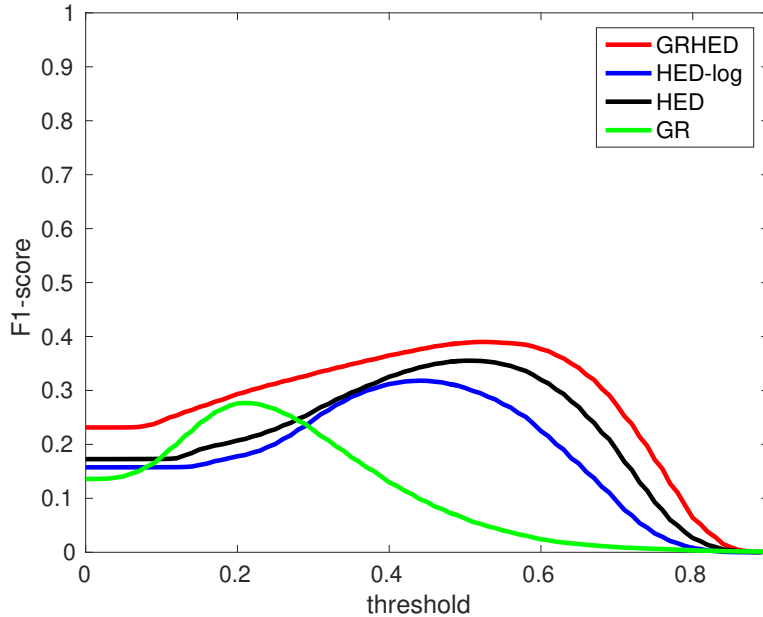
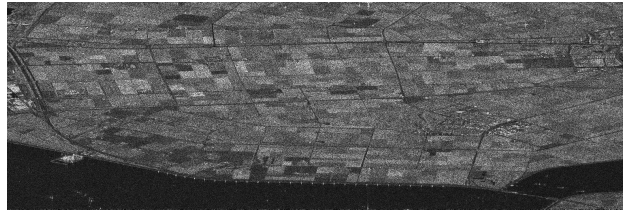
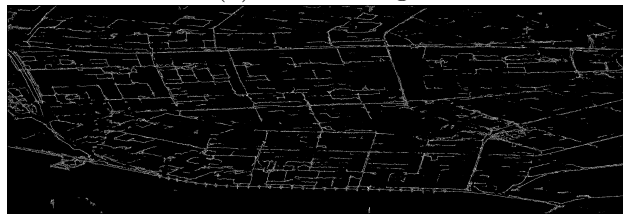


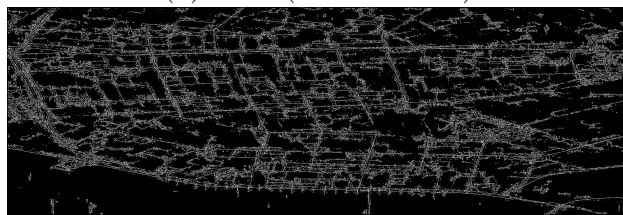
Figure 17: F1-score curves computed for GR, HED, HED-log and GRHED on a 1-look synthetic SAR image of size 1024×3072 pixels. The 1-look synthetic SAR image is obtained by multiplying the clean SAR image in Fig. 16 with 1-look speckle noise.



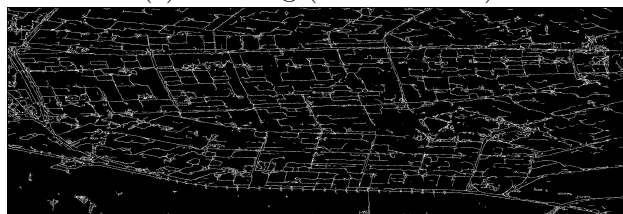
(a) 1-look image



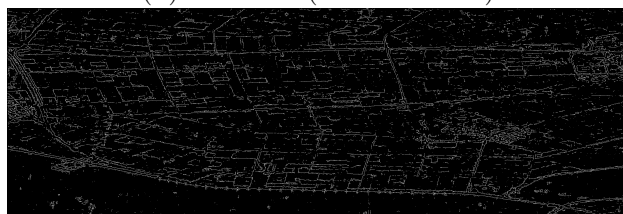
(b) HED (F1-score 0.34)



(c) HED-log (F1-score 0.28)



(d) GRHED (F1-score 0.38)



(e) GR (F1-score 0.28)

Figure 18: Edge maps computed with a threshold corresponding to $\text{pfa} (10^{-5})$ on a synthetic realistic 1-look image (Leystad, Sentinel 1) for different methods. For GR, we use the threshold corresponding to $\text{pfa} (10^{-3})$, which is very close to the threshold corresponding to the best F1-score.

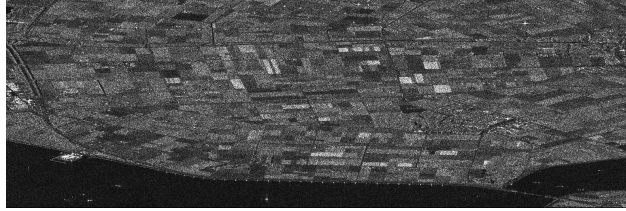
4.3.3. Further comparisons on real SAR images

In this part, we test the efficiency of GRHED with two 1-look real SAR images. We tested the efficiency of the state-of-art edge detectors AMDR [15] in SAR images, but we found it not suitable for such complex and noisy situations and did not investigate its performances further. We then compare HED and GRHED with GR on a 1-look real SAR image (Lelystad, Sentinel 1) of size 1024×3072 pixels as shown in Figure 19. From Figure 19 we can see that though GR is able to detect many true edges, but it is not able to provide a good separation between true edge pixels and noise pixels. Therefore, there are also many false detections in the edge maps produced by GR. In comparison, both HED and GRHED detect many true edge pixels with clearly less false detections. However, HED produces spurious detections in bright areas (probably because of the lack of such zones in the training set). On the other hand, GRHED does not suffer from a similar problem. On this experiment for GRHED, the number of false detections is smaller and more evenly distributed, and edges appear to be better connected.

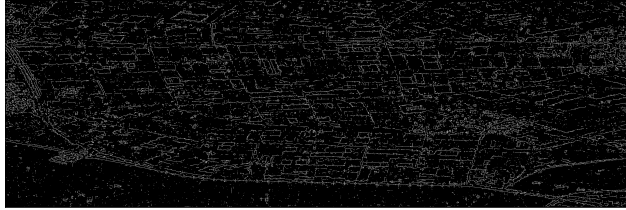
We compare GR, HED, and GRHED in another 1-look real SAR image (San Francisco, TerraSAR-X) of size 2048×2048 pixels. The edge maps obtained by these methods can be found in Figure 20. Again, the weakness of GR is that it is not able to separate the true edge pixels and noise pixels efficiently. For HED, since many homogeneous areas with high mean intensity values exist in the image, and these kinds of areas do not exist in the training images, it is difficult for HED to perform effective edge detection on them. Therefore, the edge map outputted by HED has spurious detections in many bright areas. In comparison, those bright areas do not cause troubles to GRHED because the gradient distribution computed by GR will not be influenced by the mean intensity values of homogeneous areas. What is more important, GRHED is able to separate true edge pixels and false edge pixels efficiently.

5. Conclusion

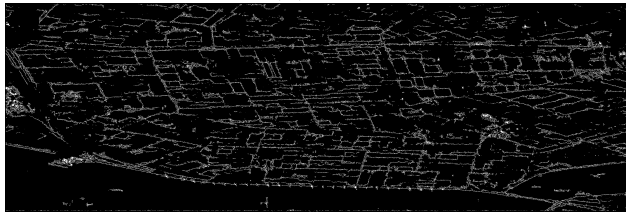
In this paper we addressed the challenging task of edge detection in 1-look real SAR images. Leveraging the available optical dataset, we proposed a framework enabling CNN models trained using simulated SAR dataset to work in real SAR images. By introducing the fixed hand-crafted layer (GR) instead of a learnable one, the proposed CNN edge detector GRHED is much less influenced by the gap between speckled optical and real SAR images. The hand-crafted layer defined by a ratio based gradient computation method ensures that all kinds of gradient distributions of real SAR images



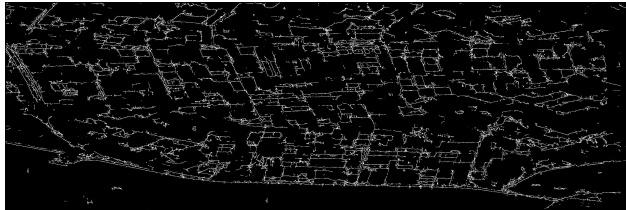
(a) 1-look image



(b) GR



(c) HED



(d) GRHED ($\alpha = 2, 3, 4, 5$)

Figure 19: Comparison of different methods on a 1-look real SAR image (Leystad, Sentinel 1). The size of the image is 1024×3072 pixels.

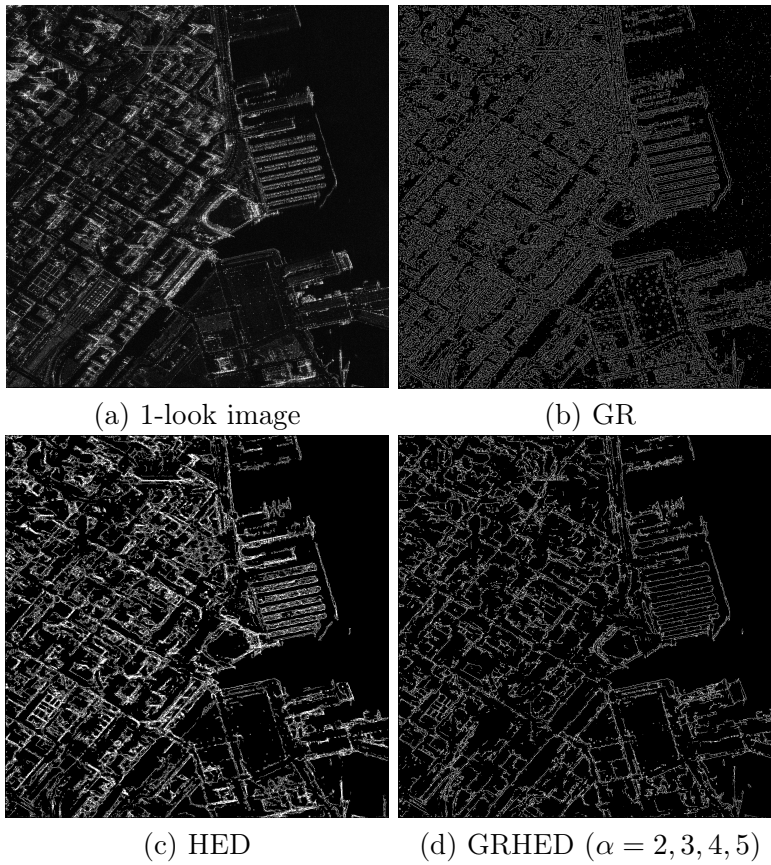


Figure 20: Comparison of different methods on a 1-look real SAR image (San Francisco, TerraSAR-X). The size of the image is 2048×2048 pixels.

are likely to be included in those of speckled optical images, but it should be pointed out that there may be some gradient distributions that do not exist in those of the training dataset. For example, when some edges with extremely high contrast appear in real SAR images, the ratio between the mean intensity values of the homogeneous areas on the opposite side of the edges is too high. From all the experiments we can see that GRHED is able to obtain stable and reliable detection results. This is especially interesting in the case of 1-look real SAR images.

Among the points that have not been addressed in this work and will be addressed in further works, we can mention the followings. First, the spatial correlation of the noise on real images has not been addressed and probably leads to a decreasing of the CNN performances. The method of [37] could be an interesting approach to take it into account. Secondly, the specific features of SAR images like bright points and lines due to strong backscatterings of diedral or triedral structures do not exactly correspond to edges. Therefore dedicated detectors should be developed for these specific structures to be combined with edge detectors.

Source code

The source code of GRHED is available at <https://github.com/ChenguangTelecom/GRHED>.

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