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A Novel Method for SAR Image Edge Detection Based on Support Vector Machine

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Abstract: A novel method for synthetic aperture radar image edge detection based on support vector machine is proposed. The experimental results show that this method can precisely realize the edge position and maintain the details of the image edges well. The edge detection results are better than those of the Canny or Sobel differential operators.

Key words: Edge detection, support vector machine, synthetic aperture radar image

INTRODUCTION

Edge detection, one of the most active subjects in image processing and machine vision, has been widely applied to pattern recognition, image segmentation, image compression and other fields. Synthetic Aperture Radar (SAR) image processing also relies on edge detection.

The edge detection approaches can be generally classified into two categories. The first category is based on the edge fitting operator, in which the small regions in the image are surface fitted at first and then the edges of the fitted surface are detected by the differential operator. The second category is based on the differential operator. Most methods in the second class utilize the filter template to acquire the gradient image. The main idea is to place the center point of the template on the pixel to be processed and then add the template modulus to the corresponding pixel weight to obtain the gradient strength of the processed pixel. The gradient image can be acquired when the filter template scans over the whole image. The gradient strength indicates the change of the gray intensity such that the edges can be determined based on the gradient strength. Popular differential operators are Robert, Sobel, Laplician and Marr. The differential operator-based methods have problems, including (1) Unsatisfactory detection result coming from the threshold selection and (2) Methods that are not robust against the noise. Generally, the noisy image is smoothed and then sharpened. However, the smoothing process discards the high frequency information of the image. Other disadvantages include (3) Edges are difficult to detect when the image has complex and abundant details and (4) Marr and Sobel operators that cannot position the edges precisely. Canny (1986) introduced a new operator according to the three evaluation principles, such as good detecting ability, precise location and finite response times of the edge detecting filter. The Canny operator is represented by the linear combination of four exponential functions and can obtain more satisfying results than other operators mentioned earlier.

The edge detection approach has been developed in previous works. Pal *et al*. (1983) proposed the fuzzy edge detection. Mallat *et al*. (1992) proposed a multiscale detection method on the basis of the wavelet decomposition. Chao *et al*. (1994) integrated the Hopfield network into edge detection. And Yang *et al*.(2001)united the information measure with the BP (Back Propagation) network to detect edge. Moreover, the Support Vector Machine (SVM) is also introduced in edge detection.

Essentially, image edge detection is a classification problem. As a solution to this problem, SVM is good at classification, has the ability to separate the edge pixels and non edge pixels effectively and is also widely used in pattern recognition technique (Cortes *et al*., 1995; Burges, 1998).Yang *et al*. (2010) cast the filtering problem as a vector-mapping approximation and solve it using SVM. Each pixel is represented as a feature vector comprising of the exponentiation of the pixel intensity, the corresponding spatial filtered response and their products. The mapping function is learned via., epsilon-SVM regression using the feature vectors and the corresponding bilateral filtered values from the training image. Sun *et al*. (2010) proposed a novel algorithm about Shot boundary detection based on Support Vector Machine. The algorithm utilizes SVM, which is trained by using of some features, to classify videos so as to test the change of shots and realizes shot boundary segmentation by distributing video frames into three categories. He *et al*. (2011) applied SVM to the digital image splicing detection. Firstly, the edge gradient matrix of an image is computed and approximate run length is calculated along the edge gradient direction. Then, some features are constructed from the histogram of the approximate run length. To further improve the detection accuracy, the approximate run length is applied on the predict-error image and the reconstructed images based on DWT to obtain more features. Finally, SVM is exploited to classify the authentic and spliced images using the constructed features. Kozempel *et al.* (2011) applied SVM into the airborne camera system, in which SVM is used to decide whether an object's descriptor represents a vehicle. Cai *et al.* (2012) proposed a color image edge detection approach based on SVM and multi-featured extraction. Guo *et al.* (2012) also applied SVM to the intelligent transportation systems for the pedestrian recognizing.

In the current work, a novel image edge detection method on SVM, called EDOS briefly, is proposed, which combines SVM and the information measure. The method is expected to precisely detect edge, simultaneously keep its detail and work robustly for the noisy image.

FEATURE VECTOR OF THE EDGE PIXEL

The intrinsic difference between the noise and the edge pixel is the intensity distribution in their neighbors. For the edge pixel, the intensity distribution is of sequence and direction and the gray mutation is structural. For the noise, the intensity distribution does not have any of the three characteristics mentioned above. In the following sections, we discuss in detail the acquisition of the feature vector of an edge pixel with the information measure.

Neighborhood homogeneity information measure: The intensity distribution in the neighbor of an edge pixel and that of non-edge pixel are different. The neighbor of an edge pixel can be separated into two parts with different intensity distributions, whereas the neighbor of a non-edge pixel is homogeneous. Suppose (i, j) is the pixel location, $R = \{(m, n)||m\text{-}I|\le L, |n\text{-}j|\le L\}$ is its neighbor and L denotes half of the neighbor scope length. The neighbor is separated into two parts, S_{k_1} and S_{k_2}, with a line passing through (i, j) with an orientation angle, θ_k, $0°\le\theta_k\le180°$, θ_k. Hence, the neighbor homogeneity measure is defined as R_{ij}:

$$R_{ij} = \max_k \left\{\left|f_{S_{k1}} - f_{S_{k2}}\right| / \left[L(2L+1)\right]\right\}, k = 1, 2, \ldots, N \quad (1)$$

Where:

$$f_{S_{k1}} = \sum_{(m,n)\in S_{k1}} x_{mn}, f_{S_{k2}} = \sum_{(m,n)\in S_{k2}} x_{mn}$$

and x_{mn} is the intensity of (m, n).

If there is an edge pixel in the neighbor, R_{ij} can achieve the maximum when θ_k is parallel to the edge locus orientation, which implies the different intensity distributions between S_{k_1} and S_{k_2}. If the neighbor is homogeneous, R_{ij} is small regardless of the value of θ_k Therefore, R_{ij} shows the variety of the intensity distribution in the neighbor of the edge pixels. The noise distribution in S_{k_1} and S_{k_2} are the same in statistical way for both neighbors with and without an edge pixel and is independent of the value of θ_k. Hence, the noise coming from S_{k_1} and S_{k_2} can be offset from each other and does not affect the value of S_{k_1} and S_{k_2}. Therefore, the neighborhood homogeneity information measure R_{ij} is robust to differentiate the edge pixels from others when the noise exists.

Image orientation information measure: One of the most important characteristics of the edge pixel is its orientability. Suppose (i, j) is the pixel location, $R = \{(m, n)||m\text{-}I|\le L, |n\text{-}j|\le L\}$ is its neighbor and L denotes half of the neighbor scope length. The neighbor is separated into two parts, $S_{\theta1}$ and $S_{\theta2}$, by a line l_θ passing (i, j) with orientation angle, θ_k, the orientability information measure is defined as M_{ij}:

$$M_{ij} = d_{\theta max}\text{-}d_{\theta min} \quad (2)$$

Where:

$$d_{\theta max} = \max_{0°\le\theta\le180°}(d_\theta), d_{\theta min} = \min_{0°\le\theta\le180°}(d_\theta),$$
$$d_\theta = \left|f_{S_{\theta1}} - f_{S_{\theta2}}\right|, f_{S_{\theta1}} = \sum_{(m,n)\in S_{\theta1}} x_{mn}, f_{S_{\theta2}} = \sum_{(m,n)\in S_{\theta2}} x_{mn}$$

and x_m is the intensity of (m, n).

If there is an edge pixel through the center point in the present neighbor, C_{ij} achieves the maximum when l_θ is parallel to the edge locus orientation. The difference between the gradient strengths of any two pixels on the edge locus is minimal because of the structural characteristics of the edge. Hence, the mean value of the gradient strength of the pixels along the boundary, C_{ij}, is approximate to the gradient strength of the current pixel. If the current neighbor is homogeneous, C_{ij} values are close to each other regardless of the value of the angle l_θ and C_{ij} is also approximate to the gradient strength of the current pixel. For the noise, C_{ij}, a mean value can reduce the influence of the gradient strength of the noise.

From the above analyses, we can construct a three-dimensional feature vector that includes the neighborhood homogeneity information measure, the image orientation information measure and the gradient strength given by:

$$I(i, j) = \{R_{ij}, M_{ij}, C_{ij}\} \tag{4}$$

SUPPORT VECTOR MACHINE

SVM has been widely applied in pattern recognition. In the SVM method, the input vector can be nonlinearly projected to a higher dimensional feature space. A creation of a linear separating hyperplane in the new feature space would result in a nonlinear separating hyperplane in the original input feature space.

Optimal separating hyperplane: SVM is proposed from the search for the optimal separating hyperplane under the linearly separable condition. The optimal separating hyperplane separates the two classes from each other and leaves the maximum margin between the two classes.

Let us consider a problem to separate two classes. X is the input sample, $\{(X_i, d_i)\}_{i=1}^N$ is the training set, $Xi \in \Re^m$ is the i-th input vector, $d_i \in \{-1, +1\}$ is the class label of i and N represents the total number of samples. If the two classes are linearly separable, an optimal separating hyperplane given by H: $g(x) = x \bullet \omega + b = 0$ exists, which separates the two classes with the maximum margin; here, all samples satisfy $|g|(x) \geq 1$ and the samples nearest to the separating hyperplane meet $g|(x) \geq 1$. The maximum margin between the two classes is $2/||\omega||$. The data points nearest to the separating hyperplane are called support vectors. The detailed rationale for the search of the optimal separating hyperplane can be found in (Burges, 1998). Finally the rationale arrives at the following equation: maximize:

$$Q(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_j d_i d_j (x_i \bullet x_j) \tag{5}$$

Equation 5 should comply with the restriction:

$$\sum_{i=1}^{N} \alpha_i d_i = 0, \; 0 \leq \alpha_i \leq C, \; i=1,2,\cdots, N \tag{6}$$

where, C is constant value and α_i is the coefficient of Lagrange function. If α_i* is the optimal resolution given by:

$$w^* = \sum_{i=1}^{N} \alpha_i^* d_i x_i \tag{7}$$

Then according to Kuhn-Tuker precondition, further reasoning should obtain the optimal separating function as follows:

$$f(x) = \text{sgn}\{(w^* \bullet x) + b^*\} = \text{sgn}\left(\sum_{i=1}^{N} \alpha_i{}^* d_i (x_i \bullet x) + b^*\right) \tag{8}$$

Support vector machine approach: SVM substitutes the inner product K(x, x’) for the dot product (x•x’) in the optimal separating hyperplane. This means that the original feature space is projected to a new feature space because most of the practical pattern recognition problems are nonlinearly separable. The optimal Eq. 5 now becomes:

$$\text{Maximize: } Q(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_j d_i d_j K(x_i, x_j) \tag{9}$$

Equation 9 should comply with the restriction:

$$\sum_{i=1}^{N} \alpha_i d_i = 0, \; 0 \leq \alpha_i \leq C, \; i=1,2,\ldots, N \tag{10}$$

where, C is a constant. Many experiments show that C can be 10 experimentally. Then, the corresponding discriminant function (8) becomes:

$$f(x) = \text{sgn}\left(\sum_{i=1}^{N} \alpha_i^* d_i K(x_i, x) + b^*\right) \tag{11}$$

where, the Gaussian kernel function is denoted as:

$$K(x, y) = \exp\left(-\frac{(x-y)^2}{2\sigma^2}\right) \tag{12}$$

According to the Kuhn-Tuker precondition (Burges, 1998) only the samples nearest to the separating hyperplane have the nonzero Lagrange product and only these samples called support vectors affect the construction of the hyperplane. This approach is known as SVM.

SVM-based edge detection method: The edge information acquired from the information measure technique can describe the characteristics of the edge pixels very well and is robust to noise. SVM approach is good at classification and can distinguish edge pixels from non-edge pixels. A novel method that combines the merits of the two approaches, called EDOS, is hereby proposed. The method begins with the calculation of a 3D feature vector, which includes the neighborhood homogeneity information measure R_{ij}, the image orientation information measure M_{ij} and the gradient strength C_{ij}. Therefore, the feature vector of an edge pixel, I(i, j) is expressed as $I(i, j) = \{C_{ij}, M_{ij}, R_{ij}\}$. Then, SVM is utilized to train the set of feature vectors, I(i, j) and finally classify them to detect the edge.

Before SVM processes the data, all data should be normalized to the range of [0, 1]:

$$\text{Normalized vector} = C\frac{\text{Original vector}}{\text{Maximum strength of vector}} \quad (13)$$

where, C is a constant and could take a value of 0.5 experimentally.

EXPERIMENT RESULTS

Initially, the computer program of EDOS is trained with a typical image-Lena photograph. Figure 1a is an original Lena image with a size of 120×120. Figure 1b is its edge image acquired with C-Means clustering approach and manual operation. Figure 1c is its edge image acquired with EDOS after training.

Compared with Fig. 1b, Fig. 1c presents more abundant detail of the original image. In particular, the tassel of the hat and Lena's hair is still clear and discernible in Fig. 1c, whereas they are a little vague in Fig. 1b. Moreover, the contour of the Fig. 1c is sharper than that of Fig. 1b. In general, Fig. 1c is more faithful to the original image, Fig. 1a.

Figure 2a is a SAR image with multiplying noise. Figure 2b is its edge image from EDOS. Figure 2c is its edge image from the Canny operator and Fig. 2d from the Sobel operator. We can see that Fig. 2c and d have blurred contours, whereas Fig. 2b has abundant details and clear contours. EDOS balances the noise effectively and locates the image's edges precisely.

Figure 3 show the experimental results of another SAR image with multiplying noise. We can see that the edges of the SAR image in Fig. 3b are clear and sharp, whereas those in Fig. 3c and d are rather vague. Moreover, it is very hard to distinguish the original image's pattern from Fig. 3c and d. The edge image from EDOS is much better than those of the Canny or Sobel operators.

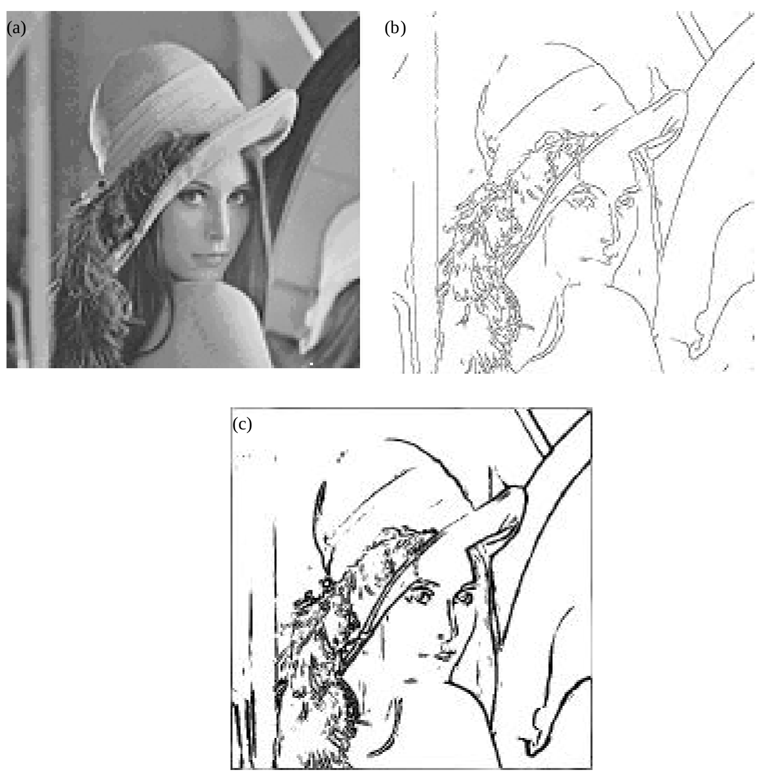

Fig. 1(a-c): Lena image for training, (a) Original Lena image, (b) Edge image from C-Means clustering and manual operation and (c) Edge image from EDOS

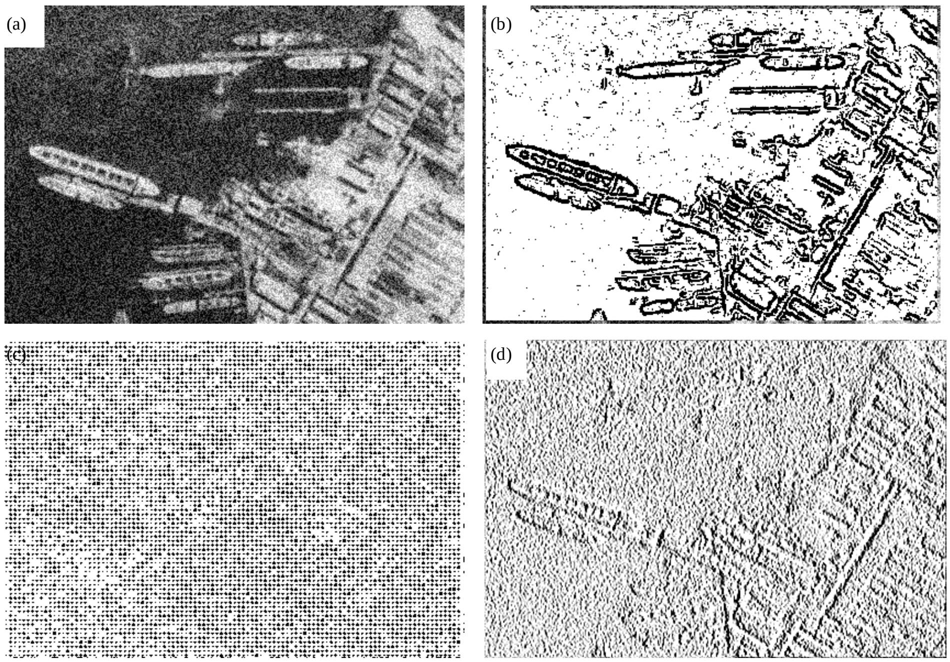

Fig. 2(a-d): Edge detection results of a SAR image with multiplying noise, (a) SAR image with noise, (b) Edge image from the proposed method and (c) Edge image from the Canny operator; (d) Edge image from the Sobel operator

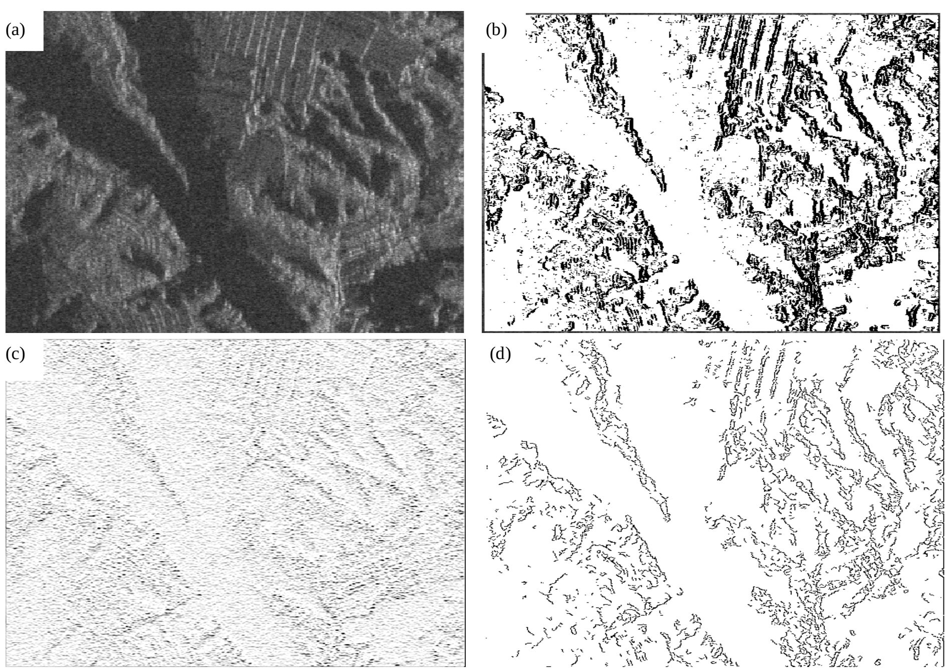

Fig. 3(a-d): Edge detection results of another SAR image with multiplying noise, (a) SAR image with noise, (b) Edge image from EDOS and (c) Edge image from the Canny operator; (d) Edge image from the Sobel operator

CONCLUSION

The proposed approach based on SVM, EDOS, is robust to noise, has the ability to precisely realize the edge position and can maintain the detail of the image edge well. Its edge detection results are better than those of the Canny or Sobel differential operators.

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