POLARIMETRIC SAR IMAGE SEGMENTATION USING AFFINITY FUNCTION FROM PROBABILISTIC BOUNDARIES AND PATCH FEATURES

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1. INTRODUCTION

We investigate the segmentation of high resolution polarimetric Synthetic Aperture Radar (PolSAR) images of urban areas. The segmentation strategy in [1] is applied in this paper. Spectral graph segmentation has the advantage of capturing non-local property. The probabilistic boundaries and patch features are integrated for spectral graph segmentation. Accurate boundaries extraction and efficient patch features improve the segmentation. On the other hand, a better segmentation corresponds to a refined binary boundary map.

Gradients of amplitude, texture, PolSAR CFAR edges and gradient magnitude are incorporated to produce an accurate probabilistic boundary map. These gradient features are combined in a supervised manner. The combination rules are learned from ground truth data using a logistic regression classifier. For a test image, a soft boundary map is generated by the classifier using all the gradient features. Probabilistic boundaries and patch features are integrated into affinity matrix construction [1] in spectral graph segmentation. Probabilistic boundary map provides an estimate of intervening contours. Learning of affinity function is treated as a supervised classification problem. Eigen decomposition of the affinity matrix results in spectral segmentations [2].

2. FRAMEWORK

2.1. Probabilistic Boundaries

We adopt the ideas from probabilistic boundaries extraction algorithm (Pb) [3]. Pb algorithm makes use of gradients of brightness, color and texture features over several orientations. It models the true posterior probability of a boundary at different orientations and every location of an image. The algorithm detects boundaries by measuring each pixel for local discontinuities in several feature images, which are provided by filtering using odd- and even-symmetric quadrature filters at a range of orientations and scales. The integration of these features using supervised fitting provides promising boundary maps. Non-maxima suppression is adopted to reduce multiple detections at the same place.

2.1.1. Gradient Magnitude

Gradient magnitude (GM) of the logarithm span image is an efficient indicator of discontinuity. It is computed by filtering an image using Gaussian derivatives at horizontal and vertical orientations. σ of Gaussian controls the scale of gradient magnitude. Strong edges are well captured with high accuracies. However, there are many false boundaries in nearly homogeneous regions. We calibrate the magnitude map using a logistic regression classifier. The classifier is trained on 20 images with ground truth boundaries. Fig. 1 shows a gradient magnitude image (σ = 2).

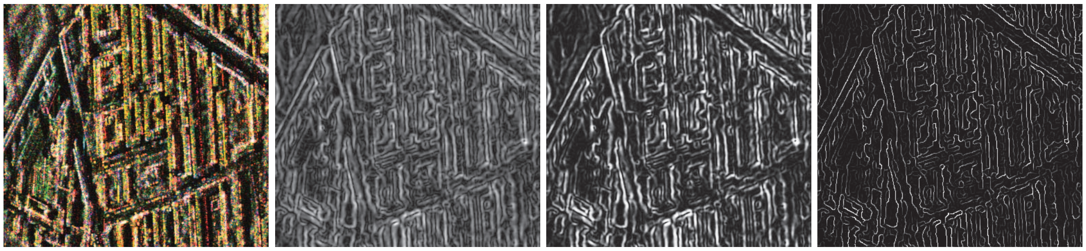
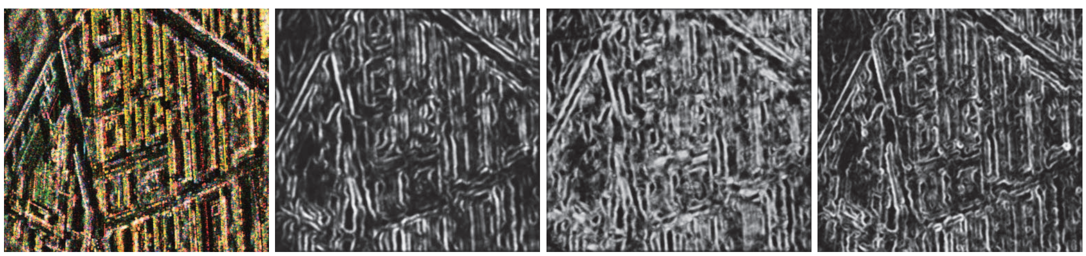


Fig. 1: Boundary detection using gradient magnitude of log span image. From left to right: original PolSAR image, gradient magnitude of PolSAR log span image, calibrated boundary map before and after non-maxima suppression.

2.1.2. Amplitude Gradient

We compute gradient map from logarithm of PolSAR span image. The logarithm span image is quantized into 32 bins. Amplitude gradients (AG) are computed over 8 orientations. For each orientation, a disc is divided into two halves. The orientation of the dividing diagonal represents the gradient orientation. The difference between histograms of the halves is calculated using Euclidean distance and bin similarity matrix. The maximization of amplitude gradient maps over 8 orientations provides an estimate of boundary strength. Fig. 2(b) shows boundary map extracted using amplitude gradient.



(a) (b) (c) (d)

Fig. 2: Boundary detection using amplitude gradient of log span image. (a) PolSAR image; (b) amplitude gradient; (c) texture gradient; (d) PolSAR CFAR gradient.

2.1.3. Texture Gradient

Two regions divided by a boundary may have different textures. Texture gradient (TG) is adopted to better identify this type of boundary. Texture feature is represented by texton histogram based on a filter bank. Similar as amplitude gradient, texton histogram is calculated by hard binning of textons in each halve of a disc, which is divided by the orientation angle. The χ^2 difference between the two texton histograms indicates the boundary strength along the current orientation. The texture gradient is maximized over 8 orientations. The double-peak effect of texton gradient is eliminated by fitting a cylindrical parabola.

We use a filter bank consisting of 28 filters, including even- and odd-symmetric filters, Gaussian and Laplacian of Gaussian at several scales. The even-symmetric filter is second-order Gaussian derivative, and the odd-symmetric filter is its Hilbert transform. Due to quick variation of amplitudes in urban areas, we choose filters with small scales. The filter bank is applied to the PolSAR logarithm span image. Fig. 2(c) shows a boundary map detected by texture gradient.

2.1.4. PolSAR CFAR Gradient

The test statistic of PolSAR CFAR detection [4] is adopted to estimate CFAR gradient (PG). The same disc filters in the estimation of amplitude and texture gradient are used here. The disc filters are applied to PolSAR covariance matrix data. The gradient is based on the test statistic between the two halves of a single disc. The similarity measures are normalized. PolSAR CFAR gradients are computed over 8 orientations.

Fig. 2(d) shows detected boundaries. CFAR gradient produces few false edges in grass and tree regions. Small bright objects, e.g. point targets, are much better localized than in other methods.

2.1.5. Combination of gradients

Combination of different gradient cues is promising. The combination rule can be learned using logistic regression classifier in a supervised manner. The classifier is trained on 20 images with ground truth boundary maps. The middle of Fig. 3 shows the detection result by combination of amplitude and texture gradients (AGTG). There are less false boundaries, especially in vegetation areas. Edges in a texturally homogeneous region are suppressed by texture gradient. The combination of amplitude, texture and PolSAR CFAR gradients (AGTGPG) provides even better results, as shown in the right of Fig. 3. The best result is obtain by incorporating all gradient cues. An example is shown in Fig. 4.

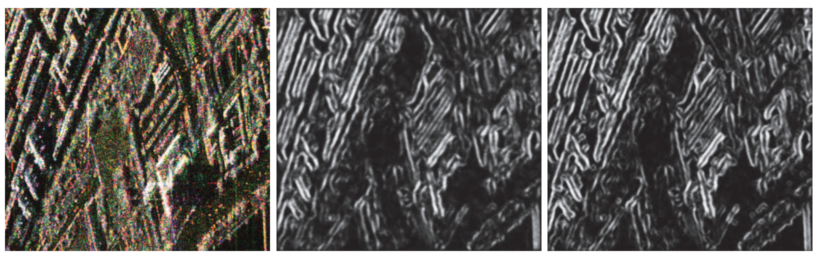


Fig. 3: Boundary detection using gradient magnitude, amplitude, texture and PolSAR CFAR gradient. From left to right: PolSAR image, amplitude & texture gradients, amplitude & texture & PolSAR CFAR gradients.

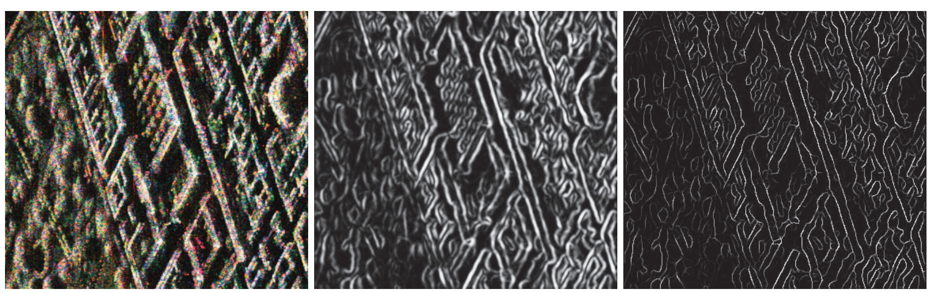


Fig. 4: Boundary detection using all gradients. From left to right: PolSAR image, boundary map before and after non-maxima suppression.

2.1.6. Accuracy Evaluation

We evaluate the probabilistic boundary methods on a testing set consisting of 50 images with ground truth segmentation. The ground truth segmentation also defines a ground truth boundary map. The boundary maps after non-maxima suppression are evaluated using the ground truth.

The performances of the different boundary detection methods are shown in Fig. 5. Precision-recall curve measures the trade off between accuracy and noise when the threshold varies. Normalized cuts (400 segments per image) segmentation of an image defines a binary boundary map, corresponding to a point in the precision-recall plot. Amplitude gradient is efficient in identifying large and evident boundaries. The integration of texture gradient and PolSAR edge detection seems to degrade the

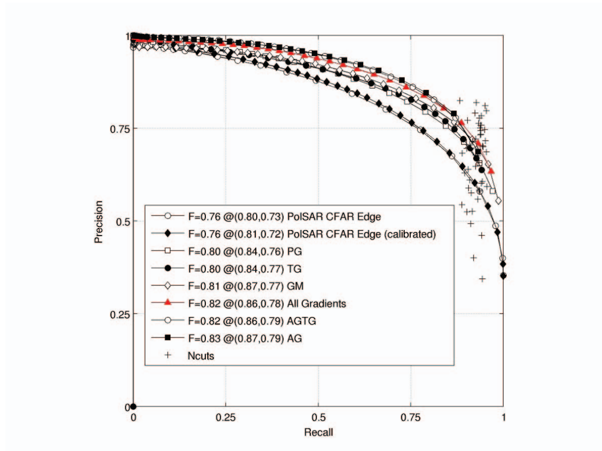


Fig. 5: Precision-recall curves of boundary detection by different methods. The points marked by a ”+” indicate the precision-recall of normalized cuts segmentation.

performance of amplitude gradient. However, the combination of cues suppresses false boundaries in homogeneous regions. Furthermore, the contrast of boundaries is enhanced. We find that the integration of magnitude gradient improves the Pb algirithm.

2.2. Segmentation using Intervening Curves and Patch Features

The probabilistic boundaries are used as features for segmentation. In addition, we extract patch based features. We measure the amplitude, polarimetry, and texture similarity between circular neighborhoods. The histogram of amplitude, polarimetric features and texton are measured by χ^2 distance. These two types of cues are combined using a logistic regression classifier trained on the ground-truth data. Affinity between two pixels are produced by the classifier. The trailing eigenvectors of the affinity matrix define segmentation results.

3. REFERENCES

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