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# AN ADABOOST-BASED ITERATED MRF MODEL WITH LINEAR TARGET PRIOR FOR SYNTHETIC APERTURE RADAR IMAGE CLASSIFICATION

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**KEY WORDS:** SAR, image classification, Linear Targets Prior, Ratio Response, MRF, AdaBoost

**ABSTRACT:**

A supervised classification method based on AdaBoost posterior probability and Markov Random Fields (MRF) model with Linear Targets Prior (LTP) is proposed in this paper. Firstly in contrast with most existing regions (*superpixels*) based models, this approach captures contiguous image regions called *superpixels* from ratio response maps of original images. Secondly, Adaboost classifier is employed to get likelihood probability for Markov Random Filed (MRF). Meanwhile, linear targets prior information (LTP) is introduced into MRF model combining with Potts prior model to engage better edges in classification results. Finally, iterative strategy in MRF model improves the performance of classification. Compared with traditional MRF model, the proposed approach has effective improvement in SAR images classification in the experiments of this paper.

## 1. INTRODUCTION

Since they can operate days and nights and under any weather conditions, Synthetic Aperture Radar (SAR) has been widely used in many fields. Furthermore, the resolution of SAR images has become higher and higher, which makes automatic analysis of SAR images rivet more people's attention. Nevertheless, strong speckle noise existing in SAR images leads to difficult image processing. And, many articles are still published on this issue, such as segmentation presented in F. Galland, 2003 and R.F.Rocha, 2008, classification in C. Tison, 2004. Segmentation, classification and annotation are the fundamental tasks of images automatic analysis, which are called as image parsing (Zhouwen Tu, 2005). Recently, popular approaches for image parsing can be considered as a combination of three strategies, Pre-Segmentation, Features Extraction and Model. See fig.1.

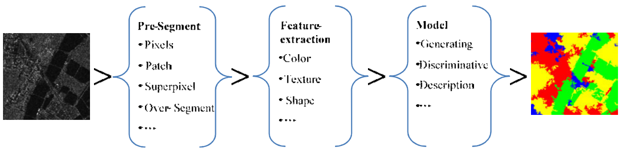


Fig 1. Framework of popular approaches for images parsing

Recent publications present many pre-segmentation methods. Such as 20×20 patches are extracted in a pLSA based MRF classification method (Verbeek, 2007). Superpixel over-segmentation is used in Regional Label Features based CRF method (Stephen, 2008). Meanshift over-segmentation method (Dorin, 2002) has been widely used in some classification articles. Multiscale segmentation based on geodesic morphology is used to get local regions for spatial reasoning (Jordi Inglada, 2009). However, there are some approaches using pixels directly without pre-segmentation. In general, a pixel can be seen as a specific style of pre-segmentation.

After pre-segmentation, features descriptors calculate the features of local regions. General features are color, texture and shape, such as SIFT-color (Joost van de Weijer, 2006) Gabor (B.S.Manjunath, 1996), LBP (T. Ojala, 2002)0, HOG (N. Dalal, 2005) and so on. Because of imaging principle, SAR images get specific features. Only one kind of general features can't describe SAR image sufficiently. Gray histogram and SoftLBP (Ahonen T, 2007) are used in this paper.

The most popular image models can be seen as one of the three basic models, or combination of two or three of them. The three basic models are (F. Han, 2008): generating model, description model and discriminant model. Generating model is a model which infers prediction from samples such as pLSA (Verbeek, 2007) and LDA (David M. Blei, 2003). Description model describes the relations of samples such as MRF (Verbeek, 2007). Discriminant model has discriminative functions which can get results from samples directly such as Adaboost (Robert E. Schapire, 2003). Meanwhile, there are some models combining two of the basic models. Specially, CRF is a unified model which combines discriminant model with description model (S.C. Zhu, 2006), and it can integrate different kinds of features and sorts of prior in a unified model more easily, and get better results by optimization.

In common sense, land surface on one side of a certain length of road always belongs to the same category, and rivers, railways and other liner targets have similar situation. The idea in this paper is to introduce this linear targets prior into MRF description model. This paper focuses on improving the edges of regions in SAR images classification results. There are three contributions of this paper: 1) Linear targets priors are introduced into MRF model. The Potts model prior can infer

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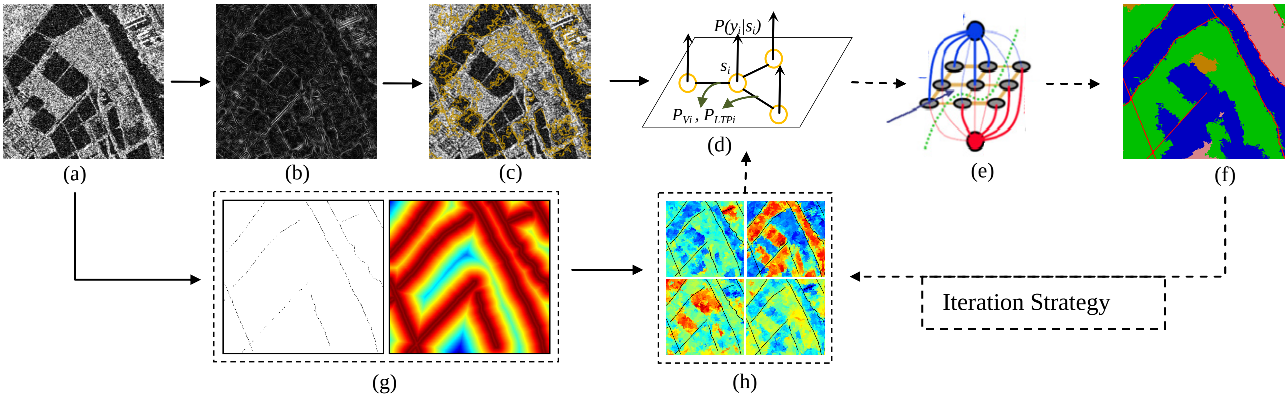



Fig. 2. Flowchart of the proposed model. (a) original image; (b) edges probability map (Ratio response map); (c) over-segmentation results (superpixels); (d) graph structure for GraphCut segmentation; (e) GraphCut segmentation; (f) segmentation results; (g) map of linear target and distance map from pre-pixels to linear targets; (h) linear target prior maps. The iteration strategy is marked with dotted lines.

consistency among homogenous regions, but can hardly consider the consistency along the linear targets like roads and rivers. 2) Superpixels of Pre-segmentation are captured on edges probability maps instead of original images. Since shapes of linear targets are always the boundaries of superpixels. In this case, more information of edges can be used for classification process. 3) Iterative MRF description model is more likely to remove noise in classification map compared with standard MRF model.

## 2. RELATED WORK

### 2.1 Edge detection

Ratio line detector D1 (F.Tupin, 1996) is derived from a coupling of two ratio edge detectors on both sides of a region (as shown in fig.3.a). Due to multiple responses to a structure, detector D1 is not accurate enough to locate the edges. Cross-correlation line detector D2 (F.Tupin, 1996) utilizes variances of regions to improves locating accuracy but with higher missing alarm ratio. Tupin (F.Tupin, 1996) merged the information from both D1 and D2 in 8 orientations.

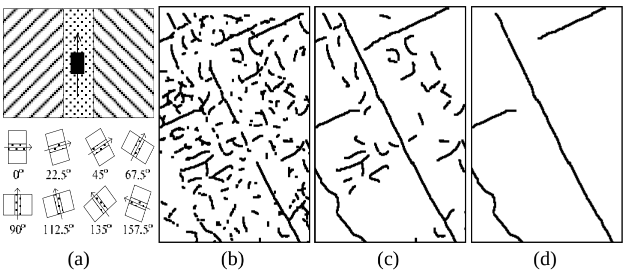



Fig.3. (a) Template and 8 orientations of template used in ratio edge detection. (b) Results of ratio edge detection. (c) Grouping results. (d) Linear targets detection results

Once again, the main motivation of this paper is improving region edges in classification results. So, the traditional edge detection can get wealth and accurate edge information from SAR images which is useful for classification. And, the proposed approach in this paper gets use of this information in over-segmentation, see details in section 3.

### 2.2 AdaBoost based MRF Model

MRF is a type of classical discriminative model. Given an image $I = \{s_1, s_2 ... s_{N_I}\}$ with $N_I$ pixels or superpixels $s_i$ and a label set $Y = \{y_1, y_2 ... y_{N_I}\}$ with $N_C$ labels, MRF model constructs a posteriori probability of $s_i$, as shown in Eq.1. Where, $\lambda > 0$ is a constant coefficient. $P_{Vi}$ is prior probability and $V_{ij}(y_i, y_j) = 1$ when $y_i = y_j$ , $V_{ij}(y_i, y_j) = 0$ when $y_i \neq y_j$. $P_{Li}$ is always captured by feature-based discriminant model like AdaBoost classifier and $P_{Li}$ tends to be $P_{Li}(y_i|f(s_i))$ where $f(s_i)$ is the features of $s_i$. For the whole image, the posterior probability is $P(Y|I,\Theta)$ where $\Theta$ is the parameter of model. Some optimization algorithms, such as GraphCut and Simulated Annealing Algorithm (SAA), can be utilized to get maximums of $P(Y|I,\Theta)$.

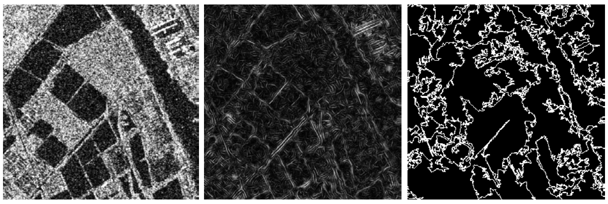
$$
\begin{aligned}
P(y_i \mid s_i) &\propto P_{Li}(y_i \mid s_i) P_{Vi}(y_i \mid y_{Vi}) \\
P_{Vi}(y_i \mid y_{Vi}) &= \exp\left(\lambda \sum_{y_i \in Vi} V_{ij}(y_i, y_j)\right) \\
P(Y \mid I, \Theta) &= \prod_{i=1}^{N_I} P(y_i \mid s_i) \\
\bar{Y} &= \operatorname*{argmax}_{Y} \{P(Y \mid I, \Theta)\}
\end{aligned}
\qquad (1)
$$

As one of the most popular description model, MRF model can balance the likelihood and prior probability in the whole image and get global optimal solution with optimization algorithms like algorithm presented in (Boykov Y, 2001). So, a linear target prior can be introduced into MRF model in this paper simply and obviously, see details in section 3.

## 3. METHODOLOGY

### 3.1 Pre-segmentations and Features Extraction

The proposed approach in this paper begins with pre-segmentation strategy using over-segmentation method to get *superpixels*. Firstly, we utilize ratio edge detector to get edges probability map of each input image (as shown in fig. 4.b).



(a) (b) (c)

Fig. 4. (a) Original image; (b) Ratio response map (edges probability map); (c) Over-segmentation results

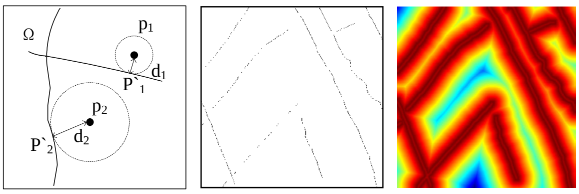
And then, Meanshift (Dorin Comaniciu, 2002) based over-segmentation algorithm is employed on the edges probability map to divide original images into superpixles (as shown in fig. 4.c).

A superpixel captured from pre-segmentation is the smallest unit in an image and can be assigned only a class label. Each superpixel in images is extracted a set of features consisted of gray histogram, SoftLBP (Ahonen T, 2007).

### 3.2 Linear Target Prior

Linear Target Priors (LTP) utilizes the shape of linear target to improve the edges of classification results. This prior information comes from the relative location between linear targets and image pixels (or superpixels) around them. For example, we wish to make use of the fact that all pixels adjoining river banks are *water* or *farmland* (in a certain length). Thus, the first is detecting the linear targets in SAR images. In this paper, the fusion operates of D1 and D2 operates is employed to detect linear targets (edges). And then, the LTP is captured in the following ways.

**3.2.1 Distance Map:** The distances from points (pixels) to lines (linear targets) are calculated as the method presented in (Kumar M.P., 2005). Given lines $\Omega$, the distance $d = \mathrm{dist}(p, \Omega)$ between point $p$ and $\Omega$ is the distance between point $p$ and point $p'$ which is the nearest point in lines $\Omega$ to point $p$ (as shown in fig.5.a). The distance map is shown in fig.5.c.



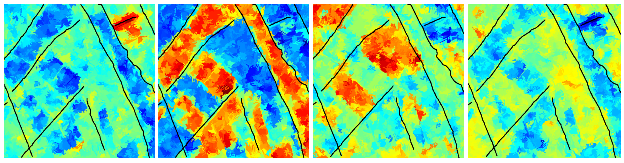

(a) (b) (c)

Fig. 5. (a) sketch of distance from pixels to lines; (b) linear target map; (c) distance map from pre-pixels to linear tagets.

**3.2.2 LTP Map:** LTP is learned from the labelled image data (classification results of previous iteration in practice), so it changes from iteration to next iteration. Firstly, the linear target $\Omega$ are divided into sub-lines with a certain length, $\Omega = \{\Omega_1, ...\Omega_{N\Omega}\}$. And a sub-line $\Omega_j$ divides its adjacent area into $K$ regions, we address them sub-line regions $R = \{R_(\Omega_j)\}^k$. Then, the LTP of a pixel $p_i$ for class $c$ is shown by Eq.2:

$$P_{LTPi}\left(c \mid p_i, \Omega, Y^{(t)}\right) = \exp\left(\sum_{j=1}^{N\Omega}\left[\mu \mathrm{dist}\left(p_i, \Omega_j\right) \sum_{k=1}^{K} \mathrm{cont}\left(c, p_i, R_{\Omega j}^k\right)\right]\right)$$
$$\mathrm{cont}\left(c, p_i, R_{\Omega j}^k\right) = \begin{cases} 1, & \text{if } p_i \in R_{\Omega j}^k \text{ and } c = \mathrm{maxlabel}\left(Y^{(t)}, R_{\Omega j}^k\right) \\ 0, & \text{other} \end{cases} \tag{2}$$

Where, $\mu$ is LTP weight and $\mathrm{maxlabel}(Y_{(t)}, R_{\Omega j}^k)$ is the maximum class of pixels in region $R = \{R_{\Omega j}^k\}$ of previous iteration classification results $Y^{(t)}$. Fig.6 shows an example of LTP map for class *building*, *water*, *farmland* and *woodland* in SAR image. These LTP probability values map to the full range of values in the cool-hot colormap.



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

Fig. 6. (a) linear target prior map for building; (b) linear target prior map for water; (c) linear target prior map for farmland; (d) linear target prior map for woodland.

### 3.3 Iterative MRF Model with LTP

The posteriori probability of the proposed model is added LTP based on Eq.1 as shown in Eq.3:

$$P\left(y_i \mid s_i, \Omega, Y^{(t)}\right) \propto P_{Li}\left(y_i \mid s_i\right) P_{Vi}\left(y_i \mid y_{Vi}\right) P_{LTPi}\left(y_i \mid s_i, \Omega, Y^{(t)}\right)$$
$$P_{LTPi}\left(y_i \mid s_i, \Omega, Y^{(t)}\right) = \sum_{p_i \in s_i} P_{LTPi}\left(y_i \mid p_i, \Omega, Y^{(t)}\right) \tag{3}$$

Where, $s_i$ is $i$-th superpixels in image and $p_i$ is a pixel in $s_i$, $P_{LTPi}$ is linear targets prior of $s_i$. The overall image posteriori probability is:

$$P(Y \mid I, \Omega, Y^{(t)}, \Theta) = \prod_{i=1}^{N_I} P\left(y_i \mid s_i, \Omega, Y^{(t)}\right)$$
$$\overline{Y}^{(t+1)} = \underset{Y^{(t+1)}}{\mathrm{argmax}}\{P(Y^{(t+1)} \mid I, \Omega, Y^{(t)}, \Theta)\} \tag{4}$$

A GraphCut-based optimization algorithm presented in Boykov Y, 2001 has been used to effectively capture the global optimal resolution of Eq.4. The training steps of the proposed Iterative MRF model with LTP have been listed in the following:

1) Utilize edge detection template in fig.3.a to get edges probability map of input images;
2) Over-segment the edges probability map to get superpixels;
3) Extract features in each superpixel;
4) Training AdaBoost classifier with labeled groundtruth data;

The testing steps of Iterative MRF model with LTP are shown in the following:

1) The same as steps 1~3 in training;
2) Detect linear targets with fusion operate of D1 and D2 in testing images;
3) Utilize AdaBoost classifier in training stagey to get $P_{Li}$;
4) Construct MRF model as Eq.1 and get optimal solution $Y(0)$**;**
5) Get $P_{LTPi}$ with $t$-th iterative solution $Y^{(t)}$;
6) Construct MRF model as Eq.4 and get optimal solution $Y^{(t+1)}$**;**
7) Repeat steps 4 and 5 until little changes existing in $Y^{(t+1)}$.

## 4. EXPERIMENTS

### 4.1 Experiments setup

Experiments are done on SAR image datasets. The datasets and parameters are illustrated as following.

**4.1.1 Data:** The SAR datasets contains a 1500×1200 pixels image that are selected from VV polarization SAR images of Guangdong Provinces of China in May 2008 of TerraSAR satellite. The spatial resolution is 1.25m*1.25m. Each image of the SAR datasets has a ground truth getting from manual labeling under ArcGIS software. Our experiments consist of 4 classed: *farmland, woodland, building, water*. Half of this image is used for training, the remaining for testing.

**4.1.2 Parameters:** In linear target detection, the template is selected with 15 pixels high, 13 pixels width and 3 pixels centre region. The threshold of D1, D2 and fusion operate are 0.35, 0.45 and 0.35 individually. The minimum region area of superpixels in Meanshift based over-segmentation is 400 pixels, with spatial bandwidth and range bandwidth are both 3 pixels. Features used here are gray histogram and SoftLBP 0. The length of sub-lines is 50 pixels and the width of sub-line regions is 20 pixels.

### 4.2 Classification Performance

The classification results of the proposed approach in this paper are shown in fig.7. Fig.7.c is the beginning of iteration result where $P_{LTPi} = 0$, that is without LTP. And there are some isolated points in the classification map. Moreover, there are many indented edges along the linear targets. In the fig.7.d, e and f, isolated points and indented edges decrease gradually since the addition of LTP.

Compared with groundtruth data labeled artificially, classification accuracies are listed in table.1. It shows that the average accuracy has been improved only a little from ieration-0 to ieration-3, but the overall classification performance has large improvement.

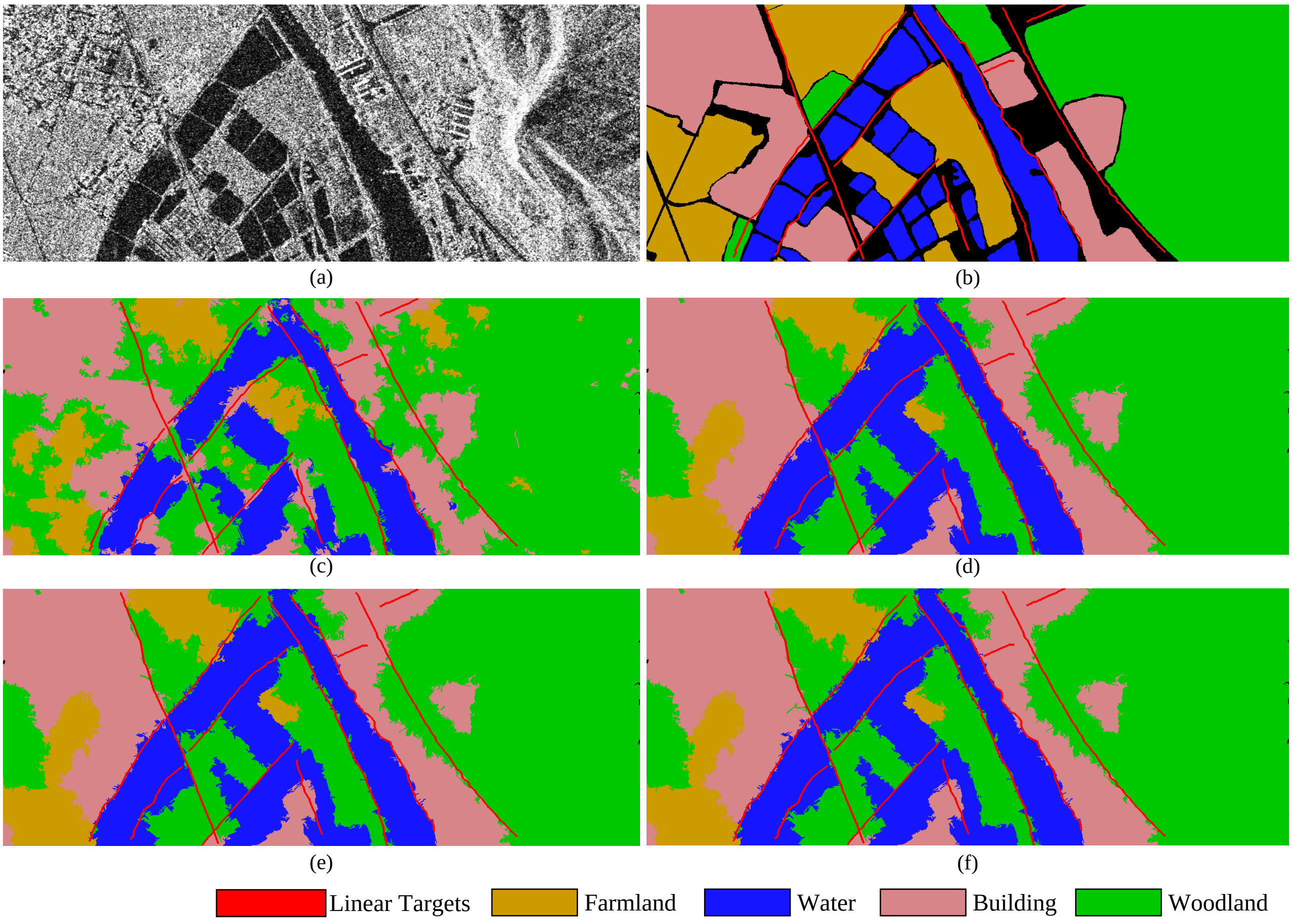



Fig. 7. Experimental Results, (a) original image; (b) groundtruth data with linear targets detected with fusion operate of D1 and D2 operates; (c) classification results in iteration 0 (without LTP); (d) classification results in iteration 1 (with LTP); (e) classification results in iteration 1 (with LTP); (f) classification results in iteration 1 (with LTP);

| *Catrgory (%)* | *Accuracy* | | | |
|---|---|---|---|---|
| | Iteration 0 | Iteration 1 | Iteration 2 | Iteration 3 |
| Building | 80.75% | 88.28% | 88.92% | 89.46% |
| Water | 92.12% | 92.93% | 90.26% | 90.14% |
| Farmland | 39.96% | 36.86% | 34.11% | 34.11% |
| Woodland | 92.03% | 95.28% | 93.97% | 93.84% |
| Average | **77.89%** | **80.27%** | **78.84%** | **78.89%** |

Tabel 1. Segmentation accuracy

## 5. CONCLUSIONS

In this paper, an AdaBoost-based iterative Markov Random Fields (MRF) with Linear Target Prior (LTP) has been proposed. Applied to Synthetic Aperture Radar (SAR) images classification, three strategies have been provided in this model to improve regions edges and isolated points in classification results and effective performance has been obtained. Firstly, due to superpixels captured from ratio response map of SAR images instead of original SAR images, edge information has been utilized more effectively. In this case, classification experiment results show distinct edges of regions. Secondly, linear target prior introduces consistency information along the linear targets into Markov model. Combined with traditional neighbourhood prior information, more reasonable classification results have been gotten in the experiment. Thirdly, the employment of iterative strategy makes the proposed approach have self-perfection in a stated degree. And the experiments have a certain improvement with the increase of iteration times.

Nevertheless, lots of information extracted from polarimetric SAR data, interferometric SAR data and polarimetric SAR interferometry data can be used for SAR image analysis.

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