SAR IMAGE CHANGE DETECTION BASED ON FUZZY MARKOV RANDOM FIELD MODEL

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ABSTRACT:

Most existing SAR image change detection algorithms only consider single pixel information of different images, and not consider the spatial dependencies of image pixels. So the change detection results are susceptible to image noise, and the detection effect is not ideal. Markov Random Field (MRF) can make full use of the spatial dependence of image pixels and improve detection accuracy. When segmenting the difference image, different categories of regions have a high degree of similarity at the junction of them. It is difficult to clearly distinguish the labels of the pixels near the boundaries of the judgment area. In the traditional MRF method, each pixel is given a hard label during iteration. So MRF is a hard decision in the process, and it will cause loss of information. This paper applies the combination of fuzzy theory and MRF to the change detection of SAR images. The experimental results show that the proposed method has better detection effect than the traditional MRF method.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) is an important breakthrough in the field of remote sensing, becoming very important way of obtaining change information. Compared with optical remote sensing, SAR has an all-weather observation capability, especially in rainy and cloudy weather conditions. SAR changes detection has been widely used in agricultural guidance, geographic mapping, resources and environment, urban planning disaster monitoring and military and other fields. SAR image change detection technology can solve many practical problems, it has a broad application prospects and become a hot research in recent years.

In recent years, researchers have proposed many SAR image change detection algorithms. These algorithms can be generally divided into algebraic operations, feature transformations, post-classification comparisons, and coherent comparisons. Image algebraic algorithm is the most commonly used, including image difference method, image ratio method and logarithmic ratio method, etc. Feature transformation method includes principal component analysis, independent component analysis and wavelet transform, etc. The post-classification comparison method refers to the classification of images first, and then compares the classification results, but the method requires a higher classification accuracy. The coherent comparison method extracts the difference map based on the correlation of the two SAR images, but the method is greatly affected by the interference baseline and time decoherence. In addition, since the MRF random field considers the spatial context of image pixels, many scholars have applied the MRF theory to SAR image change detection and obtained better detection results.

The fuzzy theory proposed by L.A. Zadeh uses the degree of membership function to describe the degree to which an element belongs to a certain class, and thus can well express and handle the ambiguity and uncertainty of the decision. Based on fuzzy theory, this paper proposes a method of detecting changes in SAR images based on fuzzy MRF (FMRF). Introducing the fuzzy theory into the Markov random field reduces the impact of the hard decision caused by the MRF method in the iterative process. The experimental results show that the proposed method can achieve better detection results than the traditional MRF method.

2. THEORETICAL BASIS

2.1 Basis of fuzzy sets

Fuzzy set theory using mathematical methods to describe and deal with the reality of the fuzzy phenomenon. It can make up for the shortcomings of using binary logic alone to describe things. In the fuzzy logic, the membership function is used to reflect the membership degree of the fuzzy set.

Let A be a set on the universe U, for any $u \in U$, order

$$C_A(u) = \begin{cases} 1, \text{当 } u \in A \\ 0, \text{当 } u \notin A \end{cases} \tag{1}$$

Then $C_A(u)$ is the membership function of set A. The value $C_A(u_0)$ of $C_A(u)$ at $u=u_0$ is called the membership degree of u_0 to A. The closer the value of $C_A(u)$ is to 1, that u belongs to the higher degree of A, on the contrary, that u belongs to the lower degree of A.

In the application of fuzzy set theory, it is necessary to make a decision by fuzzy comprehensive evaluation of the model. The steps for fuzzy comprehensive evaluation are as follows:

1) Establish the evaluation of the object set $U=\{u_1,u_2,...,u_n\}$, they used to describe the various attributes of the object.

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2) Establish the evaluation set $V=\{v_1,v_2,...,v_m\}$.
3) Establish a single factor judgment, that is, to establish a modal mapping from U to F(V). The mapping formula is:

$$f: U \to F(V), \forall u_i \in U \tag{2}$$

$$u_i \big| f(u_i) = \frac{r_{i1}}{v_1} + \frac{r_{i2}}{v_2} + \cdots + \frac{r_{im}}{v_m} \tag{3}$$

Where, $0 \le r_{ij} \le 1, 0 \le i \le n, 0 \le j \le m$

$$R = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{pmatrix}$$

R is a single factor decision matrix, the (U,V,R) constitutes a comprehensive evaluation model.
4) Comprehensive evaluation
Because of the different emphasis on the factors in *U*, we need to assign different weights to each factor, which can be expressed as a fuzzy subset $A=(a_1,a_2,\cdots a_n)$ on *U* and $\sum a_i = 1$.

After *R* and *A* are identified, the comprehensive evaluation is:

$$B = A \circ R \tag{4}$$

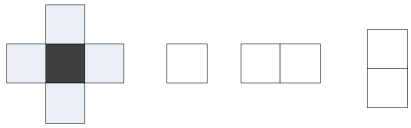
Finally, according to the principle of maximum membership, we make the final decision.

2.2 Markov Random Field Theory

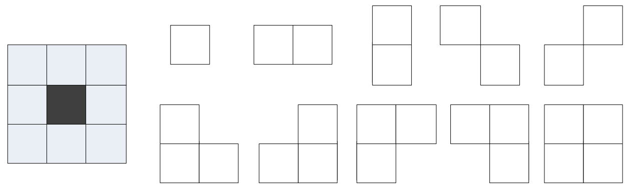
In the MRF model, two random field description images are usually used, one is the label field $X = \{x_s \mid s \in S\}$, $x_s \in \{1,2,..., l\}$ and it uses prior distribution to describe pixel local correlation; the other the an observation field $Y = \{y_s \mid s \in S\}$, and it describes the distribution of observation data using a conditional distribution function.

Let $\Omega = \{x = (x_1, x_2,..., x_{MN})\}$ be a set of all possible partitions, and the domain system satisfies the following characteristics:
1) $\delta(s) \subset S$;
2) $s \notin \delta(s)$;
3) $\forall s, r \in S, s \in \delta(r) \Leftrightarrow r \in \delta(s)$.

If each element of the subset $c \subseteq S$ satisfies the characteristic 3), then *c* is called a cliques. The common neighborhood types are 4-neighborhood and 8-neighborhood. Fig. 1. shows the two types of neighborhoods (the center pixel is the target pixel, and the surrounding pixels are its neighboring pixels) and their corresponding groups.



(*a*) 4-neighborhood



(*b*) 8-neighborhood

Fig. 1. Two types of neighborhood and their cliques

A random field *X* is called an MRF for δ iff *X* satisfies the following characteristics:
1) $P(X = x) > 0, \forall x \in \Omega$
2) $P(X_s = x_s \mid X_r = x_r, \forall r \neq S) = P(X_s = x_s \mid X_r = x_r, \forall r \in \delta(s))$.
According to characteristic 2), the correlation between pixel labels depends on the neighborhood system δ defined on *S*.

In order to estimate the best label from the observation field Y, according to the Bayes formula, the maximum posterior probability (MAP) can be used to transform the image segmentation problem into the problem of solving the maximum posterior probability.

$$\hat{x} = argmaxP_{X|Y}(x \mid y) \tag{5}$$

Where $P_{X|Y}(x \mid y) = P_X(x)P_{Y|X}(\mathrm{y} \mid x)P_Y(y)$, because the observation field is given as a constant, so:

$$\hat{x} = argmaxP_X(x)P_{Y|X}(\mathrm{y} \mid x) \tag{6}$$

Due to the equivalence of MRF and Gibbs distributions, the prior distribution $P_Y(y)$ of labeling fields can be represented by the Gibbs distribution as:

$$P_X(x) = Z^{-1}[exp(-U_1(x)/T)] \tag{7}$$

Where $Z = \sum_x [exp(-U_1(x)/T)]$ is normalization constant; $U_1(x) = \sum_{c \in C} V_c(x)$ is the prior energy function defined on the cliques of δ, *C* is the set of cliques, and $V_c(\cdot)$ is a potential energy function defined on the cliques c. Common labeling field models include Ising model, Potts model and MLL model. This paper introduces Potts model:

$$V(x_i, x_j) = \begin{cases} 0 & x_i = x_j \\ \beta & x_i \neq x_j \end{cases} \tag{8}$$

Where β is positive parameter. The more groups with the same label in the labeling field, the lower the prior energy $U_1(x)$.

For the observed field model, Gaussian functions are often used to describe the gray properties of the image, assuming that the pixel distribution of each label A obeys a Gaussian distribution:

$$P(y_s \mid x_s) = \frac{1}{\sqrt{2\pi}\sigma_{x_s}} exp\{-\frac{(y_s - \mu_{x_s})^2}{2\sigma_{x_s}^{\ 2}}\} \tag{9}$$

Assuming that the observed random variables of each pixel are independent of each other under a given label field *x*, the likelihood energy function can be expressed as:

$$U_2(x, y) = \sum_{s \in S} \left(ln(\sqrt{2\pi}\sigma_{x_s}) + \frac{(y_s - \mu_{x_s})^2}{2\sigma_{x_s}^{2}} \right) \tag{10}$$

To take the logarithm of both sides of (6), there are:

$$ln\hat{x} = argmax[-U_1(x)/T - lnZ - U_2(x, y)] \tag{11}$$

The problem of estimating the best labeling field can be converted to the problem of finding the label field corresponding to the minimum global energy $U(x, y)$, that is:

$$\hat{x} = argminU(x, y) = argmin[U_1(x, y) + U_2(x, y)] \tag{12}$$

3. SAR IMAGE CHANGE DETECTION BADED ON FUZZY MRF

Because MRF can effectively establish a context-dependent prior model and can effectively suppress the influence of speckle noise, MRF is widely used in SAR image change detection. When segmenting the difference map , regions of different categories have a high degree of similarity at the junction, and it is difficult to clearly discriminate the label of pixels near the boundary of the judgment region. In the traditional MRF method, each pixel is given a hard label during iteration. So MRF is a hard decision in the process, and it will cause loss of information.

This paper applies the combination of fuzzy theory and MRF to the change detection of SAR images, which can reduce the impact of hard decision caused by the MRF method in the iterative process. The steps to implement a change detection method based on fuzzy MRF (FMRF) are as follows:

Step1: Pre-processing the SAR images, which including radiation correction, speckle filtering, and geometric registration;
Step2: Constructing the difference map by logarithmic ratio operator;
Step3: Initializing the hard-labeled field and estimating the parameters of the observation field (where μ_{i} and σ_{i} are rhe mean and standard deviation the pixels of each hard-label, respectively);
Step4: Fuzzing hard label field and updating the fuzzy label field by an optimization algorithm;
Step5: Labeling each pixel by the principle of maximum degree of membership;
Step6: Repeating Step2~ Step4 until meeting convergence conditions and getting initial change binary image;
Step7: Post-processing the initial change binary image by regional growth method.

In Step 3, fuzzing hard label field by giving each label a vector $x_s = (x_{s1}, x_{s2},..., x_{sl}) \in [0,1]^l$. Where $(x_{s1} + x_{s2} + ... + x_{sl}) = 1$, x_{si} indicates the degree of membership of pixel *s* belonging to hard label category *i*. The expression is as follows:

$$x_{sl} = \begin{cases} 0 & x_{sl} \in [0,0.1); \\ 0.2 & x_{sl} \in [0.1,0.3); \\ 0.4 & x_{sl} \in [0.3,0.5); \\ 0.6 & x_{sl} \in [0.5,0.7); \\ 0.8 & else. \end{cases} \tag{13}$$

Therefore, the potential energy function $V_{\{s,t\}}(x)$ defined on the fuzzy label field can be expressed as the Euclidean distance of the fuzzy label between pixels:

$$V_{\{s,t\}}(x) = \beta\left\| x_s - x_t \right\| \tag{14}$$

Assume that the gray scale values of each hard label category are Gaussian distributed and the probability density function $P(y_s \mid x_s)$ can be expressed as

$$P(y_s \mid x_s) = \frac{1}{\sqrt{2\pi}\sqrt{x_{s1}\sigma_1^{2} + \cdots + x_{sl}\sigma_l^{2}}} \cdot exp\{- \frac{[y_s - (x_{s1}\mu_1 + \cdots + x_{sl}\mu_l)^2]}{2(x_{s1}\sigma_1^{2} + \cdots + x_{sl}\sigma_l^{2})}\} \tag{15}$$

Where A and B are the mean and standard deviation estimated by Step2.

4. EXPERIMENTS AND ANALYSIS

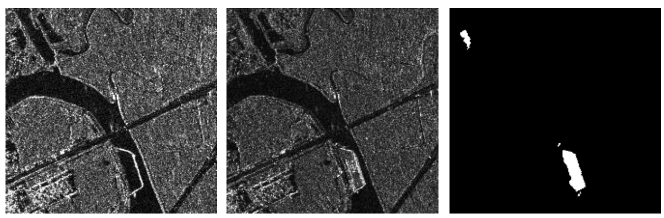
4.1 Experiment setting

The experimental data used in this paper are the X-band TerraSAR-X images. Tab. 1. introduces the experimental data.

	Pre-temporal	Post-temporal
Imaging method	StripMap	StripMap
Polarization mode	HH	HH
Imaging time	20160121	20160726
Track direction	Ascending	Ascending
Incident angle	26.4	26.4

Tab.1. TerraSAR-X data introduction

In this paper, we take part of original image in Haizhu District, Guangzhou City. The test area is 415 ×401. As shown in Fig. 2 , there are two phase images and a reference binary image.

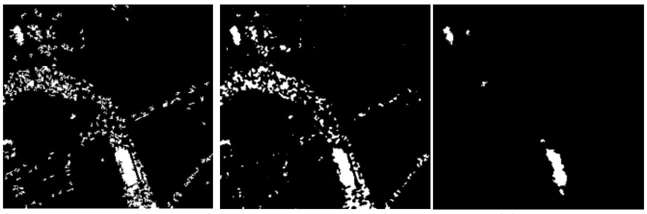


(*a*) Pre-temporal (*b*) Post-temporal (*c*) Reference image

Fig. 2. Experimental data

4.2 Experimental results and accuracy evaluation

This experiment uses the OTSU algorithm algorithm and traditional MRF algorithm for comparison. The experimental results are shown in Fig. 3, and the accuracy evaluation is shown in Tab. 2.



(*a*) OTSU (*b*) MRF (*c*) FMRF

Fig. 3. Experimental result

	False alarm rate (%)	Missed rate (%)	Overall accuracy (%)	Kappa coefficient
OTSU	5.13	7.17	94.84	0.319
MRF	4.71	9.82	95.21	0.330
FMRF	0.15	16.11	99.55	0.829

Tab.2. TerraSAR-X data introduction

4.3 Analysis of results

In the experiments in this article, there are mainly two parts of the change features. It can be seen that there are many "pseudo-changes" in rivers and roads by using OTSU algorithm and MRF algorithm. And FMRF algorithm can remove these "pseudo-changes" effectively.

From Tab. 3, The Kappa coefficient of the OTSU algorithm and the MRF algorithm is small and the detection accuracy is low. The false alarm rate of the FMRF algorithm is low. Although the missed detection rate is high, the overall accuracy and Kappa coefficient are higher.

5. CONCLUSIONS

In this paper, the fuzzy set theory is used to the traditional MRF algorithm. By fuzzing label field, it can reduce the impact of hard decision caused by the MRF method in the iterative process. This method can remove these "pseudo-changes" effectively and improve the accuracy of change detection.

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