Unsupervised Change Detection in Multitemporal SAR Images Using MRF Models

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Abstract  An unsupervised change-detection method that considers the spatial contextual information in a log-ratio difference image generated from multitemporal SAR images is proposed. A Markov random field (MRF) model is particularly employed to exploit statistical spatial correlation of intensity levels among neighboring pixels. Under the assumption of the independence of pixels and mixed Gaussian distribution in the log-ratio difference image, a stochastic and iterative EM-MPM change-detection algorithm based on an MRF model is developed. The EM-MPM algorithm is based on a maximiser of posterior marginals (MPM) algorithm for image segmentation and an expectation-maximum (EM) algorithm for parameter estimation in a completely automatic way. The experiment results obtained on multitemporal ERS-2 SAR images show the effectiveness of the proposed method.

Keywords  change detection; multitemporal SAR image; Markov random field; EM algorithm

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Introduction

Detecting land use/land cover changes using multitemporal remote sensing images is extremely important for understanding dynamic relationships and interactions between human and natural phenomena in order to promote better decision-making. In this context, optical remote sensing sensors have been used for addressing change detection applications for many years\(^1\)\(^2\). In the past few years, multitemporal images acquired by synthetic aperture radar (SAR) sensors, such as ERS-1/2 and RADARSAT, have been increasingly utilized for change detection, since they present the advantages of being independent of atmospheric and sunlight conditions over optical images.

Ratioing and subtracting are two well-known techniques for change-detection in multitemporal remote sensing images, which respectively generate a difference image to compare a pair of multitemporal images by dividing or subtracting image values pixel-by-pixel, followed by thresholding. Based on the SAR image statistics, ratioing of the intensity images is preferred above subtracting in SAR image change-detection\(^3\). Generally, the ratio image is expressed in a logarithmic scale to compress the range of variation. Despite some successful works using the ratioing change-detection method described in References [4,5], the main problem is that they only consider the information contained within a pixel to distinguish between changed and unchanged pixels in the difference image, and not exploiting the spatial contextual information around a pixel. In fact, inten-
ity levels of neighbor pixels of remote sensing imagery have significant spatial correlation and a pixel belonging to a class is likely surrounded by pixels belonging to the same class \cite{6}. On the other hand, because of the effect of inherent speckle in SAR imagery, if the information of spatial context is not considered, a lot of disjoint points rather than connected rejoin are more likely to occur in the changed results \cite{7}.

Facing the aforementioned issue, we propose a more accurate and unsupervised change-detection method oriented to the analysis of multitemporal SAR images. This method is based on the Bayesian decision theory and takes into account the spatial contextual information in the log-ratio difference image. In this paper, an MRF model is particularly employed to exploit statistical spatial correlation of intensity levels among neighboring pixels. Under the assumption of independency of pixels from each other and mixed Gaussian distribution in the log-ratio difference image, a stochastic and iterative EM-PM change-detection algorithm based on the MRF model is developed. In the EM-PM framework, the EM algorithm is employed to automatically estimate the statistical distribution parameters associated with changed and unchanged classes, and an iterative optimization algorithm MPM is proposed to exploit the interpixel class dependence for modeling the prior probabilities of classes. In order to assess the effectiveness of the proposed method, a preliminary experiment was carried out on multitemporal ERS-2 SAR SLC data acquired on 19 March 1996 and 19 November 1999 over the Shenzhen region in China.

1 Image model for change detection

The maximum a posteriori (MAP) criterion based on Bayesian theory has been widely adopted in remote sensing images classification. In fact, the MAP classification is the optimal estimation of the label for each pixel. It is likely that the classification result would be improved if a reasonable assumption could be made in order to model the prior knowledge for class labels. One assumption for modeling prior probability is spatial context in images. The MRF model has long been recognized as an accurate statistical model to characterize contextual information and has been widely used in image segmentation and restoration \cite{8}. As a consequence, an MRF model is applied to exploit the prior information of class label corresponding to changed pixel and unchanged pixel in this paper, and a mixed Gaussian distribution is used to model the class-conditional p.d.f. in the log-ratio difference image.

### 1.1 Markov random filed model

Let \( S = \{s = (i, j); 1 \leq i \leq M, 1 \leq j \leq N\} \) and \( L = \{\omega_s, \omega_1, \omega_2\} \) respectively denote the set of all pixels and the set of possible labels in the log-ratio difference image, where \( \omega_s, \omega_1, \omega_2 \) denote three classes corresponding to unchanged pixel, scattering-enhanced pixel and scattering-reduced pixel, respectively. Therefore, a label random field \( X = \{x_s, x \in L, s \in S\} \) defined on the \( S \) can be treated as an MRF with a given neighborhood system if the Markovian property for each site \( s \) \cite{9}. Based on the Hammersley-Clifford theorem, MRF can be proved to have the equivalent properties to Gibbs random filed (GRF) \cite{9}. Consequently, the p.d.f. of \( X \) has the form

\[
P_x(x) = \frac{1}{Z} \exp[-U(x)] = \frac{1}{Z} \exp \left[ -\sum_{c \in c} V_c(x_c) \right]
\]

where \( x \) represents a sample realization of \( X \); \( U(x) \) and \( V_c(x_c) \) are respectively called energy function and potential function; \( Z \) is a normalizing constant; and \( c \) indicates a clique of a neighborhood system. Note that each potential \( V_c \) depends only on the value taken on the clique sites \( x_c = \{x_s, s \in c\} \). As a consequence, local spatial correlation in \( X \) can be modeled by defining suitable potential function \( V_c(x) \).

In this paper, we adopt an isotropic multilevel logistic (MLL) model with second order neighborhood system and pairwise cliques, as shown in Fig.1.

According to the assumption of the isotropy, i.e., \( \beta_1 = \beta_2 = \beta_3 = \beta_4 \), the potential can therefore be simplified to

\[
V_c(x_s, x_r) = \begin{cases} -\beta, & x_s = x_r \\ 0, & \text{other} \end{cases}
\]
where model parameter $\beta$ ($\beta > 0$) is known as the spatial interaction parameter of the pairwise cliques. To reduce the algorithm complexity, the parameter $\beta$ is considered a deterministic constant in this paper.

![Fig.1 Second order neighborhood system and pairwise cliques](image)

### 1.2 Model for log-ratio difference image

A MAP classifier also needs a statistical model for the observed image. In Reference [5], the distribution of log-ratio difference image obtained from multimodal SAR images has been proven close to a normal distribution with equal standard deviation. The observed image model $Y \in \mathbb{S}$ can therefore be described by a mixed Gaussian distribution given the pixel label field $X$. The class-conditional distribution of the observed data $y_s$ given the class label $\omega_l$ can be assumed as:

$$p(y_s / \omega_l) = \frac{1}{\sqrt{2\pi\sigma^2_l}} \exp \left\{ -\frac{(y_s - \mu_l)^2}{2\sigma^2_l} \right\}$$

Under the assumption that all of the random variables $y$ in $Y$ are independent and identically distributed Gaussian random variables with mean $\mu_l$ and variance $\sigma^2_l$, thus the class-conditional p.d.f. of $Y$ given $X$ has the form:

$$p_{Y/X}(y / x) = \prod_{s \in S} p(y_s / x_s) = \prod_{s \in S} \frac{1}{\sqrt{2\pi\sigma^2_l}} \exp \left\{ -\frac{(y_s - \mu_l)^2}{2\sigma^2_l} \right\}$$

where $\sigma^2_l \in \{\sigma^2_n, \sigma^2_{c1}, \sigma^2_{c2}\}$ and $\mu_l \in \{\mu_n, \mu_{c1}, \mu_{c2}\}$ correspond to the mean and variance of the class, $\omega_l \in \Omega$ are the element of the parameter vector $\theta$, respectively.

In order to detect the changed sites and unchanged sites using MAP criterion, we will need to obtain the conditional probability mass function of label random field $X$ given observed field $Y$, in terms of Bayesian rule, which can be formulated as:

$$p_{X/Y}(x / y, \theta) = \frac{p_{Y/X}(y / x, \theta)p_{X}(x)}{p_Y(y / \theta)}$$

By substituting Eq.(1) and Eq.(4) into Eq.(5), one obtains the posterior energy $U(x / y)$:

$$U(x / y) = U(x) + \sum_{c \in C} V_c(x_c, x_c) + \sum_{s \in S} \left[ \frac{1}{2} \ln(2\pi\sigma^2_l) + \frac{(y_s - \mu_l)^2}{2\sigma^2_l} \right]$$

Thus, the MAP estimate which maximizes posterior probability $p_{X/Y}(x / y, \theta)$ is equivalent to minimizing the posterior energy. It can be defined by:

$$\hat{x} = \arg \min_{x \in \mathbb{X}} p_{X/Y}(x / y, \theta)$$

### 2 Change-detection based on EM-PM algorithm

#### 2.1 MPM segmentation algorithm

In this subsection we assume that parameter vector $\theta$ of the MRF model is known and describe the MPM segmentation algorithm. In practice, the solution of Eq.(7) cannot be obtained directly because the labeling of each pixel has an effect on the labels to be assigned to its neighborhood. Generally, the minimization of the posterior energy is carried out by using an iterative optimization algorithm. Three such algorithms, known as simulated annealing (SA), iterated conditional models (ICM) and maximiser of posterior marginals (MPM) have been proposed in Reference[8]. Considering a good compromise between segmentation accuracy and time-consumption, we employ the MPM algorithm to search an optimum solution of Eq.(7).

The MPM iterative algorithm is based on an optimization criterion that minimizes the expected value of the number of misclassified pixels. As we know in Reference [10], minimizing classification errors is equivalent to maximizing the marginal posterior distribution. According to the optimization criterion, the new label $\omega'_s$ for each site $s \in S$ is chosen based on the comparison of all possible labels to satisfy:
mizes the function Eq.(11), i.e., $\theta(i)$ stratifies $Q(\theta(i),\theta(i-1)) \geq Q(\theta,\theta(i-1))$, $\forall \theta$ (12)

Substituting Eq.(4) into Eq.(11) and using the Eq.(9), the solution for the estimation of $\theta(i)$ gives:

$$
\mu_{\omega}^{(i)} = \frac{1}{P(\omega)} \sum_{x \in sS} y P(x_i = \omega / y, \theta(i-1))
$$

(13)

and

$$
\sigma_{\omega}^{(i)} = \frac{1}{P(\omega)} \sum_{x \in sS} (y_i - \mu_{\omega}^{(i)}) P(x_i = \omega / y, \theta(i-1))
$$

(14)

where

$$
P(\omega) = \sum_{x \in sS} P(x_i = \omega / y, \theta(i-1))
$$

(15)

2.3 EM-MPM solution for change-detection

Combining the MPM algorithm for image segmentation and the EM algorithm for estimation of model parameters aforementioned, the EM-MPM solution for unsupervised change-detection can be summarized as follows.

1) Initialize the estimation of parameter vector $\hat{\theta}(0)$ and image configuration $\hat{x}(0)$ for $\theta$ and $X$, respectively. Choose recoding interval $k$ and iterative number $n$ in the Eq.(9).

2) Consist the following two steps in each iterative stage $i$ (from 1 to $P$) of the EM-MPM solution:  
   1) perform $n$ iterations of the MPM algorithm using $\hat{\theta}(i-1)$ as the value of $\theta$; 2) use the EM update Eqs.(13)-(15) for $\theta$ to obtain $\hat{\theta}(i)$, using the value of the class label probability in Eq.(9) as the estimation of $P(x_i = \omega / y, \theta(i-1))$ from Step 1).

After stage $P$ has been completed, the final estimate of $\theta(P)$ is computed using the EM update equations. Thus, the MPM algorithm is performed once more, using the final estimate of $\theta$ to obtain the final estimates of the marginal class label probabilities. Then the final change-detection result can be obtained with three classes corresponding to unchanged pixel, scattering-enhanced pixel and scattering-reduced pixel, respectively.

3 Experiment results

3.1 Experiment data description

In order to assess the effectiveness of the proposed approach for unsupervised change detection in the
analysis of the SAR log-ratio difference image, a preliminary experiment was carried out on multitemporal ERS-2 SAR SLC data acquired on March 19, 1996 and November 19, 1999 over the Shenzhen region in China. The images were preprocessed in some ways including radiometric calibration, co-registration, subsetting, and spatial speckle filtering. The selected area with 1 111 pixels and 700 lines covers the Shenzhen urban area and the northwestern part of Hong Kong, which contains urban area, water bodies, agriculture land, dry field, bare soil, and forest. Fig.2 and Fig.3 illustrate the two SAR intensity images in the study area, respectively.

For the interpretation of the log-ratio difference image and the estimation of change-detection results, validation data was obtained from ground truth data and two optical images acquired respectively by the TM/ETM sensors in March 3, 1996 and January 2, 2000. Fig.4 shows the log-ratio difference image obtained from the couple of SAR intensity images. According to interpretation and identification with the ground truth, the high-return changes caused by human activities and different natural conditions are marked and labeled in Fig.4, including the unwanted high-return changes of the ecosystem, i.e., the decreasing mangrove in the side of Shenzhen Gulf. Detailed information regarding the marked typical land-use changes in Fig.4 is reported in Table 1.

### Table 1 Description of marked return-high changes in Fig.4

| $\sigma^0$ | Marks            |
|------------|------------------|
| Reduced    | $A_1$ Filled sea area |
|            | $A_2$ New road        |
|            | $A_3$ New river         |
|            | $A_4$ Extending water body |
| Enhanced   | $B_1$ Decreasing mangrove |
|            | $B_2$ New buildings      |
|            | $B_3$ Developing urban area |

#### 3.2 Change-detection results and accuracy assessment

The unsupervised EM-MPM algorithm proposed in this paper was performed on the log-ratio difference image to obtain change-detection results. The changed map is showed in Fig.5, over the SAR image on November 19, 1999. Comparison of Fig.4 with Fig.5 shows that all high-return changes caused by human activities and different natural conditions were detected. In order to compare the performance of the proposed approach, the result produced by a non-context EM algorithm is shown in Fig.6. It is clear that the non-context does not provide a very clean result, and that the addition of context information results in a much more patch-like change-detection map.

For the better understanding of the results obtained by applying the two methods aforementioned, the accuracy of change-detection result was assessed by comparing the validation data from the ground truth. Table 2 and Table 3 show confusion matrices yielded by the two methods, respectively. When considering the contextual information, EM-MPM algorithm shows that all accuracy indicators are high. The
EM-MPM algorithm achieved an overall accuracy of 83.7% and a kappa value 0.71, which have improvements of around 10% and 0.2, respectively, compared to the non-context EM algorithm result.

| Class. data | Ref. data | EM algorithm | EM-MPM algorithm |
|-------------|-----------|--------------|------------------|
| σ²-reduced pixel | 9 824 | 780 | 193 | 10 797 | 9 099 | 12 968 | 700 | 218 | 13 886 | 93.39 |
| Unchanged pixel | 9 150 | 3 4393 | 5 654 | 49 497 | 69.91 | 5 850 | 34 450 | 3 298 | 43 598 | 79.02 |
| σ²-enhanced pixel | 176 | 353 | 5 614 | 6 143 | 91.39 | 332 | 386 | 7 945 | 8 663 | 91.71 |
| Sum | 19 150 | 35 536 | 11 461 | | 19 150 | 35 536 | 11 461 | |
| Producer’s accuracy (%) | 51.30 | 96.81 | 48.96 | | 67.72 | 96.94 | 69.32 | |
| Overall accuracy | 73.35% | | | | 83.70% | | |
| Kappa | 0.540 9 | | | | 0.710 1 | | |

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