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Advanced Markov random field model based on local uncertainty for unsupervised change detection

Pengfei He\textsuperscript{a}, Wenzhong Shi\textsuperscript{b*}, Zelang Miao\textsuperscript{b}, Hua Zhang\textsuperscript{a}, and Liping Cai\textsuperscript{a}

\textsuperscript{a}School of Environment Science and Spatial Informatics, China University of Mining and Technology, Xuzhou, China; \textsuperscript{b}Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Kowloon, Hong Kong

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Markov random field (MRF)-based methods are effective and popular unsupervised methods for detecting changes in remotely sensed images. In this method, the spatial contextual information is well utilized to conquer the problem of noise sensitivity in the pixel-wise change detection methods. Meanwhile, MRF also suffers from the over-smooth problem and the hard balance between denoising and detail preserving. To tackle these limitations, this letter presented an advanced MRF model based on local uncertainty (LUMRF). First, fuzzy c-means (FCM) cluster method is applied to the difference image obtained by change vector analysis to character each pixel with an initial label (change or no-change) and the corresponding membership values. To improve the detail preservation ability of MRF, the local uncertainty in a given window is subsequently computed and then integrated in the spatial energy term of MRF model. Finally, a refined change map is produced by the proposed LUMRF method. Two experiments were conducted to evaluate the effectiveness of the proposed method. The results show that, in comparison to FCM and MRF, LUMRF gives a better performance with the lowest total error detection and the performance is more robust to the parameter changes.

1. Introduction

Change detection (CD) serves as a key technology tool in obtaining the local or global change information from the remotely sensed images acquired over the same area at different times. It has been a hot research topic due to its wide range of significant applications, such as disaster monitoring, urban studies and agricultural surveys (Singh 1989). Developing CD method aims to detect the change information in a fast, automatic and accurate manner. Generally, CD methods in the literatures fall into two main categories: the supervised method and the unsupervised method. The former can provide results of multiple changes with attribute information produced by supervised classification methods. However, in many practical CD applications, the collection of appropriate and sufficient ground truth information for multitemporal or single date images is usually a difficult and expensive task. Meanwhile, the requirement for such training data dramatically slows down the CD process and makes it extremely difficult to exploit the vast amount of data that modern satellite sensors can produce. Consequently, the latter is more appealing at an operational level and has been intensively investigated in recent years.

*Corresponding author. Email: lsorzhi@polyu.edu.hk
Generally, there are two key points in implementing the unsupervised CD. One is the expression of change information between bi-temporal images. Chen et al. (2013) proposed to use spectral gradient difference to quantitatively describe the spectral shape and the shape difference between two spectra. Feature-based difference, e.g. texture (Li and Leung 2002) and geometry (Phalke and Couloigner 2005), is also an effective way to describe changes with special characteristics. Nevertheless, the most popular change information expression method is to create the multispectral difference image with spectral change vectors (SCV) by subtracting the spectral feature vectors, pixel by pixel, in one image from the other acquired at a different date. Changes are then identified by analysing the difference image.

Another problem arises with the identification criterion for detecting the change information. A common solution is the thresholding method that distinguishes the change pixels from unchanged pixels in the difference image by an optimal threshold (Bazi, Bruzzone, and Melgani 2005; Bruzzone and Prieto 2000). Due to the instability of the remote sensing imaging process and the complexity of the image scene, the optimal threshold is challenging to decide and the CD map is seriously affected by noises. To fix this limitation, lots of significant research on advanced CD methods, which are robust to noises, have been presented, including improved fuzzy c-means (FCM) (Ghosh, Mishra, and Ghosh 2011), level set (Bazi, Melgani, and Al-Sharari 2010), genetic algorithm (Celik 2010), Markov random field (MRF) (Chen and Cao 2013), etc. In particular, MRF-based method has been receiving much attention owing to its complete mathematical theory and prominent spatial contextual information-based image modelling. MRF provides a measure for the characterization of contextual constrains and derivation of the probability distribution of the interacting features (Li 2009). Usually, the contextual information is well incorporated by means of maximizing a posteriori probability (MAP-MRF framework) (Li 1995), in which the pixel labelling is converted to solving the problem of minimizing an energy function contributed by spectral and spatial information. Although the traditional MRF improves the CD accuracy to some extent, as a matter of fact, it suffers from a trade-off between the spectral component and spatial component in the energy function. Besides, the traditional MRF models assume that the labels of the pixels in a given neighbourhood are consistent, and thus, the neighbouring pixels’ weights are equivalent (Chen and Cao 2013). This assumption is reasonable in the plain areas without many image details. But in the detailed areas, such as edges, ridges and valleys, the over-smooth problem may often occur and image detail structures would be usually damaged due to the neglect of the pixels’ inconsistency in these areas. Although many studies have been conducted trying to solve this problem over the years, the uncertainty of the pixel label has still not been considered in the spatial model, which leads to unsatisfactory CD results.

Based on the aforementioned analysis, this letter proposed an advanced MRF model integrated with local uncertainty (LUMRF) for unsupervised CD on remotely sensed images. The proposed method mainly consists of four steps, as summarized by Figure 1. First, change vector analysis technique (Bruzzone and Prieto 2000) is applied to generate the difference image. Then, FCM (Bezdek 1981) is adopted to produce the preliminary change map as well as the corresponding membership values belonging to the change pixel and no-change pixel, respectively. Next, the label uncertainty of each pixel in a neighbourhood window is characterized with entropy (Foody 1995) based on the membership values and then the spatial item is reformulated by simultaneously considering the label and its uncertainty. Finally, the refined CD map is generated by iteratively minimizing the sum of the spatial item and the spectral item.
2. Methodology

Considering two multispectral images $X_1$ and $X_2$ of size $M \times N$ with $B$ bands acquired over the same geographical area at two different times, suppose that such images have been well-preprocessed, including radiometric calibration and co-registration. Let $X_{b,i}(i = 1, 2)$ be the values of $M \times N$ pixels in the $b^{th}$ ($1 \leq b \leq B$) band of $X_i$. Let $X_D = \{X_{b,D}|X_{b,D} = X_{b,2} - X_{b,1}, 1 \leq b \leq B\}$ be the SCV found by subtracting the value for each pixel in one image from the value in the other image. The final values of pixels in the difference image can be defined as (Bovolo, Marchesi, and Bruzzone 2012)

$$X_D' = \sqrt{\sum_{b=1}^{B} X_{b,D}^2} = \sqrt{\sum_{b=1}^{B} (X_{b,2} - X_{b,1})^2} \quad (1)$$

Let $S = \{(m,n)|m \in [1,M], n \in [1,N]\}$ be the set of sites in the difference image. A neighbourhood system for $S$ is defined as

$$N = \{N_{(m,n)}|\forall (m,n) \in S\}$$

where $N_{(m,n)}$ is the collection of sites neighbouring $(m, n)$. Figure 2(a) shows the $3 \times 3$ neighbourhood system used in this letter.

2.1. Local uncertainty

An important assumption in MRF is that the pixel tends to be of the same class with its neighbours. However, the preliminary label of the difference image, especially in the detail areas, is not definitely sure because of the inherent uncertainty in the image data and the algorithm itself. Thus, in terms of the spatial energy in MRF, it is unreasonable to
identify a pixel simply according to the number of neighbours with the same label. In this letter, the preliminary label with an uncertainty description of each pixel is obtained by using the FCM clustering method.

The FCM algorithm is an iterative clustering method making the pixels in the same cluster have high similarity while lower similarity between each cluster and the cluster of each pixel is identified by a fuzzy way with membership matrix. In terms of CD problem, FCM attempts to find fuzzy partitioning of the given data set by minimizing the objective function $J_w$ iteratively

$$J_w = \sum_{S=(1,1)}^{(M,N)} \sum_{l=1}^{2} u^w_S d^2(x_S, v_l)$$

(2)

where $x_S = x_{(m,n)}$ is the pixel grey value set in the difference image, $l$ is the cluster number – either 1 (change) or 2 (no-change), $u^w_S$ is the degree of membership of $x_S$ in the $l$th cluster, $w$ is the weighting exponent on each fuzzy membership, $v_l$ is the centre of cluster $l$, $d^2(x_S, v_l)$ is a distance measure between $x_S$ and cluster centre $v_l$.

At this point, each pixel in a neighbourhood system has owned an initial label $l$ (change or no-change) and two membership values $u_{N_i,c}$ and $u_{N_i,nc}$ ($i = 1, \ldots, 8$) belonging to change and no-change classes, respectively. Then, the uncertainty of each pixel label in the window (see Figure 2(b)) is measured by entropy (Foody 1995)

$$E_{N_i} = -u_{N_i,c} \log_2 u_{N_i,c} - u_{N_i,nc} \log_2 u_{N_i,nc}$$

(3)

2.2. Advanced MRF model

In the MAP-MRF framework (Li 1995), the maximum a posteriori probability method is applied to refine the pixel labels of the preliminary change map. The formulation could be defined as

$$L = \arg \max \{p(x|l)p(l)\}$$

(4)

where $p(x|l)$ is the probability density function of Gaussian distribution, $p(l)$ is the priori probability of the pixel label and $L$ is the value of class number $l$ which makes $p(x|l)p(l)$ the maximum.
Formula (4) is equivalent to minimize the following energy function for each pixel

\[ U_{\text{MRF}} = U_{\text{spectral}}(x) + U_{\text{spatial}}(x) \quad (5) \]

where \( U_{\text{spectral}}(x) \) in the Gaussian case is the spectral energy formulated as

\[ U_{\text{spectral}}(x) = \frac{1}{2} \ln(2\pi\sigma_l^2) + \frac{1}{2} (x - \mu_l)^2 (\sigma_l^2)^{-1} \quad (6) \]

in which \( \mu_l \) and \( \sigma_l^2 \) denote the mean and variance of class \( l \), respectively.

The spatial energy \( U_{\text{spatial}}(x) \) in Equation (5) is computed as

\[ U_{\text{spatial}}(x) = \beta \sum_{i=1}^{8} I(I_l(x_{(m,n)}), l(x_{N_i})) \quad (7) \]

\[ I(I_l(x_{(m,n)}), l(x_{N_i})) = \begin{cases} 0 & I_l(x_{(m,n)}) = I(x_{N_i}) \\ 1 & I_l(x_{(m,n)}) \neq I(x_{N_i}) \end{cases} \quad (8) \]

\( \beta \) in formula (7) is a manually set parameter that tunes the influence of the spatial contextual information on CD process. Formula (8) is the Potts model in MRF which is used to describe the class label a priori probability.

Then, ICM is used to minimize Equation (5) due to its high effectiveness as suggested by Bruzzone and Prieto (2000).

In this letter, the label fuzziness of each pixel is incorporated in the spatial energy formulated as

\[ I_{LU}(I_l(x_{(m,n)}), l(x_{N_i})) = \begin{cases} -1 - E_{N_i} & I_l(x_{(m,n)}) = I(x_{N_i}) \\ 1 - E_{N_i} & I_l(x_{(m,n)}) \neq I(x_{N_i}) \end{cases} \quad (9) \]

\[ U_{\text{spatial}}(x) = \beta \sum_{i=1}^{8} I_{LU}(I_l(x_{(m,n)}), l(x_{N_i})) \quad (10) \]

in which the uncertainty of neighbour labels are fully considered when the spatial item is calculated. In terms of the pixel label with high uncertainty, the entropy will be close to 1 and its spatial contribution will be near to 0. By this way, the over-smooth problem is well controlled especially in the detailed areas with high uncertainty and the final refined CD map would avoid the problem of image detail structure destruction in the traditional MRF. Besides, the results are not sensitive to the value of \( \beta \) manually set in MRF.

3. Experiments and results

The proposed LUMRF method was compared to the FCM and MRF methods by experimenting on two multispectral remotely sensed data sets to verify the effectiveness. Therein, the iteration step in MRF was determined as 50 and different values of \( \beta \) were tested to verify the robustness of MRF and LUMRF, respectively. The CD results are evaluated by three indexes: false alarms (FA, the number of no-change pixels in the ground truth that are incorrectly detected as change), missed detections (MD, the number of change pixels in the ground truth that are incorrectly detected as no-change) and total errors (TE, the total number of the wrongly detected pixels). Let \( TN \) and \( TC \) be the total number of the
no-change and change pixels in ground truth, respectively. The FA rate (Fr) is calculated by \( Fr = \frac{FA}{TN} \times 100\% \). The MD rate (Mr) is calculated by \( Mr = \frac{MD}{TC} \times 100\% \) and the TE rate (Tr) is calculated by \( Tr = \frac{TE}{(FA + MD)} \times 100\% \). The experiments were programmed with MATLAB 8.0 (a product of MathWorks company, Natick, MA, USA) running on Intel(R) Core(TM) i5 CPU(1.80GHz). The average time consumption of five runs for each method is also reported. In the following sections, both the data sets and the experiments carried out are detailed.

3.1. Experiment 1

The first experiment was conducted with the data set made up of two multispectral images (1305 pixels × 1520 pixels) in Alaska, USA, on 22 July 1985 and 13 July 2005 acquired by Landsat 5 Thematic Mapper (TM) sensor. A subset (400 pixels × 400 pixels) of the two scenes was cut for the experiment, as presented in Figure 3(a) and (b). It is obvious that the ice cover has changed and the resulting changes of the boundary are also easily found by flickering the overlaid two images. The ground truth of the CD map was created by the manual analysis (see Figure 3(c)).

The experimental results of the three methods are shown in Figure 4(a)–(c). From the visual analysis, it can be seen that FCM results in a high rate of omission detection.

![Figure 3](image1.png)

**Figure 3.** Data set used in experiment 1. Landsat-5 TM band 4 optical image acquired on (a) 22 July 1985 and (b) 13 July 2005, in Alaska, USA. (c) Manually created ground truth of the change detection map yielded based on (a) and (b), in which the white areas are the changed areas while the black areas are the unchanged areas.

![Figure 4](image2.png)

**Figure 4.** Change detection results of the data set in Figure 3 based on different methods. (a) FCM; (b) MRF (\( \beta = 2 \)); (c) LUMRF (\( \beta = 2 \)).
especially in the regions with weak change details such as the boundary changes of ice cover. This is because that FCM only uses the spectral information without considering the spatial context information. Besides, it identifies the pixel label by simply comparing the membership values belonging to the change class and no-change class, respectively, regardless of the general overlap problem of the two classes. Seen from Figure 4(b), although the change details were successfully detected by MRF, the emerged over-smooth problem destructs the detail structure and results in the faults detection easily. This is because MRF overuses the spatial information without considering the neighbouring pixels’ label uncertainty. As regards the proposed LUMRF method, the spatial contextual information is effectively utilized in an uncertain way in LUMRF by incorporating with local uncertainty. The more uncertain the neighbouring pixel’s label, the weaker its effects on the central pixel. Thus, the weak changes are correctly detected and the details are well preserved by LUMRF, as shown in Figure 4(c).

As a further illustration, Table 1 reports the quantitative assessment of each method and its time consumption. The total errors of FCM, MRF and LUMRF are 2.29%, 3.48% and 1.56%, respectively, which indicates that LUMRF achieves the best CD detection performance among these three methods. LUMRF has the most time consumption (about 2.5 times than MRF) because there is more auxiliary information calculated in the CD process to make more accurate CD results. The decline in the volume of total errors coincides with the improvements in LUMRF that considers the influence of the local uncertainty. In this letter, LUMRF still remains the limitation of manually setting the \( \beta \) value as MRF does. Nevertheless, the performance of LUMRF is more robust to the different \( \beta \) values because it effectively controls the spatial information item by incorporating the local uncertainty. Figure 5(a) shows the comparison of the performance of MRF and LUMRF in terms of different \( \beta \) values (0.5–3.0). It is obvious that the total errors of LUMRF are all lower than MRF and it is faster to be levelling off at the lowest point of about 1.5, which indicates that LUMRF achieves a more accurate and more robust performance than MRF.

### 3.2. Experiment 2

The second experiment was conducted with the data set acquired by Landsat-7 Enhanced Thematic Mapper Plus (ETM+) in August 2001 and August 2002 in Heilongjiang province, China. A section (262 pixels × 257 pixels) of the two scenes was selected as the experimental area presented in Figure 6(a) and (b). The ground truth data set generated by the manual method is given in Figure 6(c).

Figure 7(a)–(c) presents the experimental results of FCM, MRF and LUMRF, respectively. Same as the discussion in experiment 1, FCM (see Figure 7(a)) results in a high

<table>
<thead>
<tr>
<th>Change detection methods</th>
<th>False alarms</th>
<th>Missed detections</th>
<th>Total errors</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of pixels</td>
<td>%</td>
<td>No. of pixels</td>
<td>%</td>
</tr>
<tr>
<td>FCM</td>
<td>123</td>
<td>0.08</td>
<td>3544</td>
<td>36.4</td>
</tr>
<tr>
<td>MRF</td>
<td>5366</td>
<td>3.57</td>
<td>200</td>
<td>2.05</td>
</tr>
<tr>
<td>LUMRF</td>
<td>1437</td>
<td>0.96</td>
<td>1051</td>
<td>10.79</td>
</tr>
</tbody>
</table>
rate of omission detection because it only uses spectral information. In contrast, MRF (see Figure 7(b)) produces more homogeneous regions in consideration of the spatial contextual information. However, it also suffers from the over-smooth problem which leads to a high rate of false detection here. Compared with FCM and MRF, LUMRF gives a more precise CD result, as shown in Figure 7(c). The over-smooth problem in MRF is
effectively controlled here because LUMRF incorporates the local uncertainty in the spatial item.

From Table 2, it can be seen that the total errors of FCM, MRF and LUMRF are 4.66%, 2.23% and 1.72%, respectively, which again verifies the superiority of LUMRF, although it has the most time consumption (about 2.5 times than MRF). Figure 5(b) shows the performance comparison of MRF and LUMRF in terms of different $\beta$ values (0.5–3.0). It is obvious that the total errors of LUMRF are lower than MRF for most $\beta$ and it is faster to be levelling off at the lowest point of about 1.5, which indicates that LUMRF achieves a more accurate and more robust performance than MRF.

### Table 2. Accuracy assessment for experiment 2.

<table>
<thead>
<tr>
<th>Change detection methods</th>
<th>False alarms</th>
<th>Missed detections</th>
<th>Total errors</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM</td>
<td>19 0.03</td>
<td>3121 27.78</td>
<td>3140 4.66</td>
<td>1.62</td>
</tr>
<tr>
<td>MRF</td>
<td>2030 3.62</td>
<td>144 1.28</td>
<td>2174 2.23</td>
<td>4.82</td>
</tr>
<tr>
<td>LUMRF</td>
<td>294 0.52</td>
<td>864 7.69</td>
<td>1158 1.72</td>
<td>11.87</td>
</tr>
</tbody>
</table>

4. Conclusions

This letter presented an advanced MRF model integrated with local uncertainty for unsupervised CD. In terms of the over-smooth problem and the trade-off between denoising and detail preserving, the proposed LUMRF deals well with the change details by taking the local uncertainty into account. Two experiments were conducted and the results well confirmed the effectiveness of the proposed method, and thus, it provides an innovative solution for advanced CD from remotely sensed image. Although LUMRF was found to be robust to the trade-off weight $\beta$, this parameter stability comes at the cost of requiring the interaction with users. Future work will therefore focus on the histogram technology that should allow us to automate the parameter setting process for each new data set we have to deal with.
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