DECISION FUSION FOR THE UNSUPERVISED CHANGE DETECTION OF MULTITEMPORAL SAR

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ABSTRACT:

The unsupervised change detection of multitemporal SAR usually can get different results through different threshold selection algorithms. It is hard to determine what kinds of results are the best. In this paper, a novel automatic approach to the unsupervised identification of changes in multitemporal SAR image is proposed. This approach, unlike traditional ones, fuses many kinds of change detection results based on fuzzy logic theory. There are two steps in the proposed approach. In the first step, multitemporal SAR images are processed by many threshold selection algorithms separately, and several kinds of change detection maps are generated. In a second step, a framework for combing information from several individual threshold selection algorithms is proposed based on fuzzy logic theory. The robustness of the proposed approach is tested and validated with four threshold selection algorithms on SAR images in two regions. Experimental results, obtained on two sets of multitemporal SAR images, prove the validity and robustness of the proposed approach compared to each threshold selection algorithm.

1. INTRODUCTION

Change detection using remote sensing images is an important application domain in remotes sensing. It finds the changes that occurred in land covers by analyzing multitemporal images acquired at different time. Automatic change detection in images of a given scene acquired at different times is one of the most interesting topics in image processing. Recently, with the development of data processing and sensors, change detection is applied in many applications such environment monitoring, land evaluation, forest coverage assessment, disaster estimation, and urban changes. Change detection in multitemporal remote sensing images is characterized by several factors and it can be classified to three classes according to the change detection approaches. The first approach is based on classification. It determines the results by analyzing before and after classification results. The second approach compares and analyzes multitemporal remote sensing images based on pixels. Comparison and analysis of multitemporal remote sensing images based features is the third approach. Several change detection methods have been proposed in remote sensing literature, such as difference image, ratio image approach, change vector analysis, VI(vegetation index), and PCI(primary component). F. Melgani used several threshold selection methods in the change detection in optical remote sensing and the results obtained on each algorithm are compared and analyzed. In [], Yakoub Bazi proposed an unsupervised change detection method based on general gauss distribution model, and corresponding experiment results using multitemporal SAR images proved the efficiency and advantage of this method. At the same time, Model variables, speckle noise and factors influencing threshold were discussed. Gabriele Moser developed a Fisher transform method based on a ratio algorithm using SAR images and combined EM algorithm and MRF theory to detect changes. It proved that this approach appeared ascendant characteristic of robustness in resisting noise.

All these methods forementioned have their own characteristics and advantages in change detection with multitemporal SAR images. However, they always obtains different results according to different methods for a given data sets. Therefore, none of them strictly outperforms all the others. So, it is a challenging task to determine which one is the best, because: 1) in an unsupervised change detection process, ground truth is unavailable and prior knowledge can not be obtained, so the choice is not appropriate. 2) the effectiveness of a thresholding algorithm depends on statistical characteristics of the difference image, however, it is not always specific for a given data set.

In this paper, we propose to aggregate the results of different change detection approaches to reach robuster final decisions than any single algorithm. Decision fusion can be defined as the process of fusing information from several individual data sources. Therefore, an approach based on decision fusion using fuzzy logic theory is proposed. The proposed algorithm is based on fuzzy sets and possibility theory. The framework of the algorithm is modeled as follows. For a given data set, n change detection results are obtained according to each algorithm. For an individual pixel, each algorithm provides an output a membership degree for each of the considered detection algorithms. The set of these membership values is then modeled as a fuzzy set. Fusion strategy is performed by aggregating the different fuzzy sets provided by the different detection algorithm. It is adaptive and does not require any further training.

The paper is organized as follows. Fuzzy set theory and measures of fuzziness are briefly presented in section Ⅱ-A. Section Ⅱ-B present the model for each detection in terms of fuzzy set. Particular information fusion is discussed in section Ⅱ-C. Membership degrees of individual pixel based on neighbor system is described in section Ⅲ-A, and fuzzy degree calculation method is analyzed in section Ⅲ-B, and then experimental results are presented and analyzed in section Ⅳ. Finally, conclusions are drawn.

2. FUZZY LOGIC FUSION MODEL FORMULATION

2.1 Difference image

Let X_0 and X_1 be two coregistered SAR images acquired over the same area at times t_0 and t_1, respectively. The change detection problem is formulated as a binary classification problem by marking each pixel with "changed" or "unchanged" labels. And each pixel is mapped into the set $\Omega=\{\omega_c,\omega_u\}$ of possible labels, where ω_c and ω_u represent the unchanged and changed classes, respectively. The image-ratioing approach, which generates a ratio image R by dividing pixel-by-pixel is adopted. Let us consider an ensemble of M different detection algorithms. Let R_i (i=1,2,…M) be the change map generated by the *i*th detection algorithm of the ensemble. The aim of the proposed approach is to generate a global change map by ensemble of change map. The proposed automatic and unsupervised change-detection approach includes some main steps(see Fig.1): 1)preprocessing based on statistical filtering; 2)comparison of the pair of multitemporal SAR images and getting several detection results by different algorithms; 3)calculating membership degree of individual pixel based on neighbor system according to statistical distribution model; 4) creating final change map based on fuzzy logic theory.

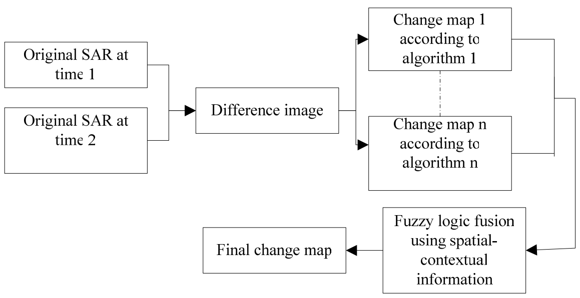


Fig.1 Flow chart of the proposed decision fusion approach

2.2 Fuzzy set theory

A fuzzy subset F of a reference set U is a set of ordered pairs $F=\{(x,u_F(x))\mid x\in U\}$. Where $u_F:U\rightarrow[0,1]$ is the membership function of F in U.

1) Logical operation: classical Boolean operations extend to fuzzy sets, with F and G as two fuzzy sets, classical extensions are defined as follows:

① Union: The union of two fuzzy sets is defined by the maximum of their membership function.

$$\forall x\in U,(u_F\cup u_G)(x)=\max\{u_F(x),u_G(x)\}$$

② Intersection: The intersection of two fuzzy sets is defined by the minimum of their membership function.

$$\forall x\in U,(u_F\cap u_G)(x)=\min\{u_F(x),u_G(x)\}$$

③ Complement: The complement of a fuzzy set F is defined by

$$\forall x\in U,u_{\bar F}(x)=1-u_F(x)$$

2) Measures of Fuzziness: Fuzziness is an intrinsic property of fuzzy sets. To measure how fuzzy a fuzzy set is, and thus estimate the ambiguity of the fuzzy set, several definitions have been proposed. Ebanks proposed to define the degree of fuzziness as a function f with the following properties.

1) $\forall F\subset U$, if $f(u_F)=0$ then F is a crisp set.

2) $f(u_F)$ is maximum if and only if $\forall F\subset U,u_F(x)=0.5$

3) $\forall(u_F,u_G)\in U^2,\ f(u_F)\ge f(u_G)$ if：

$$\forall x\in U$$
$$u_G(x)\ge u_F(x),if\ \ u_F(x)\ge 0.5$$
$$u_G(x)\le u_F(x),if\ \ u_F(x)\le 0.5$$

4) $\forall F\subset U,\ f(u_F)=f(u_{\bar F})$.

A set and its complement have the same degree of fuzziness.

5) $\forall(u_F,u_G)\in U^2$,

$$f(u_F\cup u_G)+f(u_G\cap u_F)=f(u_F)+f(u_G)$$

2.3 Change map representation

A changed and unchanged problem is considered for which m different change maps are available. For a given pixel, the output of *ith* detection algorithm is the set of numerical values, i.e

$$\{u_i^c(x),u_i^u(x)\}$$

Where $u_i^j(x)\in[0,1]$,after normalization, is the membership degree of pixel x to changed or unchanged classes according to algorithm *i*. The higher this value, the more likely the pixel belongs to the corresponding class. Depending on the detection algorithm, $u_i^j(x)$ can be of a different nature: probability, membership degree at the output of a fuzzy classifier. In any case, the set $\pi_i(x)=\{u_i^j(x),\ j=1,...,\ n\}$ can be regarded as a fuzzy set. Therefore, for each pixel, m fuzzy subsets are computed and create input for the change map fusion process.

$$F_{set}(x)=\{\pi_1(x),\pi_2(x),...,\pi_i(x),...,\pi_m(x)\}$$

Fuzzy set theory provides various combination operators to aggregate these fuzzy sets. Many combination operators are discussed detailedly in the[]

3. MEMBERSHIP DEGREE

3.1 Membership degree based on spatial-contextual model

Let r be a fixed positive number, and let $N_i(r);i\in D$ be a system of neighborhoods defined by

$$N_i(r)=\{j\in D\mid 0<d(i,j)\le r\}$$

Where $d(i, j)$ denotes the distance between centers of pixels i and j. Hence, the value r means a radius of the neighborhood. Fig.() illustrates the neighborhood with unit radius(first-order neighborhood). The second-order neighborhood is expressed by the configuration of the area D. and a number of neighborhood $|N_i(r)|$ is dependent to the local configuration around the pixel i.

Set η is the neighbor system of pixel i, $\eta = \{\eta_i, i \in X, i \notin \eta_i, \eta_i \subset X\}$ and $\{\eta^1, \eta^2, ..., \eta^m\}$ be constituted by a series of neighbor system. m is the rank of neighbor system.

$\eta^m = \{(k,l) : 0 < (k-i) + (l-j) \le m\}$, Figure.2 is neighbor system.

5	4	3	4	5
4	2	1	2	4
3	1	0	1	3
4	2	1	2	4
5	4	3	4	5

Fig.2 Sketch of neighbor system

On the hypothesis of obtaining M change map $A_i = (i = 1,2,..M)$ according to a series of change detection algorithms and each objective pixel will get M membership degrees. Membership degree combines information from the neighbor system of objective pixels. Each pixel x_i, $x_i \in \omega_c$, is regard as objective pixel, and membership degree is calculated on the theory of the difference between the objective pixel and neighbor pixel. Set D=[$d^k_{i,j}$], $d^k_{i,j}$ is the difference measure of pixel $a^k_{i,j}$ and neighbor system, $a^k_{m,n} \in \omega_c$.

$$d^k_{i,j} = \sum_{m,n \in \eta_{i,j}} \delta(a^k_{i,j}, a^k_{m,n}) / \mathrm{N}(\eta_{i,j}) \tag{1}$$

$\delta(a^k_{i,j}, a^k_{m,n})$ is the indicator function, which allows to obtain the difference of $a^k_{i,j}$ and $a^k_{m,n}$. It is defined as

$$\delta(y_{ij}, y_{gh}) = \begin{cases} 1, & if \quad a^k_{i,j} = a^k_{m,n} \\ 0, & otherwise \end{cases} \tag{2}$$

Set $U = \{u^1_{i,j}, u^2_{i,j}, ...u^M_{i,j}\}$ as the membership degree set of objective pixel $a^k_{i,j}$, based on Γ distribution function, $u\ (\ x\ )$ is defied as

$$u(x) = \begin{cases} 1 & 0 \le x < t \\ e^{-k(x-t)} & x \ge t(k > 0) \end{cases} \tag{3}$$

B.Information fusion

The purpose of data fusion combing information from several sources is to improve the final decision. Generally, the following three operators are used in membership degree information fusion.

Conjunctive combination:

$\pi_\wedge(x) = \cap^m_{i=1} \pi_i(x)$,

$\pi_\wedge(x) \le \min(\pi_i(x)), i \in [1, m]$

Disjunctive combination:

$\pi_\wedge(x) = \cup^m_{i=1} \pi_i(x)$,

$\pi_\wedge(x) \ge \max(\pi_i(x)), i \in [1, m]$

Compromise combination:

$\pi_\wedge(x) = \cup^m_{i=1} \pi_i(x)$,

$\pi_\wedge(x) \ge \max(\pi_i(x)), i \in [1, m]$

fuzzy degree is defined as

$$d(u) = \frac{1}{\ln 2}[-u_c(x)\ln u_c(x) - u_u(x)\ln(u_u(x))]$$

$$= \frac{1}{\ln 2}[-u_c(x)\ln u_c(x) - (1-u_c(x))\ln(1-u_c(x))]$$

4. EXPERIMENTAL ANALYSIS AND RESULTS

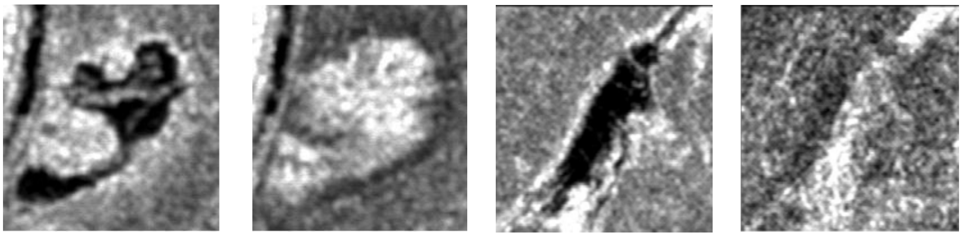
To assess the performance of the proposed approach, two multitemporal data sets corresponding to geographical areas of Wuhan, Hubei province, China and the Poyang Lake, Jiangxi province, China are our experimental data. The first two data sets used in the experiments are composed of two images acquired in the same area by SAR on a satellite. The area shown in Figure1 was a section (195*204 pixels) of a scene acquired in the middle southern of Wuhan, Hubei province, China. The second data set used in experiments was composed of a section (273*285 pixels) of two SAR image from the same sensor too. The two images were acquired in the Poyang Lake, Jiangxi province, China, as shown in Figure.3 (b). By comparing two images at the same area, we can see water body covered a significant part of land in the selected area. Water body in SAR image usually appears “black” region.

After geometrical correction, using log-rarioing operator, $X = \log(X_1 / X_2)$,difference image X can be obtained. But there is no obvious discrimination between ω_c and ω_u by analyzing the histograms of the two difference images. After the noise removement using Gamma-MAP by 7*7 pixels window, there is great improvement of discrimination between

ω_c and ω_u . Therefore, we can conclude that speckle noise is a key factor that influences multitemporal SAR images change detection. The two difference images are obtained by log-ratioing operator are shown in Figure .4

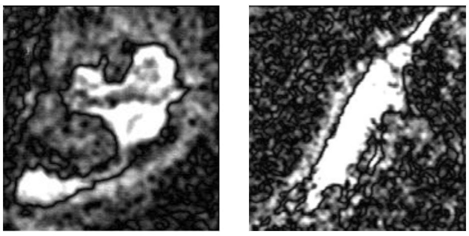
In order to prove the advantage of the proposed approach compared with a single change detection algorithm, a series of algorithms are employed, such as circular segmentation, Otsu, KSW and KI(Kittler and Illingworth). Circular segmentation algorithm is a simple approach in image processing, using single threshold of histogram. Otsu is a histogram segmentation method based on maximization of variation between classes. KSW algorithm is an automatic threshold selection method. Shannon entropy is introduced in the method, and its threshold is acquired maximizing the distribution information of target and background information. KI algorithm is based on minimal error by Beysin estimation theory. The hypothesis is that ω_c and ω_u follow a certain distribution model, such as Gaussian model. Four different kinds of change maps are obtained according to corresponding algorithms, the threshold T_i and results are illustrated in Table.1 and Figure.5(a) ~ Figure.5(d) respectively.

The objective of this experiment is to assess the effectiveness of the proposed membership degree function based on spatial-contextual models. Based on each change map A_i , we can get membership degree of objective pixel using formula (3). The results is shown in Figure.4. Finally, we can get the final change map by applying the entropy fuzzy degree technique (formula (4)) to fuse series of membership degree maps and the results are shown in Figure.5(e).



(a.1) SAR in Wuhan at time 1 (a.2)SAR in Wuhan at time 2 (b.1) SAR in Poyang lake at time 1 (b.2) SAR in Poyang lake at time2

Fig.3 Original multitemporal SAR images



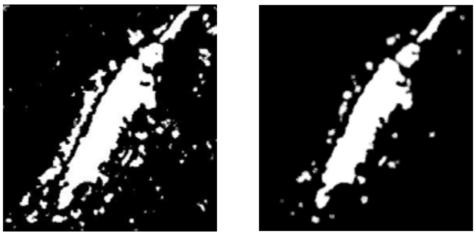
(a) difference image Whuan (b) difference image Poyang lake

Fig.4 Log-ratioing images

Threshold selection algorithm	Wuhan		Poyang Lake	
	threshold	Change ratio	throshold	Change ratio
circular segmentation	143	16.7%	142	10.3%
Otsu	159	11.3%	150	9.7%
KSW	175	10.8%	141	10.4%
KI	193	9.7%	93	17.5%
FDF(fuzzy decision fusion)		12.1%		12%

Tab.1 Segmentation results of series of algorithms

(a) circular segmentation (b) Otsu (c) KSW



(d) KI (e) FDF

Fig.5 Change map using series of algorithms

5. CONCLUSION

In this research, a novel automatic approach to unsupervised change detection in multitemporal SAR images is proposed. The presented approach is based on fuzzy set theory and fuses an ensemble of change maps. A series of algorithms are used to obtain different change maps, which are explored in the fuzzy logic fusion algorithm as input data sets. The approach in this paper generates the change map by taking into account the spatial-contextual information contained in the ensemble of change maps. The proposed approach presents two important advantages over the single change detection algorithm of the ensemble. Firstly, it provides a well-founded methodological framework for automatic analysis of an ensemble of change maps and can get robust results compared with single change map of ensemble. Secondly, spatial-contextual information is exploited in this fusion algorithm.

Experimental results reported in this paper show the effectiveness of the proposed approach. An important characteristic of the proposed approach is that it does not need any priori knowledge of changed and unchanged pixels in different images. Therefore, it can be also applied to multitemporal SAR images. However, the proposed technique is not noise resisting. Speckle noise is the characteristic of SAR image. Therefore, how to reduce the influence of speckle noise and get more accurate change map will be our future work.

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