URBAN CHANGE DETECTION USING COHERENCE AND INTENSITY CHARACTERISTICS OF MULTI-TEMPORAL ERS-1/2 IMAGERY

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ABSTRACT:

In this paper, the potential of multitemporal ERS-1/2 InSAR data for detecting urban land-cover changes is investigated on a test area within Shanghai city, China. A new unsupervised change-detection approach is proposed, which is characterized by the combined use of two temporal variations of backscattering intensity and long-term coherence from multitemporal ERS-1/2 SAR images. The proposed approach is made up of two steps: feature extraction and unsupervised 2-D (two dimensional) thresholding. In the first step, two features are based on the concepts of backscattering intensity variation and long-term coherence variation respectively, and have been defined according to the analysis of different signal behavior of interferometric SAR in the presence of land-cover classes in urban area. In the second step, an unsupervised 2-D thresholding technique based on maximum 2-D Renyi's entropy criterion is proposed, which is performed on the two difference images derived from the two change features to produce an accurate change-detection map with two classes "change" and "no-change". Experimental results obtained from a set of six multitemporal ERS-1/2 SAR images confirm the effective of the proposed approach, and that ERS-1/2 InSAR data could be exploited for detecting urban land-cover changes.

1. INTRODUCTION

As we known, detecting land-cover changes using multitemporal remote sensing images is one of the most important applications of remote sensing. In the past few years, multitemporal images acquired by synthetic aperture radar (SAR) remote sensing satellites, such as ERS-1/2 and RADARSAT, have been increasingly used for change detection, since they present the advantages to be independent of atmospheric and sunlight conditions over optical images. But the potential of C-band single polarization intensity imagery is limited for this purpose, due to the presence of speckle noise and the errors from SAR calibration which may produce noisy change images (Engdahl & Hyyppä, 2003). Interferometric SAR can provide complementary information to the backscattering intensity in the form of interferometric coherence, which can reveal reliable information about the land-cover changes that may not be evident in the intensity data alone (Rignot and Van Zyl, 1993; Liu et al., 2001; Preiss M. et al., 2003).

Previous studies of the potential of using multitemporal InSAR data for change detection have achieved some promising results. Rignot et al. used backscattering intensity ratio and coherence value from repeat pass ERS-1 SAR data to identify scene changes, respectively. It was found that changed results obtained by using each method under the same environment did not always agree and that each method gave a complementary characterization of scene changes (Rignot and Van Zyl, 1993). Considering the phase temporal stability of anthropogenic structures in the urban area between SAR images acquisition, Grey et al. used a multitemporal sequence of ERS interferometric coherence data for mapping urban change within South Wales, UK (Grey and Luckmana, 2004). In that study, coherence-based maps of urban change were produced by differencing pairs of long-term coherence images and only approximately 50% building development detection accuracy was achieved (Grey and Luckmana, 2004). Despite some interest works have been proposed in the literature, there has been little attempt to detect land-cover changes simultaneously using backscattering intensity and interferometric coherence characteristics from multitemporal InSAR data. On the other hand, the optimal threshold selection in an automatic way is also a critical step during the unsupervised change-detection process.

In this paper, a new unsupervised approach is proposed to detect land-cover changes in urban area, which takes into account the two temporal variations based on backscattering intensity and long-term coherence from ERS-1/2 InSAR data. The proposed approach mainly includes the following two steps. In the first step presented in section II, two classes of feature extractions are considered based on the analysis of interferometric SAR signature physics in urban area. The section III presents the second step, in which an automatic thresholding based on the 2-D (two dimensional) Renyi's entropy is carried on the 2-D histogram for unsurprised change detection. The 2-D histogram is constructed from two difference images obtained by using two previous change measures in the first step. The experimental results are illustrated in section IV, which carried out on a set of six ERS-1/2 SAR SLC images within Shanghai city of China, in order to appreciate urban development between 1993 year and 1999 year. Section V contains some conclusions and discussions.

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2. FEATURE EXTRACTION FOR CHANGE DETECTION IN URBAN AREA

2.1 Analysis of interferometric SAR signature physics in urban area

A study on the feature extraction to be considered in the proposed approach is carried out based on the analysis of interferometric SAR signature physics in urban area.
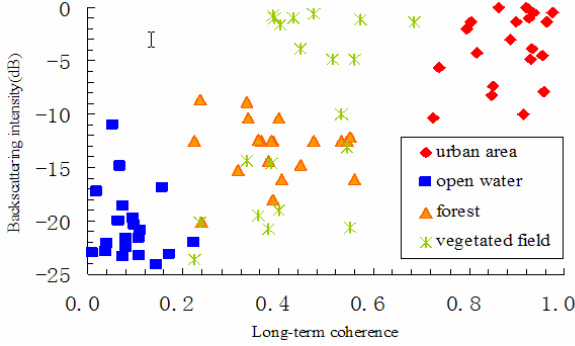

Fig.1 Qualitative analysis of the distribution of urban areas and non-urban areas in the long-term coherence and backscattering intensity feature space

In this study, urban areas mean build-up or man-made areas compared to nonurban areas (non build-up) which associated with natural land-cover categories, for instance, forest, open water and vegetated field. An urban scene is a target of considerable complexity and consists of a variety of buildings with different dimensions and orientations. In theory, urban areas are in general characterized by high backscattering intensity value due to the predominance of single or double bounce from roof or wall-ground structures and other metallic structures (Strozzi and Wegmuller, 1998; Weydahl, 2001). In contrast, natural land-cover categories within nonurban area present relatively low intensity value. Hence, it seems appropriate to choose a feature of urban change based on an estimation of intensity temporal variation from multitemporal SAR intensity images, in order to identify new build-up area. However, as the same as the urban development, some vegetated fields may also have high temporal intensity variation because of a stronger influence of soil moisture changes, vegetation growth, and cultivation activity between the acquisition dates considered(Bruzzone et al., 2004). In Fig.1, a high temporal intensity variation in vegetated fields is indicated with large range from -23.5 dB to 0 dB. In this case, a lot of false alarms may occur in detecting new build-up.

In order to improve the effectiveness of the considered features, a further information source should be exploited from the multitemporal InSAR data. A most promising possibility could be to utilize the interferometric coherence as a second parameter, since it provides complementary information to the backscattering intensity (Rignot and Van Zyl, 1993). In particular, within urban areas, coherence remains high even between image pairs with long scale time (assuming that they have small perpendicular baselines). In contrast, naturally land surfaces are significantly influenced by temporal decorrelation and lose coherence within a few days (Grey and Luckmana, 2004). The capability of separating urban area from non-urban area, as well as the complementation between long-term coherence and backscattering intensity, is shown in the qualitative signature diagram illustrated in Fig.1. Consequently,

long-term coherence image, which were computed from a pair of SAR images with small perpendicular baseline, are considered to discriminate between urban and nonurban areas. It is depended on a higher temporal phase stability of the built up structures compared to most natural targets. Moreover, a sequence of such coherence images could be used to automatically detect urban changes.

Based on the analysis above, we considered backscattering temporal variation and long-term coherence variation as the features for mapping urban changes, which are described in the following subsections.

2.2 Feature extraction for detecting urban development

Prior to change detection, preprocessing steps of multitemporal SAR data are often necessary to establish a more direct link between data and physical phenomena. In this study, some basic preprocessing steps are performed, including radiometric calibration, co-registration of the images, multi-temporal and spatial speckle filtering. The following feature extraction step is applied to the preprocessed multitemporal SAR images and obtains two so-called difference images for the classification in the next step.

2.2.1 Backscattering intensity variation feature (BSIV)
Bruzzone *et al.* discussed six different temporal intensity variation estimators from multitemporal SAR images (Bruzzone et al., 2004). Out of the six evaluated estimators, here we select the "maximum-minimum ratio in dB" in this study, because it is relatively simple and easier to understand but effective. It is defined in (1) applied to N preprocessed backscattering intensity images:

$$r = 10\log_{10}\left(\frac{\sigma_{\max}}{\sigma_{\min}}\right) \qquad (1)$$

As an alternative to the temporal variation defined in (1), a new temporal variation estimator considering context information around a pixel can be utilized according to the following equation:

$$r^* = 10\log_{10}\left(\frac{\max(\mu_\sigma)}{\min(\mu_\sigma)}\right) \qquad (2)$$

where μ_σ is the local estimate of the mean backscattering coefficient computed in each image. r and r^* reveal changing areas by measuring the strongest radiometry contrast in a time series, but the later could be more robust in mitigating the affect of the multiplicative speckle noise.

2.2.2 Long-term coherence variation feature (LTCV)
The degree of coherence of two SAR SLC images not only determines the quality of topography or deformation information derived by SAR interferometry, but also contains valuable information for land-use and land-cover classification (R.Touzi et al., 1999). In practice, the coherence can be estimated in (3), in which z_1 and z_2 denote the first and second complex SAR images respectively, i and L are the sample number and signal measurements respectively (Liao M.S and Lin.H, 2003). In our study, we utilized the long-term coherence computed from ERS-1/2 images with 35 days separation and with small perpendicular baseline (<300m), to confirm that pairs of the images have high coherence within urban area.

$$\left|\hat{\gamma}\right| = \left|\frac{\sum_{i=1}^{L} z_{1i} z_{2i}^{*}}{\sqrt{\sum_{i=1}^{L} \left|z_{1i}\right|^{2}} \sqrt{\sum_{i=1}^{L} \left|z_{2i}\right|^{2}}}\right| \qquad (3)$$

In this study, when estimating the long-term coherence variation from a pair of long-term coherence images, a common method can be used to generate another difference image by applying a pixel-by-pixel subtraction.

3. THRESHOLDING BASED ON 2-D RENYI'S ENTROPY

The second step of the proposed approach performs an unsupervised classification by applying a thresholding technique to obtain a change map with two classes "change" and "no-change". This proposed thresholding technique can automatically find an optimal threshold based on maximum 2-D Renyi's entropy criterion. It involves the 2-D Renyi's entropy computation on a 2-D histogram constructed from the two previous difference images obtained in the first step, and the determination of the parameters of Renyi's entropy based on a genetic algorithm.

Let $I_d = \{i(m,n) | 1 \le m \le M, 1 \le n \le N\}$ and $C_d = \{c(m,n) | 1 \le m \le M, 1 \le n \le N\}$ denote the two difference images above respectively, assuming that they were scaled and have the same gray level $G = \{0,1,2....,L-1\}$. A 2-D histogram is constructed from I_d and C_d, which is an array ($L \times L$) with the entries representing the total number of occurrences, $n(i,j)$ of the pair ($i(m,n); c(m,n)$). Then a joint probability mass function of the 2-D histogram is defined in (4)

$$p(i,j) = \frac{n(i,j)}{N \times M} \qquad (4)$$

where $i, j \in G$.

A threshold vector (t,s) on a 2-D histogram is in general determined by using a given criterion in the literature. In our study, the criterion of maximum 2-D Renyi's entropy is used to obtain a threshold vector which can separate the two peaks on the 2-D histogram corresponded to change and no-change classes. Sahoo et al. presented the thresholding theory based on 2-D Renyi's entropy (Sahoo and Arora, 2004). The 2-D Renyi's entropy associated with no-change class and change class distribution are given by

$$H_n^{\alpha}(t,s) = \frac{1}{1-\alpha} \ln \sum_{i=0}^{t} \sum_{j=0}^{s} \left(\frac{p(i,j)}{P_2(t,s)}\right)^{\alpha} \qquad (5)$$

and

$$H_c^{\alpha}(t,s) = \frac{1}{1-\alpha} \ln \sum_{i=t+1}^{L} \sum_{j=s+1}^{L} \left(\frac{p(i,j)}{1-P_2(t,s)}\right)^{\alpha} \qquad (6)$$

in which α denotes the order of Renyi's entropy, and $P_2(t,s)$ presents the posteriori class probability of no-change class, t and s represent the threshold of the gray level of the

pixel in I_d and C_d respectively. Then the optimal threshold pair $(t^*(\alpha), s^*(\alpha))$ can be obtained by

$$(t^*(\alpha), s^*(\alpha)) = Arg \max_{(t,s) \in G \times g} \left[H_c^{\alpha}(t,s) + H_n^{\alpha}(t,s)\right] \qquad (7)$$

The optimal estimation of the parameter set, α, t and s, is an optimization problem. In particular, the parameter α is a constant and the genetic algorithm is applied to search for the optimal solution in this study.

Once the threshold vector (t,s) is determined, the change map with two classes, corresponding to change and no-change, can be obtained by

$$f_{s,t}(m,n,change) = \begin{cases} 1 & i(m,n) > t \text{ and } c(m,n) > s \\ 0 & otherwise \end{cases} \qquad (8)$$

4. EXPERIMENT RESULTS

In order to assess the effectiveness of the proposed approach for detecting urban land-cover changes with multitemporal InSAR data, a preliminary experiment was carried out on two groups of multitemporal ERS-1/2 SAR SLC data over the city of Shanghai in China acquired between April 1993 and June 1999. Detailed information regarding the six images is reported in Table 1. Two pairs of images, image 2-3 and image 5-6 (see Table 1) with a short perpendicular baseline and with a 35-day separation, were used to obtain two long-term coherence images. The images were preprocessed in some ways including radiometric calibration, co-registration, subsetting, multi-temporal and spatial speckle filtering. In particular, the preprocessed images were geocoded into the local map coordinate system of Shanghai city and have a spatial resolution 20m x 20m. The selected area with 1190 pixels and 720 lines is located in the east of Shanghai city and includes dense urban area, mix urban area, open water, agriculture land, and vegetated field. It covers the Pudong Economic Development Region, in which urban development dramatically increased during the past decade. Fig.2 illustrates the two intensity images out of the six considered SAR images in the study area. For the identification and the validation of change-detection results, ground truth data within the selected area was obtained from a SPOT panchromatic imagery with 10m resolution acquired in 3 March 1995 and 2 Jan 2000 respectively, and two city-maps in 1: 10 000 scale of 1995 and 1999 respectively.

Image number	Sensor	Orbit	Date	Per. Baseline (m)
1	ERS-1	09166	17.4.1993	
2	ERS-1	09667	22.5.1993	-13
3	ERS-1	10168	26.6.1993	
4	ERS-2	20899	20.4.1999	
5	ERS-2	21400	25.5.1999	47
6	ERS-2	21901	29.6.1999	

Table 1 List of Multitemporal ERS-1/2 SAR Images in Shanghai City

Two change measures for detecting the urban development were derived according to the backscattering intensity variation (BSIV) and the long-term coherence variation (LTCV)

described in Section 2. The measure of "maximum-minimum ratio in dB" was computed with 5 x 5 windows on the six preprocessed SAR intensity images (Fig.3 (a)). And another difference image was obtained by simply differencing coherence images 22/5/1993-26/6/1993 and 25/45/1999-29/6/1999 (Fig.3 (b)). Compared to grand truth data, the Fig.3 shows well that two difference images are sensitive to urban development (bright pixels). But the areas with high backscattering intensity variation in Fig.2 (a) include also the temporal changes in some vegetated fields due to vegetation growth (e.g. agriculture lands in the upper right portion and open lands at the center portion). An automatically thresholsing based on 2-D Renyi's entropy was performed by jointly using the difference images, and the changed results (red pixels) with threshold vector (208, 191) is illustrated in Fig.4 (a). Used for comparison, another change map is showed in Fig.3 (b), which was obtained by only using the difference image based on BSIV (See Fig.3 (a)) with the same threshold value 208. The accuracy of the change-detection was assessed by comparing the pair of change-detection results with the known reference sites of urban development from the ground truth. In the case, the change-detection results are represented in Table 2 in terms of overall error, false alarms and missed alarms. As expected, the change measure of BSIV causes high false alarms, since new build-up is difficultly distinguished from some vegetated fields with the same high BSIV. For instance, some green lands in parks were detected in error in Fig.4 (b). In contrast, the proposed approach in this paper, taking account into the two change measures from BSIV and LTCV, can considerably decrease the false alarms from 2012 pixels to 235 pixels.

CHANGE MEASURES	OVERALL ERROR	FALSE ALARMS	MISSED ALARMS
BSIV	2533	2012	521
BSIV&LTCV	713	235	478

Table 2 Validation of changed results with different measures

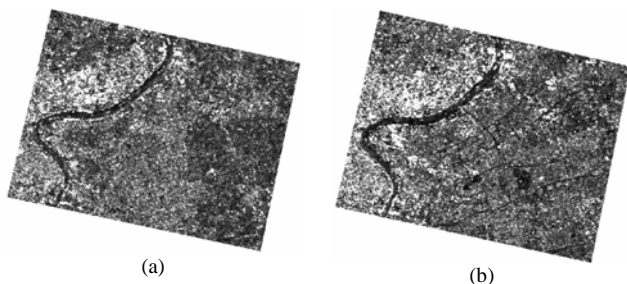(a)   (b)

Fig.2. Two out of six multitemporal SAR images of Shanghai, China. (a) May 22, 1993. (b) May 25, 1999.

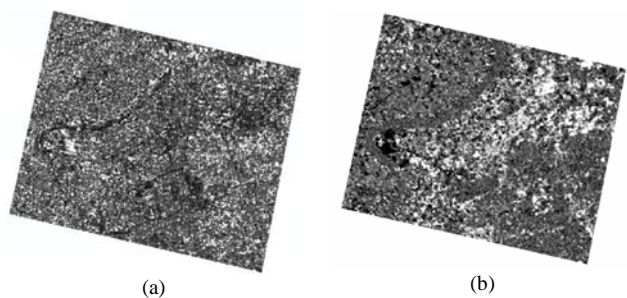(a)   (b)

Fig.3. Two difference images for detecting the urban development based on (a) BSIV (b) LTCV.
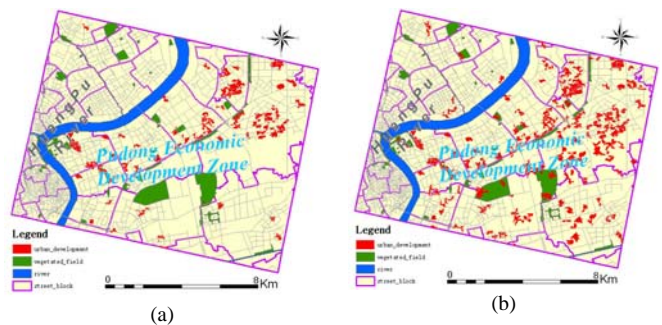

(a)   (b)

Fig.4. Change maps for detecting the urban development (a) applying a threshold vector (208, 191) on the two difference images based on BSIV and LTCV (b) applying a threshold value 208 on the difference image based on BSIV.

5. CONCLUSIONS

In this paper, the potential of multitemporal ERS-1/2 InSAR data for detecting urban land-cover changes was investigated on a test area within Shanghai city, China. Two change measures based on the backscattering intensity variation and the long-term coherence variation from a set of six ERS-1/2 SAR images were utilized in the change-detection. An unsupervised 2-D thresholding technique was performed on the two difference images derived from the two change measures to obtain a change map with two classes "change" and "no-change". This proposed thresholding technique can automatically find an optimal threshold based on maximum 2-D Renyi's entropy criterion. Change-detection accuracy was assessed using independent reference data including two high-resolution optical images and two city-maps. It is found that the change-detection results applying the both of change measures are better than those with the only change measure of backscattering intensity variation. This study shows that ERS-1/2 InSAR data could be exploited for detecting urban land-cover changes.

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