Spatio-temporal Similarity Analysis Strategy of SAR Image Time Series for Land Development Intensity Monitoring

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Abstract—Land development intensity is one key indicator of Major Function Oriented Zoning (MFOZ). For land development intensity monitoring in a large area, SAR image time series with medium resolution provides an appropriate way, because of its large-scale and high-temporal frequency measurements. According to time-series characteristics of cultivated land and construction land pixels, a spatio-temporal similarity analysis strategy considering mixed pixels and noise is presented to extract change nodes and change pixels. This strategy mainly includes three components: (1) Construction of pixel-level SAR image time series; (2) Iterative binary partition mean square error (MSE) model to ascertain change nodes; (3) Spatio-temporal similarity analysis based on pixel-level SAR image time series to determine the change range of cultivated land to construction land. Through the monitoring of conversion of cultivated land to construction land across multiple periods leveraging pixel-level SAR image time series in Chengdu, several conclusions can be drawn from this study. (1) This study has illuminated the utility of pixel-level SAR image time series for land development intensity monitoring, especially in those areas with cloud cover the majority of the time. SAR images are not affected by cloud cover and provide continuous time-series information. (2) The spatio-temporal similarity measure was able to effectively extract change nodes and change range of cultivated land to construction land. Generally, the correctness of 85.82% and completeness of 84.78% were achieved.

Keywords: Spatio-temporal Similarity SAR Image; Time Series; Land Development Intensity; Monitoring

I. INTRODUCTION

Land development intensity is one key indicator of Major Function Oriented Zoning (MFOZ), which is the blueprint for portraying the future development and protection pattern of China's territory [1-2]. It refers to the ratio of construction land and total area in a certain region. So monitoring the Land development intensity is equal to monitoring the conversion of cultivated land to construction land. Therefore, the primary goal of this study is to exploit the application potential of pixel-level SAR image time series with medium spatial resolution in land cover change detection, especially in monitoring the conversion of cultivated land to construction land. The time-series method is specifically chosen because it provides a way to exploit dense time stacks of SAR data, and can enhance the ability of monitoring land development intensity, able to extract change nodes and change pixels.

II. STUDY AREA AND DATA SETS

A. Study area

The study area is located in Chengdu City of Sichuan Province, China (Figure 1). Longitude ranges from 103.71°E to 104.45°E, and latitude ranges from 30.47°N to 30.97°N. The heterogeneity of the landscape, the growth in urban fringe areas, and the cloudy weather most of the time make this city one of the most difficult areas to accurately characterize land cover change. Chengdu has a triple-cropping system of rice, wheat, and vegetables, and the weather is primarily mild because of its humid subtropical climate. Chengdu has received incentives and investment for growth from the central government that led

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to rapid urban expansion beginning in the 1990s, and which has continued to the present day (Schneider 2012).

B. Data sets

For the study area, 28 ENVISAT ASAR IMP Mode images taken from 2004 to 2011 were selected as experimental data for time series processing. All images conformed to the standard 1-level product with spatial resolution of about 30m and single polarization (VV). High resolution Google Earth images are used as ground truth data to assess the accuracy.

III. METHODOLOGY

According to time-series characteristics of cultivated land and construction land pixels, a spatio-temporal change detection strategy considering mixed pixels and noise is presented to extract change nodes and change pixels. This strategy mainly includes three components: (1) Construction of pixel-level SAR image time series; (2) Spatio-temporal similarity analysis based on morphological-structural characteristics of time series to determine the change range of cultivated land to construction land; and (3) Iterative binary partition mean square error (MSE) model to ascertain change nodes.

A. Satellite Image Time Series Modeling

Based on the selected SAR dataset over the study area, a series of processing has to be implemented to construct pixel-level SAR image time series. These steps include (1) preprocessing, (2) co-registration and (3) de-noising. The preprocessing includes selection, subsetting, mosaicing of images, metadata updating, radiometric correction, topographical correction, etc. Co-registration is compulsory to the construction of pixel-level SAR image time series. In order to achieve accurate spatio-temporal analysis between images, a relative image to image registration was implemented using the locally adaptive registration method proposed by [12]. A high-quality image was selected from the data set as the master image, and then relative geometric matching on all other (slave) images was performed. In order to reduce the influence caused by speckle noise, adaptive multi-temporal SAR filtering [13] was used to de-noise SAR image time series in a sequential manner. A measured increase of the equivalent number of looks showed a clear reduction of speckle noise in the SAR images. This is important for analyzing the images at pixel level. Furthermore, no obvious changes in the mean radiometric features were observed.

B. Probability Analysis of Change Node

Here, iterative binary partition MSE model was used to determine change nodes from cultivated land to construction land, where mixed pixel and change type were considered. Assuming that pixel-level SAR image time series \( V = \{ (v_1, t_1), (v_2, t_2), \ldots, (v_m, t_m) \} \) changed at \( t_m \) and reached a relatively stable state, the time series \( V \) could be divided into \( V_1 = \{ (v_1, t_1), (v_2, t_2), \ldots, (v_{m-1}, t_{m-1}) \} \) and \( V_2 = \{ (v_m, t_m), (v_{m+1}, t_{m+1}), \ldots, (v_n, t_n) \} \). The mean values of \( V_1 \) and \( V_2 \) were \( V_1 \) and \( V_2 \), respectively. MSE was defined as the mean square error of the time series \( V \). If a change node existed, then Equation (2) was satisfied. When \( i = m \), MSE was minimum.
Then the time nodes of $V_1$ and $V_2$ were calculated using the above MSE method. Subsequently, iterative binary partition was implemented. Only when the difference $\Delta v$ of $V_1$ and $V_2$ was smaller than the threshold, the calculation would be stopped and the node would not be regarded. The threshold was determined depending on the previously described $\Delta v$ of three types of change. If cultivated land accounted for two-thirds and others (such as construction land, water and grass) accounted for one-third of the pixel’s area, then the minimum $\Delta v$ would be selected as the threshold for processing mixed pixels.

C. Spatio-temporal Similarity Analysis

According to the spatial resolution of SAR images, this study used a sliding window to measure the spatial neighborhood similarities. Considering the relationship between time series of the central pixel and adjacent pixels within the window, spatio-temporal similarity operator was constructed. Here, neighborhood connectivity was used, which is the number of pixels in the 8-neighborhood pixel $(x,y)$ having a similarity bigger than $\alpha$. Spatio-temporal similarity is defined as

$$S(x,y) = \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{1}{\sum_{i=1}^{n} \sum_{j=1}^{m} \left( TS_m(t_{(x+i,y+j)}, t, \alpha) \cap TS_s(t_{(x+i,y+j)}, t, \sigma) \right) - 1}$$

where $TS_m(t_{(x+i,y+j)}, t, \alpha)$ represents morphological similarity, and $TS_s(t_{(x+i,y+j)}, t, \alpha)$ represents structural similarity, and $\alpha$ represents the threshold for improved DTW similarity (Petitjean, Inglada, and Gancarski 2012). $v$ and $\sigma$ represent the threshold for the mean and variance respectively between time series $t_{(x+i,y+j)}$ and standard time series $t$. When series $t_{(x+i,y+j)}$ satisfies the threshold condition, $TS_m(t_{(x+i,y+j)}, t, \alpha)$ or $TS_s(t_{(x+i,y+j)}, t, \alpha)$ is equal to one and else equal to zero. Here, $S(x,y)$ is an integer from 0 to 8. If $S(x,y)$ is bigger than 6, then the pixel $(x,y)$ has the same type as sample change type.

IV. EXPERIMENT AND RESULT ANALYSIS

A. Monitoring results

Time series curves of grassland, water, cultivated land, construction land, and the conversion of cultivated land to construction land in different periods were obtained by sampling the constructed pixel-level SAR image time series. A sample of 50-100 points was selected for each category and subsequently averaged. As shown in Figure 3, the curves presented good shape similarity before and after the change node. Before the change node, the curve presented the characteristic of cultivated land time series, while it presented the characteristic of construction land time series after the change node. This further demonstrates that change pixels can be detected by analyzing the change characteristics of time series. Note that during the transition phase the curve presented the characteristic of mixed-pixel time series.

B. Accuracy analysis

To evaluate the accuracy of the proposed method, a stratified-random sample of 400 points was selected for ‘change’ and ‘no change’ categories, respectively. Then, point by point verification was carried out by comparing the historical images of Google Earth in corresponding periods. Two comparative experiments were designed in this study to assess the method. This test also utilized ML, SVM, and DT in the classification procedure of SAR image time series, and evaluated the accuracy (Figure 5 and Table 1). Results showed that the proposed method was significantly superior to the traditional methods. The correctness and completeness of our method reached 85.82% and 84.78%, respectively, far higher than the other three methods. The reason is that the other three methods simply accumulate information, whereas they lack analysis on time-series structure and are unable to make full use of the seasonal time-series characteristics of cultivated land, as well as without considering the spatial proximity of pixels.
Figure 5. Traditional classification methods versus the proposed method using SAR image time series.

Table 1. Averaged accuracy of traditional classification methods and our method using SAR image time series.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Method</th>
<th>Maximum likelihood</th>
<th>Decision tree</th>
<th>Support vector machine</th>
<th>Our method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Averaged Correctness</td>
<td>60.56%</td>
<td>71.17%</td>
<td>72.92%</td>
<td>85.82%</td>
<td></td>
</tr>
<tr>
<td>Averaged Completeness</td>
<td>62.62%</td>
<td>72.02%</td>
<td>72.44%</td>
<td>84.78%</td>
<td></td>
</tr>
</tbody>
</table>

V. CONCLUSION

Through the monitoring of conversion of cultivated land to construction land across multiple periods leveraging pixel-level SAR image time series in Chengdu, several conclusions can be drawn. (1) Cultivated land in the study area converted to construction land had an area of 7.05 km² in the period of 2008-2009, followed by the period of 2009-2010 with an area of 5.86 km², and the period of 2010-2011 with an area of 1.72 km². (2) This study has illuminated the utility of pixel-level SAR image time series for land cover change detection, especially in those areas with cloud cover most of the time. SAR images are not affected by cloud cover and provide continuous time-series information. (3) The spatio-temporal similarity measure was able to effectively extract change nodes and change range of cultivated land to construction land. Generally, the correctness of 85.82% and completeness of 84.78% were achieved.

In the future, the synthetic use of optical remote sensing data and SAR images will help us to better monitor the land cover change. The combination of optical remote sensing data and SAR images time series will bear tremendous potential in earth observations, which may be a hot topic in the next few years. More advanced data diming techniques will be introduced and developed into remote sensing time series application area.

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REFERENCES