AUTOMATIC LAND COVER CHANGE DETECTION BASED ON IMAGE ANALYSIS AND QUANTITATIVE METHODS

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ABSTRACT:

The methods of Automatic land use and land cover change detection based on remote sensing image has been widely applied in research for LUCC (Land Use and Cover Change), nature resource management and environment monitoring & protection. Taking into account that multi-temporal remote sensing data also were used to retrieve important information for change detection, and several relevant algorithms have been developed, e.g., Image Differencing, Principal Component Analysis, Post-classification Comparison and Change Vector Analysis etc. to automatically detect the changed information. However, while changes are automatically monitored, the case that time one (T1) data is existed land use and land cover maps, and another time (T2) data is remotely sensed imagery is also very common. Under the condition that one time (T1) data is existed land use and land cover map, and another time (T2) data is remotely sensed imagery, how to detect change automatically is still an unresolved issue. The frequently adopted method is to interpret the registered and superimposed T1 data and T2 data, which is time consuming and has a big workload. In fact, the unchanged information is the main information. Therefore T1 data has a great deal of land use and land cover information consistent with T2 data. If the useful information is mined by the computer, and the knowledge database of land use and land cover classes based on the statistic information is established, the changed information can be automatically and quantitatively detected via the guide of the knowledge. This paper developed a land use and land cover class knowledge-oriented method for automatic change detection under this situation. Firstly, the land use and land cover map in T1 and remote sensing images in T2 were registered and superimposed precisely. Secondly, the remote sensing knowledge database of all land use and land cover classes was constructed based on the unchanged parcels in T1 map. We can make good use of many different methods of image analysis to extract information of texture, conformation, color and so on. At the same time, we utilize the methods of quantitative Remote Sensing to compute some important parameters, such as LAI (leaf area index), NDVI, reflectivity, soil water content etc. we can input all these information into knowledge database according to land cover classes and extracting method. Thirdly, guided by T1 land use and land cover map, feature statistics for each parcel or pixel in remote sensing images were extracted. Finally, land use and land cover changes were found and the change class was recognized through the automatic matching between the knowledge database of remote sensing information of land use and land cover classes with the extracted statistical information in that parcel or pixel. Figure 1 shows the work flow of automatic land cover change detection. Experimental results and some actual applications show the efficiency of this method.

1. INTRODUCE

To accurately and quickly obtain the space-temporal information of land cover change by Remote Sensing is the key technology of resource and ecological environmental monitoring and the international LUCC research, and it has become the focus of the international remote sensing studies. Considering that multi-temporal remote sensing data is used as information source for change monitoring, several methods have been developed, such as Image Differencing, Principal Component Analysis, Post-classification Comparison and Change Vector Analysis etc. to automatically detect the changed information $^{[1,2,3,4]}$. However, while changes are automatically monitored, the case that time one (T1) data are land cover maps, and another time (T2) data are remotely sensed image is very common. The frequently adopted method is registering and superimposing T1 data and T2 data, which is time consuming and has a big workload. In fact, the unchanged information is the main information; therefore T1 data has a great deal of land cover information consistent with T2 data. If the useful information is mined by the computer, and the knowledge database of land cover classes based on the statistic information is established, the changed information can be automatically and quantitatively detected via the guide of the parcel-knowledge.

2. PRINCIPLES AND TECHNICAL PROCESS

While using T1 data (land cover map) and T2 data (remote sensing image) to monitor changes, there are a large number of unchanged parcels in T1 data, which are consistent with the ground surface information presented by the remote sensing image. These parcels can provide enough information. By mining the information, the effective knowledge used for change detection can be obtained. When T1 data and T2 data are registered and superimposed precisely, the region and the class of the unchanged land cover in T2 image partitioned by parcels in T1 data are easily known.

Take the parcels in T1 data as the unit, then select the land cover sample data class by class. After calculating the statistical data, the database of each land cover class can be established. When T1 data is superimposed precisely on T2 data, take the parcels in T1 data as the unit and its land cover class as the reference, then calculate the corresponding feature statistical values in T2 data. After comparing it with the class knowledge information class by class in T1 data, the changed and unchanged positions and the regions can be detected, and the changed class can be recognized by matching the knowledge information of each class in the knowledge database.

3. KEY METHODS

3.1 Construction of the Knowledge Database of Remote Sensing Information of Land cover Classes

When T1 data is superimposed on T2 data, the layers of each land use and land cove class can be established. In each layer, take the parcels in T1 data as the unit, then select the relevant land cover sample data in T2 image. The knowledge database of remote sensing information of land cover classes can be constructed by calculating the feature statistics of each land use class of the sample data. Generally, the feature statistics include the following values:

- (1) Spectral features, such as the spectral value of each band and the spectrum character curve etc.
- (2)Statistical values, such as the maximum values, the minimum value, mean value, variance and covariance etc.
- (3) Histogram features, such as the distribution, mean value, variance, skewness and entropy etc.
- (4) Texture features, such as self-correlation coefficient, entropy, homogeneity and dissimilarity etc.
- Band algebra operation, such as ratio and vegetation (5) indices etc.

3.2 Construction of the Discrimination Rules

Discrimination rules are the rulers to measure the changes of the land cover classes. Several discrimination rules, such as the Minimum Distance Rule, the Bayesian Rule and the Decision Tree etc. can be established according to the information in the knowledge database and the real-timely calculated feature statistics during the change detection process.

3.3 Automatic Change Detection

First, overlap T1 data and T2 data. Second, guided by the parcel boundary and its class information in T1 data, take the integrated parcels in T1 data as the unit, then compute the feature statistics class by class in T2 data. According to the given discrimination rule, and comparing the computed value with the feature value of the parcels in T1 data in the knowledge database, the changed regions can be detected automatically.

For example, T2 is the color image with R,G and B bands. Parcels in T1 data are used as the computing unit. Mean value and the variance value of each classes are used as the image feature value, and the Minimum Distance Rule is used as the discrimination rule. Then, there exists the following equation:

$$D_{\mu_{ij}} = \sqrt{w_R(\overline{\mu}_{R_i} - \mu_{R_j})^2 + w_G(\overline{\mu}_{G_i} - \mu_{G_j})^2 + w_B(\overline{\mu}_{B_i} - \mu_{B_j})^2}$$
$$D_{\sigma_{ij}} = \sqrt{w_R(\overline{\sigma}_{R_i} - \sigma_{R_j})^2 + w_G(\overline{\sigma}_{G_i} - \sigma_{G_j})^2 + w_B(\overline{\sigma}_{B_i} - \sigma_{B_j})^2}$$

Where, W_R , W_G , W_B are the weight of R,G,B bands respectively; μ and σ are the mean value and the variance value of each class in each band in the knowledge database; $\overline{\mu}$ and $\overline{\sigma}$ are the mean value and the variance value of the parcel to be detected in



Figure. 1. Change Detection Result with the Minimum Distance Rule

$$D_{\mu_{ii}} D_{\sigma_{ii}}$$

 $D_{\mu_{ij}}$ and $D_{\sigma_{ij}}$ are less than the given each band. When threshold, the parcel in T2 data is not changed, otherwise it is changed. (See Fig. 1.)

Besides the parcel, the pixel can also be used as the computing unit in T2 data. The statistic Z value of each pixel

can be calculated based on the following equation:

$$Z_{jk} = \sum_{i=1}^{N} \left(\frac{r_{ijk} - \mu_{ic_{jk}}}{\sigma_{ic_{jk}}} \right)$$

Where, i is the image band number, N is the total number of

the bands, C_{jk} is the specified class, Y_{ijk} is the pixel value in (j,k) in i band, μ_{ic} is the mean value of the class C in i band, σ_{ic} is the variance value of the class C in i band, and j,k are the

column number and the raw number of the image respectively.

3.4 Recognition of Changed Classes

The changed class can be recognized through the automatic matching between the remotely sensed knowledge database of all land cover classes and the extracted statistics in that parcel. Multiple criterions and the Decision Tree are the effective methods.

3.5 Detection and Recognition of Crossing Parcels

In the case that the changed region in T2 data is corresponding to a part of a parcel or corresponding to several parcels in T1 data, the image segmentation method can be used to divide the specific region in T1



Fig. 2. Updated Land Use Map

data into several uniform parcel units, and the same method described above can be applied in each divided unit to fulfill the change detection and the class recognition.

4. EXPERIMENTS

Based on the method presented in this paper, the software for class knowledge-oriented automatic land cover change detection was developed using AUTOCAD and VC++6.0, and the land cover maps of Shenzhen city, China were updated using TM 30m multi-spectral data, SPOT 10m Pan data in 2000 and the land cover maps in 1999. Compared with the change detection using multi-temporal RS images, the method presented in this

paper has the better class recognition accuracy up to 90%. Fig. 2 is an example of the updated land cover map.

5. CONCLUSIONS

The approach, that automatically detect the land cover changes in the case that time one (T1) data is existed land cover map and another time (T2) data is remotely sensed imagery is put forwarded in this paper. Experimental results and the actual applications show the efficiency of this method. It could be enriched and further improved in the later research.

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