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A Scene Change Detection Framework for Multi-Temporal Very High Resolution Remote Sensing Images

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Abstract

The technology of computer vision and image processing is attracting more and more attentions in recent years, and has been applied in many research areas like remote sensing image analysis. Change detection with multi-temporal remote sensing images is very important for the dynamic analysis of landscape variations. The abundant spatial information offered by very high resolution (VHR) images makes it possible to identify the semantic classes of image scenes. Compared with the traditional approaches, scene change detection can provide a new point of view for the semantic interpretation of land-use transitions. In this paper, for the first time, we explore a scene change detection framework for VHR images, with a bag-of-visual-words (BOVW) model and classification-based methods. Image scenes are represented by a word frequency with three kinds of multi-temporal learned
dictionary, i.e., the separate dictionary, the stacked dictionary, and the union dictionary. Three features (multispectral raw pixel; mean and standard deviation; and SIFT) and their combinations were tested in scene change detection. Post-classification and compound classification were evaluated for their performances in the “from-to” change results. Two multi-temporal scene datasets were used to quantitatively evaluate the proposed scene change detection approach. The results indicate that the proposed scene change detection framework can obtain a satisfactory accuracy and can effectively analyze land-use changes, from a semantic point of view.

Keywords: Scene change detection, VHR image, remote sensing, BOVW, post-classification, compound classification.

1. Introduction

The technology of computer vision and image processing is attracting more and more attentions in recent years [1-7], and has been applied in many research areas like remote sensing image analysis [8], [9]. Dynamic analysis of landscape variations is very important for understanding the interactions between human development and natural phenomena [10]. Since the advent of remote sensing technology, it has been a major source of information for change detection studies to detect, identify, and analyze the changes in landscape conditions, because of its broad view, high temporal frequency, and consistent observations [11-R3]. Change detection with multi-temporal remote sensing images has proven effective in many applications [15], [16].
In recent years, numerous studies have addressed the automatic and accurate detection of changes from multi-temporal images [17]. The main methods can be categorized into the following groups: 1) image difference [18]; 2) image transformation [19]; and 3) classification-based methods [20]. Since classification-based change detection methods can indicate the detailed “from-to” change types for further analysis, they are very convenient for practical applications [21]. Nowadays, the new remote sensing technology with a higher resolution has brought about a revolution in the analysis of multi-temporal datasets [22]. In addition to the detailed characterization and monitoring of landscape changes with object-oriented methods [23], very high resolution (VHR) imagery also provides unique opportunities for the semantic interpretation of land-use transitions.

Meanwhile, classifying image scenes into semantic classes has attracted increasing attention in the pattern recognition field [24-26]. Due to the abundant and detailed spatial information provided by VHR imagery, the remote sensing scenes can be characterized as semantic land-use classes based on the spatial and structural patterns of the landscapes encoded in the imagery [27]. A great deal of research has focused on remote sensing scene classification [28]. The bag-of-visual-words (BOVW) model has been explored as an effective and robust feature encoding approach to obtain the statistical characteristics of thematic objects for remote sensing scenes [29]. It can provide a mid-level representation to bridge the huge semantic gap between the extracted low-level features in the image and the high-level concepts of human beings [30]. The combination of multiple features, such as texture features and SIFT feature
descriptors, can improve the performance of scene classification [31], [32]. Topic models derived from text categorization, such as probabilistic latent semantic analysis (pLSA) and latent Dirichlet allocation (LDA), have been proposed to reduce the dimension and increase the accuracy [33], [34].

With the increasing availability of high-resolution images covering the Earth’s surface, it is now available to develop change detection methods for a scene scale. It can provide a new point of view to analyze and monitor urban development, such as the expansion of industrial and residential area. The problem is that the changes of thematic landscapes inside a scene may not lead to the variation of the scene classes. The traditional change detection approaches, such as the pixel-wise and object-wise methods, can only identify the changes of the thematic objects, such as the growth of vegetation and the appearance of new buildings. However, their variations inside the scene will not modify the land-use category from a residential area to an industrial area. This illustrates the semantic gap between landscape changes and scene changes. It is therefore necessary and significant to explore scene change detection, which takes into consideration the semantic comprehension of the land-use variations.

However, to the best of our knowledge, no previous studies have focused on this topic. Therefore, in this paper, we explore a scene change detection framework for multi-temporal VHR remote sensing imagery, and evaluate its performance in the application of urban development management. The scene classification method is based on a BOVW model with three different features, i.e., the multispectral raw pixel; the mean and standard deviation; and the SIFT feature descriptor. Three kinds of
dictionary, i.e., the separate dictionary, the stacked dictionary, and the union dictionary, are proposed to make use of the multi-temporal information to improve the performance. Post-classification and compound classification approaches for the scenes are addressed to extract the semantic land-use change information. Finally, the urban development is mapped and analyzed with the land-use transition interpretation.

The remainder of this paper is organized as follows. Section 2 introduces scene classification with the BOVW approach. Section 3 explores the change detection process for multi-temporal scene data. Experiments with two multi-temporal VHR imagery datasets and a discussion are presented in Section 4. Finally, the conclusion of this paper is drawn in Section 5.

2. Scene Classification with BOVW

In the BOVW approach, a scene can be identified by the thematic objects it contains. The idea of BOVW derives from text analysis, where the documents can be classified according to the frequencies of the words contained therein, regardless of the word order [35]. For scene classification, BOVW aims at representing the image scene with the statistical frequency of the visual words as its characteristic feature for the following classification process, as shown in Fig. 1. The procedure of BOVW scene classification can be described as follows: 1) randomly select image patches from the scene images in the scene dataset; 2) learn a dictionary from the feature sets of the selected patches; 3) for each scene, extract the features of the patches in the image as visual words; 4) encode the features of the visual words with the learned
dictionary; 5) pool the feature codes to obtain the word frequency representation as the characteristic for the image scene; 6) repeat steps 3–5 to represent all the scenes with the word frequency; and 7) classify the image scenes into semantic scene classes.

Next, we introduce the strategies of the framework used in this paper in detail.

2.1 Feature Extraction

The features of the patch should be representative and distinguishable to describe the different thematic objects for the visual words. In this paper, we evaluate the performance of scene change detection with three descriptive features, which are the raw pixel vector (RAW), the mean and standard deviation (MSTD), and the dense SIFT feature (SIFT).

The raw pixel vector is widely used as a low-level descriptor for image patches [24]. For a multi-band image patch with the size of \( m \times n \) and \( b \) bands, it is represented as a column vector \( \mathbf{x} \in \mathbb{R}^L \), where \( L = m \times n \times b \). The image patch can be reshaped row-wise or column-wise, and filled into the raw pixel vector band by band.

The MSTD is a simple descriptor for an image patch to represent its characteristics. The mean value and standard deviation of each band are calculated and listed in a column vector \( \mathbf{x} \in \mathbb{R}^L \), where \( L = 2 \times b \).
The final descriptor we use is the dense SIFT descriptor. The SIFT descriptor is invariant to translation, rotation, and scaling in the image domain and is robust with regard to illumination variation [36]. Previous work has proved that in the application of scene classification, the dense SIFT descriptor is more effective than sparse interest points [24], [27]. In this paper, we use the first principal component of PCA as the input of the dense SIFT descriptor, and obtain the descriptor vector \( x \in \mathbb{R}^L \), where \( L=128 \). We use the dense SIFT implementation provided by Lazebnik et al. [37] to extract the features.

Different features can also be combined for a better classification performance. In this paper, we use a simple approach to combine multiple features by stacking the word frequencies of the different features into a higher-dimensional representation vector. It is worth noting that we stack the word frequencies instead of the original features directly, since the word frequencies of the different features are at the same scale, and we do not have the problem of feature normalization.

2.2 Dictionary Learning

The dictionary must be comprehensive and representative of the visual words. The learned dictionary is then used to quantize the extracted features by assigning the labels of the visual words.

One way to prepare the source data for dictionary learning is to use all the features extracted from all the scenes in the learning process. However, when the volume of the input scene data is large, the dictionary learning will be time-consuming. Therefore, in this paper, we randomly select abundant sample patches from the scene
images in the dataset to generate the input data matrix \( \mathbf{X} = [x_1, x_2, \ldots, x_M] \). The number of samples is usually very large, such as \( M = 100000 \).

In order to reduce the redundancy of the input data, zero component analysis (ZCA) whitening is applied to remove the correlations between the different dimensions [49].

K-means clustering is an effective feature representation learning method and can be quickly implemented at a large scale [38]. This approach has also been applied in many studies of scene classification [33]. The whitened input dataset is quantized into \( K \) clusters by the K-means algorithm, and their centers are the elements of the learned dictionary \( \mathbf{D} = [d_1, d_2, \ldots, d_K] \).

2.3 Feature Encoding and Pooling

After obtaining the dictionary, the training and testing scenes can be represented with the encoded features as \( \mathbf{P}^{\text{train}} = [p_1^{\text{train}}, p_2^{\text{train}}, \ldots, p_T^{\text{train}}] \) and \( \mathbf{P}^{\text{test}} = [p_1^{\text{test}}, p_2^{\text{test}}, \ldots, p_N^{\text{test}}] \), where \( T \) and \( N \) are the numbers of training and testing scenes. Dividing the image patches with a non-overlapping grid is a traditional approach. However, Bosch et al. [24] proved that overlapping patches can lead to a better performance. Therefore, in this paper, the image patches used for the feature extraction are squared windows with a size of \( m \times n \), and they cover the whole image scene with a step of \( s \) moving in the horizontal and vertical directions. The ZCA whitening matrix obtained in the dictionary learning should be used before the encoding to preprocess the features. The whitened feature of each patch is then quantized to the visual word that has the greatest similarity in the dictionary.

After feature encoding, the pooling process should be applied to represent the scene
with the encoded words. In this paper, we compute the histogram of the labeled words in the scene, and normalizing it to be the word frequency, since it is very robust in practical applications [35].

2.4 Classification

The dictionary representation is the input data for the scene classification. A dictionary will usually consist of hundreds of words, and thus the representation for the scene is very high dimensional data. Since the number of training samples is usually much smaller than the data dimension, we choose support vector machine (SVM) as the classifier in this paper [39]. LIBSVM was applied with a linear kernel to classify the scenes in our experiments [40].

3. Scene Change Detection

Since the scene change detection aims to analyze the land-use transition from a semantic point of view, supervised information provided by interpreters is essential for the semantic definition of the different scene classes. Inspired by traditional change detection, we use a classification-based method to determine the scene changes. In this paper, post-classification (comparing the class maps after separate classification) and compound classification (classifying the stacked multi-temporal scene) are proposed and evaluated for the scene change detection. In addition, as the temporal information is important in multi-temporal image analysis, we also attempt to add the temporal information into the learned dictionary.
3.1 Post-Classification and Compound Classification

Post-classification and compound classification are the two most commonly used classification-based change detection methods in land-cover/land-use change mapping and ecosystem monitoring [21], [41]. They can provide the “from-to” change type information for the following detailed analysis. For the proposed scene change detection framework, we also employ these two approaches to map the changed scenes and to identify the change types, as shown in Fig. 2.

Fig. 2. Scene change detection of (a) post-classification, and (b) compound classification.

Fig. 2 (a) shows that, in post-classification, the multi-temporal scenes are classified separately as \( L^1 = [l_1^1, l_2^1, \ldots, l_N^1] \) and \( L^2 = [l_1^2, l_2^2, \ldots, l_N^2] \). The scene labels after scene classification are compared to identify the change conditions of the
corresponding scenes at the same location. The compound classification classifies the multi-temporal scene pair to be \( L_{\text{from-to}} = \left[ l_{\text{from-to}}, l_{\text{from-to}}, \ldots, l_{\text{from-to}} \right] \) at one time, with the stacked word frequency, as shown in Fig. 2 (b). Theoretically, the accuracy of post-classification is limited since the misclassified scenes at each time point will lead to errors in the change detection result, no matter whether or not the corresponding scenes at another time are correctly classified. Although the compound classification approach can solve this problem with one-pass classification, the direct selection of training samples for all the “from-to” scene classes is too complex. Therefore, we generate the simulated training samples for the compound classification with separate training samples in the multi-temporal dataset.

3.2 Multi-Temporal Dictionary Learning

A multi-temporal scene dataset covers the same study site at different times. Therefore, the multi-temporal information may be useful to improve the performance of the temporal analysis, rather than a totally separate process. The dictionary is the reference for the scene classification, and thus it may be a good idea to add the temporal information into the dictionary learning process. In order to explore the different possibilities, we propose three approaches to build the dictionary, as shown in Fig. 3.
Fig. 3. Multi-temporal dictionary learning approaches of (a) separate dictionary, (b) stacked dictionary, and (c) union dictionary.

1) Separate dictionary (SP): The multi-temporal scene datasets are processed separately to build two dictionaries. The image scenes are then encoded and represented by their own dictionaries. This is the basic approach for the multi-temporal BOVW method, as shown in Fig. 3 (a).
2) Stacked dictionary (ST): Two sub-dictionaries are learned by their own image scene dataset and stacked into one dictionary. The stacked dictionary is then used to represent the image scene in different scene datasets, as shown in Fig. 3 (b).

3) Union dictionary (UN): As Fig. 3 (c) shows, sample patches from the multi-temporal image scene datasets are randomly selected and gathered into one training sample set. The dictionary is then learned from the set with multi-temporal patches and is used to encode the image scenes acquired at different times. The precondition for both the stacked dictionary and union dictionary is that the training samples must be transformed into one scale; otherwise, the dictionary will be non-uniform.

3.3 Procedure

The procedure of scene change detection can be summarized as follows: 1) A large amount of patches are randomly selected from the multi-temporal datasets of scene images as training samples; 2) The dictionary is learned according to the three multi-temporal dictionary learning approaches; 3) The training scenes and test scenes are encoded with the learned dictionary and represented as word frequencies with feature pooling; 4) Post-classification and compound classification are employed to obtain the change information.

4. Experiments and Discussion

4.1 Hanyang Dataset

In order to evaluate the performance of the scene change detection, we used two
VHR images covering the area of Hanyang in the city of Wuhan, China (Fig. 4). The multi-temporal images were acquired by the IKONOS sensor on February 11th, 2002, and June 24th, 2009, respectively. The spatial resolution was 1 m after the fusion of the pan and multispectral images by the GS algorithm in ENVI. The image size was 7200×6000 with four bands, which were the red, green, blue, and near-infrared (NIR) bands. Georeference and accurate co-registration were performed to guarantee that the corresponding scenes cover the same area.

![Fig. 4. Color images of the Hanyang area in the city of Wuhan, acquired on (a) February 11th, 2002, and (b) June 24th, 2009.](image)

With this data, we obtained the scenes from the large image by a non-overlapping grid with a cell size of 150×150. In this way, we generated 1920 test scenes (48×40) for each time point. Eight classes were selected from the study scene by visual interpretation, as shown in Fig. 5. In the study area, all the small villages represented as sparse houses had been changed into other classes over the interval, and so the third scene class did not exist in 2009. It was therefore filled by the blank image in Fig. 5 (c).
Fig. 5. Examples of training scenes acquired at different times belonging to: (a) parking, (b) water, (c) sparse houses, (d) dense houses, (e) residential area, (f) idle area, (g) vegetation area, and (h) industrial area.

The reference maps of the whole images are shown in Fig. 6. A total of 55.52% and 74.01% of the scenes for the images in 2002 and 2009, respectively, are labeled. The undefined scenes are mostly a mixture of several classes of scene, and none of them can be defined as the main land-use class. In order to choose representative and typical scenes for training, we extracted the training scene samples separately from the whole study scene, instead of the subset of test samples, which may be easier to implement in practical applications. The numbers of training and test samples, and the reference percentages are shown in Table I. In total, we selected 1066 and 1421 scenes in 2002 and 2009, respectively, for testing, and 963 common scenes for the multi-temporal change detection.
In this paper, in order to obtain robust results with satisfactory accuracies, we chose the number of training patches for the dictionary learning as 100000, the patch size as 10×10, the step for the patches as 5, and the number of the dictionary as 1000. Since the dictionary is learned by randomly selected patches, we ran each case 10 times and computed the statistical values. Different parameters of the algorithm will lead to different accuracies and runtimes. However, the objective of this paper is the exploration of a scene change detection framework for multi-temporal VHR images. Therefore, these parameters were determined for a balance between accuracy, complexity, and speed.
Table I

(a) Number of training and test samples, and the reference percentage for each scene class in 2002.

<table>
<thead>
<tr>
<th>Code</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>9</td>
<td>20</td>
<td>24</td>
<td>19</td>
<td>16</td>
<td>24</td>
<td>21</td>
<td>24</td>
<td>157</td>
<td></td>
</tr>
<tr>
<td>Test</td>
<td>854</td>
<td>11</td>
<td>252</td>
<td>139</td>
<td>69</td>
<td>41</td>
<td>206</td>
<td>226</td>
<td>122</td>
<td>1920</td>
</tr>
<tr>
<td>Per. %</td>
<td>44.48</td>
<td>0.57</td>
<td>13.13</td>
<td>7.24</td>
<td>3.59</td>
<td>2.14</td>
<td>10.73</td>
<td>11.77</td>
<td>6.35</td>
<td>100.00</td>
</tr>
</tbody>
</table>

(b) Number of training and test samples, and the reference percentage for each scene class in 2009.

<table>
<thead>
<tr>
<th>Code</th>
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<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>11</td>
<td>30</td>
<td>0</td>
<td>29</td>
<td>34</td>
<td>20</td>
<td>15</td>
<td>43</td>
<td>182</td>
<td></td>
</tr>
<tr>
<td>Test</td>
<td>499</td>
<td>20</td>
<td>275</td>
<td>0</td>
<td>77</td>
<td>258</td>
<td>126</td>
<td>228</td>
<td>437</td>
<td>1920</td>
</tr>
<tr>
<td>Per. %</td>
<td>25.99</td>
<td>1.04</td>
<td>14.32</td>
<td>0.00</td>
<td>4.01</td>
<td>13.44</td>
<td>6.56</td>
<td>11.88</td>
<td>22.76</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Firstly, we evaluated the performance of the classical K-means approach and the simplified sparse approach (Sparse) proposed by Cheriyadat [27]. The quantitative assessment was made by overall accuracy (OA) with the reference test samples. The performance of the change detection result was evaluated according to the OA of the “from-to” change map. The statistical plots for K-means and Sparse with the three dictionary learning approaches and the post-classification change detection method are shown in Fig. 7. The feature in this experiment is the RAW feature. For the statistical box, the whiskers illustrate the maximum and minimum OAs, the white square shows the mean value, and the horizontal lines of the box indicate the range of OA with 25%, 50%, and 75%. Fig. 7 illustrates that the K-means approach outperforms the Sparse approach in both one-time scene classification and the “from-to” change detection. In the comparison of the three dictionary learning approaches, they all obtained similar results, and the stacked and union dictionaries obtained a slightly better performance than the separate dictionary in the “from-to” result.
The performances of different features and their combinations were evaluated with the K-means approach and post-classification. The quantitative assessment is shown in Fig. 8, where “R” means RAW, “M” means MSTD, “S” means SIFT, and “+” means combination. This shows that in the 2002 dataset, the combined features obtained better performances, except for the combination of MSTD and SIFT. In the 2009 dataset, the combination of RAW and SIFT got the highest OA, and the RAW feature also obtained good results. In the final change detection result, the combination of RAW and SIFT got the best results, and only the MSTD and SIFT combination did not get a better accuracy than the single features. The reason for this may be that the MSTD feature did not provide enough information and also obtained the lowest accuracy. However, its combination outperforms the single feature of MSTD. The evaluation illustrates that the combination of different features results in better performances, since the different features carry complementary information. However, the inclusion of MSTD in the combination of RAW and SIFT reduces the accuracy, which is because the redundancy of information also negatively affects the classification performance in certain cases. Comparatively, the union dictionary has a
slightly higher mean OA than the others, which means that the temporal information can enrich the diversity of words in the dictionary.

![Fig. 8](image)

Fig. 8. Mean and standard deviation of OA with different features and their combinations in the datasets of (a) 2002, (b) 2009, and (c) the “from-to” change detection result.

![Fig. 9](image)

Fig. 9. OA of each classification with different features and their combinations.

Since the combination of different features is stacking the word frequencies, Fig. 9 shows the OA of the different features and their combinations in 10 classification runs with the union dictionary. It can be observed that the combination of different features clearly improves the performance in each classification, compared with the single features.
The performances of post-classification and compound classification based on the same representation of RAW+SIFT are shown in Fig. 10. The training samples for compound classification are generated by the traversal of all possible combinations of separate training samples for the multi-temporal datasets. The dashed line with triangular labels indicates the OA of compound classification, and the solid line with square labels indicates that of post-classification. Fig. 10 illustrates that, in most cases, compound classification slightly outperforms post-classification. However, under the same conditions, for the training and classification process after representation, compound classification costs 1885.7 s, while post-classification only costs 5.2 s, since the large amount of classes and samples makes it more difficult to find the best classification model. Therefore, we recommend post-classification in practical applications, because of its efficiency and effectiveness.

Since the traversal of training samples is too time-consuming, we wanted to evaluate the performance of a random combination of training samples. We therefore randomly combined the training samples from the numbers of 50 to 400 with the representation of RAW+OA and the union dictionary, which can obtain the highest
OA for the “from-to” change detection result. We then repeated each case 10 times. The statistical plot is shown in Fig. 11, where the dashed line is the OA obtained with the same representation and sample traversal. It can be found that by increasing the number of random training samples, the mean OA approaches that of sample traversal, with a smaller variance. This illustrates that increasing the number of random training samples improves the performance, but this does not obtain better results than sample traversal. Above all, post-classification is a more useful approach than compound classification with generated training samples.

Fig. 11. The OA with different numbers of random training samples.

Fig. 12 shows the scene maps in 2002 and 2009 with a high “from-to” change detection accuracy, obtained by the RAW+SIFT features, the K-means approach, the union dictionary, and post-classification. The OA of each map is 85.65% and 84.03%, and the “from-to” change detection accuracy is 76.43%. It can be observed that the small villages represented as sparse houses disappeared in 2009. Instead of sparse houses, industrial areas and residential areas expanded very quickly. Most idle areas in 2002 were transformed into other land-use classes. It is worth noting that the scene change detection can reveal the detailed land-use transitions. In that after seven years,
the west side of Hanyang has developed to be a residential area, and the east side has become an industrial area, while the traditional approaches just regard both of them as impervious surfaces.

![Fig. 12. Scene maps for multi-temporal images acquired in (a) 2002 and (b) 2009 with eight classes. The OAs are 85.65% and 84.03%, and 76.43% for the “from-to” change detection.](image_url)

The statistics of the scenes in 2002 and 2009 are shown in Table II. Here, it can be clearly found that, in 2002, there were many land-use areas with the type of sparse houses and idle areas, since the urbanization of the Hanyang area had just started at this time. By 2009, many of these land-use areas had been changed into residential areas and industrial areas, because of the city expansion, which is shown by the

<table>
<thead>
<tr>
<th>Class</th>
<th>2002</th>
<th>2009</th>
<th>+/−</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Parking</td>
<td>9</td>
<td>13</td>
<td>+4</td>
</tr>
<tr>
<td>2. Water</td>
<td>292</td>
<td>312</td>
<td>+20</td>
</tr>
<tr>
<td>3. Sparse house</td>
<td>447</td>
<td>0</td>
<td>−447</td>
</tr>
<tr>
<td>4. Dense house</td>
<td>55</td>
<td>132</td>
<td>+77</td>
</tr>
<tr>
<td>5. Residential</td>
<td>201</td>
<td>507</td>
<td>+306</td>
</tr>
<tr>
<td>6. Idle</td>
<td>354</td>
<td>178</td>
<td>−176</td>
</tr>
<tr>
<td>7. Vegetation</td>
<td>249</td>
<td>267</td>
<td>+18</td>
</tr>
<tr>
<td>8. Industrial</td>
<td>313</td>
<td>511</td>
<td>+198</td>
</tr>
</tbody>
</table>

The statistics of the scenes in 2002 and 2009 are shown in Table II. Here, it can be clearly found that, in 2002, there were many land-use areas with the type of sparse houses and idle areas, since the urbanization of the Hanyang area had just started at this time. By 2009, many of these land-use areas had been changed into residential areas and industrial areas, because of the city expansion, which is shown by the
increasing number of these two scene classes.

![Fig. 13. “From-to” change map: (a) change from sparse houses, (b) change to residential area, and (c) change to industrial area. The scenes include parking (1-white), water (2-blue), sparse houses (3-cyan), dense houses (4-purple), residential area (5-brown), idle area (6-yellow), farmland (7-green), and industrial area (8-red).](image)

The “from-to” change maps for the transition of the three important scene classes are shown in Fig. 13. The color in the change map indicates the different scene classes. Fig. 13 (a) shows that sparse houses changed into other land-use classes. This illustrates that most sparse house areas changed to residential areas and vegetation. It can also be found that residential areas appeared in the left-top part of the study area in Fig. 13 (b). Comparatively, industrial areas expanded to the right-bottom part and covered many idle areas and vegetation areas, shown in Fig. 13 (c). Fig. 13 shows the “from-to” land-use transition map of the three most important scene classes in the urban expansion. It can be seen that the scene change detection is able to provide semantic interpretation of the land-use transition for urban management, which cannot be achieved by the traditional approaches.

4.2 Hankou Dataset

We also chose another multi-temporal dataset from the Hankou area of Wuhan to
further evaluate the proposed approach. The source images of the multi-temporal dataset were obtained on August 11th, 2002, and May 11th, 2008. They were also acquired by IKONOS and panchromatic to be VHR with a 1-m resolution and four bands. Georeference and accurate co-registration were performed as pre-processing. Since the source images covering Hankou are too complex to label all the scenes, we extracted multi-temporal scene pairs from the VHR images for the quantitative assessment. The size of scene was 150×150. Seven classes of land-use scene were selected from the source images, which are shown in Fig. 14. As discussed in the Hanyang experiment, the training samples were selected separately from each source image. A total of 411 scene pairs were extracted for the test. A total of 104 and 92 training samples were selected in 2002 and 2008 for classification. The numbers of training and test samples of the different classes are shown in Table III.

![Fig. 14. Examples of multi-temporal scene pairs acquired in 2002 and 2008 belonging to: (a) water (1), (b) dense houses (2), (c) vegetation area (3), (d) agricultural area (4), (e) residential area (5), (f) idle area (6), and (g) industrial area (7).](image)

The parameters, such as patch size, dictionary number, etc., were set the same as those in the Hanyang experiment. The training patches for the dictionary learning were randomly selected from the multi-temporal dataset of the scene pairs, instead of the source images.
### Table III

(a) Number of training and test samples, and percentage of test for each scene class in 2002.

<table>
<thead>
<tr>
<th>Code</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>16</td>
<td>17</td>
<td>14</td>
<td>15</td>
<td>15</td>
<td>10</td>
<td>17</td>
<td>104</td>
</tr>
<tr>
<td>Test</td>
<td>125</td>
<td>61</td>
<td>66</td>
<td>34</td>
<td>60</td>
<td>25</td>
<td>40</td>
<td>411</td>
</tr>
<tr>
<td>Per. %</td>
<td>30.42</td>
<td>14.84</td>
<td>16.06</td>
<td>8.27</td>
<td>14.60</td>
<td>6.08</td>
<td>9.73</td>
<td>100.00</td>
</tr>
</tbody>
</table>

(b) Number of training and test samples, and percentage of test for each scene class in 2008.

<table>
<thead>
<tr>
<th>Code</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>13</td>
<td>14</td>
<td>11</td>
<td>9</td>
<td>20</td>
<td>11</td>
<td>14</td>
<td>92</td>
</tr>
<tr>
<td>Test</td>
<td>87</td>
<td>68</td>
<td>30</td>
<td>16</td>
<td>119</td>
<td>33</td>
<td>58</td>
<td>411</td>
</tr>
<tr>
<td>Per. %</td>
<td>21.17</td>
<td>16.55</td>
<td>7.30</td>
<td>3.89</td>
<td>28.95</td>
<td>8.03</td>
<td>14.11</td>
<td>100.00</td>
</tr>
</tbody>
</table>

The mean and standard deviation of the OA with the different features and their combinations with the three dictionaries is shown in Fig. 15. It can be observed that in the 2002 dataset, RAW+SIFT obtained the best results, and the single RAW feature also performed well. In the 2009 dataset, the combination of features outperformed the single features in all cases. Therefore, in the post-classification results, they are affected by both classification results, and RAW+SIFT obtained higher accuracies than the other features. Fig. 15 indicates that RAW+SIFT is a very effective combination of features for scene change detection.

![Fig. 15](image)

**Fig. 15.** Mean and standard deviation of OA with different features and their combinations in the dataset of (a) 2002, (b) 2008, and (c) the “from-to” change detection result.

Fig. 16 shows the OA of different single features and their combination in the 2002 and 2008 datasets, and the post-classification result. The dictionary type was the union dictionary. The combination of RAW and SIFT leads to an obvious improvement over the separate features in every case. The other combinations result
in only a limited increase in accuracy. This is because the combination of features can be both complementary and redundant. In summary, RAW+SIFT was found to be the best combination in our experiments.

![Graph 16](image16.png)

**Fig. 16.** OA of each classification with different features and their combinations.

![Graph 17](image17.png)

**Fig. 17.** OA of post-classification and compound classification for the post-classification result.

We then evaluated the performances with the RAW and SIFT combination for post-classification and compound classification, as shown in Fig. 17. The training samples were generated by traversal for the compound classification. It can be seen that, in most cases, the compound classification got a lower accuracy than the post-classification. Considering the complexity of the compound classification, post-classification is more effective in scene change detection.

**Fig. 18** shows the OA statistic of the “from-to” change detection results with
different numbers of random training samples. This illustrates that increasing the random training samples leads to higher accuracies, approaching that of the sample traversal. The generation of training samples for compound classification is not a good approach for change detection. However, the direct selection of the “from-to” samples from the dataset is also very difficult to achieve, because of the large amount of possible types and the rareness of some samples. Thus, compound classification may not be so practical in real applications, and needs further research.

![Graph showing Overall Accuracy vs Random Training Samples](image)

**Fig. 18.** The OA with different numbers of random training samples.

5. Conclusion

In this paper, we have explored a scene change detection framework to monitor land-use transitions from a semantic point of view. Firstly, the features of random patches are extracted to learn a dictionary. Three dictionary learning approaches based on multi-temporal patches are addressed: the separate dictionary, the stacked dictionary, and the union dictionary. The image patches are then represented by word frequency with the learned dictionary, according to the BOVW model. Finally, post-classification and compound classification are applied to detect the “from-to” changes of the land-use classes.
The experiments show that the proposed framework is effective in analyzing the semantic change of remote sensing image scene, and shows its practical significance in the study of city development. A combination of features can clearly improve the performance, and RAW+SIFT is the best combination for scene identification in these cases. K-means is more effective than the simple Sparse approach in dictionary learning, and dictionary learning with multi-temporal information can improve the performance, since it can enrich the diversity of the dictionary. The experimental results also illustrate that, although a compound classification may slightly increase the accuracy over that of post-classification, it is too time-consuming, and thus post-classification is recommended in practical applications. In summary, the proposed scene change detection framework has great potential in land-use monitoring and city management, since the traditional change detection approaches cannot discriminate the semantic land-use variations. The improvement of scene change detection framework is the focus of our future work.

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References


