Gabor-Filtering-Based Completed Local Binary Patterns for Land-Use Scene Classification

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Abstract—Remote sensing land-use scene classification has a wide range of applications including forestry, urban-growth analysis, and weather forecasting. This paper presents an effective image representation method, Gabor-filtering-based completed local binary patterns (GCLBP), for land-use scene classification. It employs the multi-orientation Gabor filters to capture the global texture information from an input image. Then, a local operator called completed local binary patterns (CLBP) is utilized to extract the local texture features, such as edges and corners, from the Gabor feature images and the input image. The resulting CLBP histogram features are concatenated to represent an input image. Experimental results on two datasets demonstrate that the proposed method is superior to several existing methods for land-use scene classification.

Keywords—Gabor filtering; local binary patterns; land-use scene classification; extreme learning machine

I. INTRODUCTION

Land-use scene classification aims to assign semantic labels (e.g., building, river, forest, mountain, etc.) to aerial or satellite images. It has a wide range of applications including agricultural planning, forestry, urban-growth analysis, and land use management. With the rapid development in sensor technology, high-resolution remote sensing images can be obtained using the advanced space-borne sensors. High-resolution remote sensing images with rich spatial and texture information have made it possible to categorize different land-use scene classes automatically [1].

There has been a great deal of effort in employing computer vision techniques for classifying aerial or satellite images. The Bag-of-Words (BoW) model [2] is one of the most popular approaches in image classification and image retrieval applications. In the BoW model, local image features such as color and texture are first quantized into a set of visual words using some clustering methods. An image is then represented by frequencies of the set of visual words. Although the BoW model has demonstrated the effectiveness for the remotely sensed land-use scene classification [1, 3], it ignores spatial relationships of the local features. To incorporate spatial context to the BoW model, a spatial pyramid matching (SPM) framework was proposed in [4] by partitioning an image into subregions and computing a BoW histogram for each subregion. Histograms from all subregions were concatenated to form the SPM representation of an image. In [5], a multi-resolution representation was incorporated into the BoW model to improve the SPM framework by constructing multiple resolution images and extracting local features from all the resolution images with dense regions. Since the SPM method uses the absolute spatial information, it may not improve the classification performance for images exhibit rotation and translation variations due to rotated camera views. To overcome this limitation, a pyramid-of-spatial-relations (PSR) model was proposed in [6] to capture both absolute and relative spatial relationships of local features.

The above-mentioned methods focused on improving the BoW framework by incorporating spatial information for land-use scene classification; however, extracting effective local features that can capture the rich texture information of the high-resolution remote sensing images was not exploited. On the other hand, some works have been applied to classify the scene by considering the spatial information of the local features. In [7], local structural texture descriptors and structural texture similarity with nearest neighbor classifier were utilized for semantic classification of aerial images. In [8], Gabor descriptor and Gist descriptor were evaluated individually for the task of aerial image classification. In [9], a global feature descriptor named enhanced Gabor texture descriptor (EGTD) and a local scale-invariant feature transform (SIFT) [10] descriptor were combined in a hierarchical approach to improve the remote sensing scene classification performance. In [11], four types of features consist of DAISY [12], geometric blur [13], SIFT [10], and self-similarity [14] were used within the framework of multifeature joint sparse coding with spatial relation constraint. Although fusing a set of different features may enhance the discriminative power, it requires parameter tuning for each feature and the feature dimensionality may be increased significantly.

Gabor filters [15] and local binary patterns (LBP) [16] have been successfully applied for a variety of image processing and machine vision applications (e.g., [17-19]). In this paper, we present an efficient image representation method using Gabor-filtering-based completed local binary patterns (GCLBP). More specifically, multi-orientation Gabor filters are first applied to a remotely sensed input image to obtain multiple Gabor feature images which capture different orientation information of the input image. Completed local binary patterns (CLBP) [20] operator, a complete modeling of the LBP operator, is then employed to extract the rotation invariant texture features (histograms) from the Gabor feature images as well as the input image. The overall framework of the proposed representation approach is illustrated in Fig. 1. For classification, kernel-based extreme learning machine (KELM) [21] is utilized due to its efficient computation and good classification performance.

The remainder of this paper is organized as follows. Section II provides relevant background and related work. Section III describes the details of the proposed image representation approach. Section IV presents the experimental data and setup as well as comparison of the classification performance between the proposed method and the existing methods. Finally, Section V makes several concluding remarks.

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II. RELATED WORK

A. Gabor Filtering

A Gabor wavelet is a filter whose impulse response is defined by a sinusoidal wave multiplied by a Gaussian function. In the 2D spatial domain, a Gabor filter, including a real component and an imaginary term, can be represented as

\[ G_{a,b,\theta,\sigma,\gamma}(x,y) = \exp\left( -\frac{a^2 + \gamma^2}{2\sigma^2} \right) \exp\left( j \left( 2\pi a\theta + \gamma \right) \right) \]

where

\[ a' = a\cos\theta + b\sin\theta \]
\[ b' = -a\sin\theta + b\cos\theta. \]

Here, \( a \) and \( b \) denote the pixel positions, \( \delta \) represents the wavelength of the sinusoidal factor, \( \theta \) represents the orientation of the Gabor wavelet (e.g., \( \pi/8, \pi/4, \pi/2 \), etc.). Note that we only need to consider \( \theta \in [0^\circ, 180^\circ] \) since symmetry makes other directions redundant. \( \gamma \) is the phase offset and \( \gamma \) is the spatial aspect ratio (the default value is 0.5 [17, 18]) specifying the ellipticity of the support of the Gabor function. \( \psi = 0 \) and \( \psi = \pi/2 \) return the real and imaginary parts of the Gabor filter, respectively. Parameter \( \sigma \) is the standard deviation of the Gaussian function and it is determined by \( \delta \) and spatial frequency bandwidth \( \beta \) as

\[ \sigma = \frac{\delta}{\pi} \sqrt{\frac{\ln 2}{2 \beta^2}} \]

A visualization of Gabor filters for four orientations is presented in Fig. 2.

![Fig. 2. Two-dimensional Gabor kernels with four orientations, from left to right: 0°, π/4, π/2, and 3π/4.](image)

Typically, the Gabor texture feature image in a specific orientation is the magnitude part of convolving the input image with the Gabor function \( G(a,b) \).

B. CLBP

LBP [16] is a simple yet efficient operator to summarize local gray-level structure of an image. Given a center pixel \( t_c \), its neighboring pixels are equally spaced on a circle of radius \( r \) \((r > 0)\) with the center at \( t_c \). If the coordinates of \( t_c \) are \((0,0)\) and \( m \) neighbors \( \{t_i\}_{i=0}^{m-1} \) are considered, the coordinates of \( t_i \) are \((-r\sin(2\pi i/m), r\cos(2\pi i/m))\). The LBP is computed by thresholding the neighbors \( \{t_i\}_{i=0}^{m-1} \) with the center pixel \( t_c \) to generate an \( m \)-bit binary number. The resulting LBP for \( t_c \) can be expressed in decimal form as follows:

\[ LBP_{m,r}(t_c) = \sum_{i=0}^{m-1} s(t_c - t_i)2^i = \sum_{i=0}^{m-1} s(d_i)2^i, \]

where \( d_i = (t_c - t_i) \) is the difference between the center pixel and each neighbor, \( s(d_i) = 1 \) if \( d_i \geq 0 \) and \( s(d_i) = 0 \) if \( d_i < 0 \). The LBP only uses the sign information of \( d \), while ignoring the magnitude information. However, the sign and magnitude are complementary and they can be used to exactly reconstruct the difference \( d \). In the CLBP scheme, the image local differences are decomposed into two complementary components: the signs and magnitudes (absolute values of \( d_i \), i.e., \(|d_i|\)). Fig. 3 shows an example of the sign and magnitude components of the CLBP extracted from a sample block. Note that “0” is coded as “−1” in CLBP [see Fig. 3(c)]. Two operators, namely CLBP-Sign (CLBP_S) and CLBP-Magnitude (CLBP_M), are used to code these two components. CLBP_S is equivalent to the traditional LBP operator. The CLBP_M operator is defined as follows:

\[ CLBP_{M, m, r} = \sum_{i=0}^{m-1} p(|t_i|, c)2^i, \]

where \( c \) is a threshold that is set to the mean value of \(|d_i|\) from the whole image. The CLBP-Center part which codes the values of the center pixels is not used here.

<table>
<thead>
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<td>-1</td>
<td>-1</td>
<td>21</td>
<td>6</td>
<td>9</td>
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Fig. 3. (a) 3x3 sample block; (b) the local differences; (c) the sign component of CLBP; and (d) the magnitude component of CLBP.

C. Extreme Learning Machine (ELM)

ELM [22] is an efficient learning algorithm for single-hidden-layer feed-forward neural networks (SLFNs). The hidden node parameters in ELM are randomly generated leading to a much faster learning rate.

Let \( y = [y_1, y_2, ..., y_C] \in \mathbb{R}^C \) be the class to which a sample belongs, where \( y_i \in \{1, -1\} \) \((1 \leq k \leq C)\) and \( C \) is the number of classes. Given \( n \) training samples \( \{x_i, y_i\}_{i=1}^{n} \), where \( x_i \in \mathbb{R}^m \) and \( y_i \in \mathbb{R}^C \), the model of a single hidden layer neural network having \( L \) hidden nodes can be expressed as
\[
\sum_{j=1}^{L} \beta_j (w_j \cdot x_i + e_j) = y_i, \quad i = 1, \ldots, n.
\]

where \( h(\cdot) \) is a nonlinear activation function (e.g., Sigmoid function), \( \beta_j \in \mathbb{R}^c \) denotes the weight vector connecting the \( j \)th hidden node to the output nodes, \( w_j \in \mathbb{R}^d \) denotes the weight vector connecting the \( j \)th hidden node to the input nodes, and \( e_j \) is the bias of the \( j \)th hidden node. The above \( n \) equations can be written compactly as:

\[
H \beta = Y,
\]

where \( \beta = [\beta_1; \ldots; \beta_L] \in \mathbb{R}^{cL} \), \( Y = [y_1; \ldots; y_n] \in \mathbb{R}^{nc} \), and \( H \) is the hidden layer output matrix of the neural network expressed as

\[
H = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_n) \\ \end{bmatrix} = \begin{bmatrix} h(w_1, x_1 + e_1) & \ldots & h(w_L, x_1 + e_L) \\ \vdots & \ddots & \vdots \\ h(w_1, x_n + e_1) & \ldots & h(w_L, x_n + e_L) \end{bmatrix}_{L \times n}.
\]

\( h(x_i) = [h(w_1, x_i + e_1), \ldots, h(w_L, x_i + e_L)] \) is the output of the hidden nodes in response to the input \( x_i \). A least-squares solution \( \hat{\beta} \) of the linear system \( H \hat{\beta} = Y \) is found to be

\[
\hat{\beta} = H^+ Y,
\]

where \( H^+ \) is the Moore-Penrose generalized inverse of matrix \( H \).

As a result, the output function of the ELM classifier can be expressed as

\[
f_{L}(x_i) = h(x_i)\hat{\beta} = h(x_i)H^+ \left( \frac{1}{\rho} + HH^+ \right)^{-1} Y,
\]

where \( 1/\rho \) is a regularization term. A kernel matrix \( \Omega_{ELM} = h(x_i) \cdot h(x_i) = K(x_i, x_i) \) is considered if the feature mapping \( h(x_i) \) is unknown. Therefore, the output function of KELM is given by

\[
f_{L}(x_i) = \left( \begin{array}{c} K(x_i, x_1) \\ \vdots \\ K(x_i, x_n) \end{array} \right)^T \left( \frac{1}{\rho} + \Omega_{ELM} \right)^{-1} Y.
\]

The label of a test sample is assigned to the index of the output nodes with the largest value.

### III. PROPOSED IMAGE REPRESENTATION APPROACH

Inspired by the success of Gabor filters and LBP in computer vision applications, we propose an efficient image representation approach for land-use scene classification using Gabor-filtering-based CLBP. The Gabor filter belongs to a global operator while LBP is a local one. As a consequence, Gabor features and LBP features represent texture information from different perspectives.

An input land-use scene image is first convolved with the Gabor filters with different orientations to generate the Gabor-filtered images. The magnitudes of the Gabor-filtered images are used as the Gabor texture feature images. Fig. 4(b) - (e) are the Gabor feature images obtained by the Gabor filters with four orientations (\( \theta = 0, \theta = \pi/4, \theta = \pi/2 \), and \( \theta = 3\pi/4 \)). As we can see, the Gabor feature images reflect the global signal power in different orientations. In order to enhance the information in the Gabor feature images, we encode the Gabor feature images with the CLBP operator (i.e., CLBP_S and CLBP_M). Each Gabor feature image results in one CLBP_S coded image (equivalent to an LBP coded image) and one CLBP_M coded image.

Fig. 4 (a1) - (e1) show the CLBP_S coded images for the Gabor feature images and Fig. 4 (a2) - (e2) show the CLBP_M coded images for the Gabor feature images. It is obvious that the detailed local spatial texture features, such as edges, corners, and knots, are enhanced in the CLBP_S and CLBP_M coded images. Moreover, CLBP_S and CLBP_M coded images contain complementary texture information which motivates us to use CLBP in our image representation method to enhance the discriminative power. The CLBP operator is also applied to the input image. Histogram is computed from each CLBP_S and CLBP_M coded images. Finally, all the histograms are concatenated or stacked as a composite feature vector before it is fed into a KELM classifier. The overall framework of the proposed image representation approach (GCLBP) is illustrated in Fig. 1. Note that we use rotation invariant pattern in CLBP to achieve image rotation invariance.

### IV. EXPERIMENT

To evaluate the efficacy of our proposed image representation method for remote sensing land-use scene classification, we conduct experiments using two publicly available datasets. The classification performance of the proposed method is compared with the state-of-the-art performance reported in the literatures. In our experiments, the radial basis function (RBF) kernel was employed in KELM.

#### A. Experimental Data and Setup

The first dataset is the 21-class land-use dataset with ground truth labeling [3]. The dataset consists of images of 21 land-use classes selected from aerial orthomagery. Each class contains 100 images with sizes of 256x256 pixels. This is a challenging dataset due to a variety of spatial patterns in these 21 classes. Sample images of each land-use class are shown in Fig. 5. To facilitate a fair comparison, the same experimental setting reported in [3] was followed. Five-fold cross-validation is performed in which the dataset is randomly partitioned into five equal subsets. There are 20 images from each land-use class in a subset. Four subsets are used for training and the remaining subset is used for testing. The classification accuracy is the average over the five cross-validation evaluations.

The second dataset used in our experiments is the 19-class satellite scene dataset [23]. It consists of 19 classes of high-resolution...
satellite scenes collected from Google Earth (Google Inc.). There are 50 images with sizes of 600x600 pixels for each class. The images are extracted from large satellite images. An example of each class is shown in Fig. 6. The same experimental setup in [24] was used. We randomly select 30 images per class as training data and the remaining images as testing data. The experiment is repeated 10 times with different realizations of randomly selected training and testing images and classification accuracy is averaged over the 10 trails.

![Fig. 5. Examples from the 21-class land-use dataset: (1) agricultural, (2) airplane, (3) baseball diamond, (4) beach, (5) buildings, (6) chaparral, (7) dense residential, (8) forest, (9) freeway, (10) golf course, (11) harbor, (12) intersection, (13) medium density residential, (14) mobile home park, (15) overpass, (16) parking lot, (17) river, (18) runway, (19) sparse residential, (20) storage tanks, (21) tennis courts.](image)

![Fig. 6. Examples from the 19-class satellite scene dataset: (1) airport, (2) beach, (3) bridge, (4) commercial, (5) desert, (6) farmland, (7) football field, (8) forest, (9) industrial, (10) meadow, (11) mountain, (12) park, (13) parking, (14) pond, (15) port, (16) railway station, (17) residential, (18) river, (19) viaduct.](image)

B. Parameter Tuning

First of all, we study the Gabor filter parameters for land-use scene classification. According to (4), the parameters of Gabor filter with different $\delta$ and $bw$ are investigated. Four Gabor orientations ($\theta=0, \theta=\pi/4, \theta=\pi/2, \theta=3\pi/4$) are used. The parameters for the CLBP operator are set as: $m=10$ and $r=3$. For the 21-class land-use dataset, we randomly select four subsets for training and the remaining subset for testing. For the 19-class satellite scene dataset, 30 images per class are randomly selected for training and the remaining images for testing. Fig. 7 and 8 show the classification results for the two datasets, respectively. From the results, the optimal $\delta$ for the 21-class land-use dataset is $8$ and the optimal $bw$ is $4$. The optimal $\delta$ for the 19-class satellite scene dataset is $6$ and the optimal $bw$ is $2$. Therefore, we fix these parameters in our subsequent experiments. We further examine different choices of orientations for the Gabor filter. Two orientations include $[0, \pi/2]$, four orientations include $[0, \pi/4, \pi/2, 3\pi/4]$, six orientations include $[0, \pi/6, \pi/3, \pi/2, 2\pi/3, 5\pi/6]$ , and eight orientations include $[0, \pi/8, \pi/4, 3\pi/8, \pi/2, 5\pi/8, 3\pi/4, 7\pi/8]$ . Fig. 9 illustrates the classification performance of GCLBP with different orientations. Thus, four orientations include $[0, \pi/4, \pi/2, 3\pi/4]$ were chosen for the experiments.

Then, we assign appropriate values for the parameter set $(m, r)$ of the CLBP operator. The classification results with various CLBP parameter sets are listed in Tables I and II for the two datasets, respectively. Note that the dimensionality of the CLBP histogram features is dependent on the number of neighbors $(m)$. Therefore, larger $m$ will increase the feature dimensionality and computational complexity. In our experiments, we choose $(m, r)=(10, 3)$ for the 21-class land-use dataset and $(m, r)=(8, 3)$ for the 19-class satellite scene dataset in terms of classification accuracy and computational complexity, making the dimensions of the GCLBP features for the 21-class land-use dataset and the 19-class satellite scene dataset $1080$ and $360$, respectively. Furthermore, in all the experiments, the parameters for KELM (RBF kernel parameters) were chosen as the ones that maximized the training accuracy by means of a 5-fold cross-validation.

![Fig. 7. Classification accuracy (%) versus varying $\delta$ and $bw$ for the proposed GCLBP method for the 21-class land-use dataset.](image)

![Fig. 8. Classification accuracy (%) versus varying $\delta$ and $bw$ for the proposed GCLBP method for the 19-class satellite scene dataset.](image)
Fig. 9. Classification accuracy (%) versus different Gabor filter orientations for the proposed GCLBP.

<table>
<thead>
<tr>
<th>TABLE I. CLASSIFICATION ACCURACY (%) OF GCLBP WITH DIFFERENT PARAMETERS (m, r) OF THE CLBP OPERATOR ON THE 21-CLASS LAND-USE DATASET</th>
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<tbody>
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<tr>
<th>TABLE II. CLASSIFICATION ACCURACY (%) OF GCLBP WITH DIFFERENT PARAMETERS (m, r) OF THE CLBP OPERATOR ON THE 19-CLASS SATELLITE DATASET</th>
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<tbody>
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<td>m=10</td>
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<td>m=12</td>
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C. Comparison With the State of the Art

To evaluate the effectiveness of the proposed GCLBP representation method, a comparison of its performance with previously reported performance in the literatures was carried out on the 21-class land-use dataset under the same experimental setup (i.e., 80% of the images from each class are used as training, and the remaining images are used as testing). Since the images in the dataset are color images, we convert the images from the RGB color space to the YCbCr color space and use the Y component (luminance) to obtain the grayscale images. The GCLBP features are extracted from the grayscale images. We also implement the method which uses the CLBP operator on the input image only, denoted as CLBP. The comparison results are reported in Table III, which demonstrates that our method achieves superior classification performance over the other methods. Especially, our method achieved better performance than the popular BoW classification framework, which demonstrates the effectiveness of the proposed GCLBP approach for remote sensing land-use scene classification. Moreover, the proposed GCLBP has 4.5% improvement over the CLBP method since the multi-orientation Gabor filters captured the global texture information in different directions.

We also present the confusion matrix of our method for the 21-class land-use dataset in Fig. 10. For a compact representation, numbers along the x-axis and y-axis in this figure are used to indicate the land-use scene classes listed in Fig. 5. The diagonal elements of the matrix denote the mean class-specific classification accuracy (%).

![Confusion Matrix for 21-Class Land-Use Dataset](image)

Fig. 10. Confusion matrix of our method for the 21-class land-use dataset.

The comparison results for the 19-class satellite scene dataset are listed in Table IV. Although the multiple features fusion method described in [24] achieved higher classification accuracy than our method, three different sets of features including SIFT features, Local Ternary Pattern Histogram Fourier (LTP-HF) features, and color histogram features were used, thus leading to increased computational complexity. The confusion matrix of our method for the 19-class satellite scene dataset is shown in Fig. 11. The numbers along the x-axis and y-axis in this figure are used to indicate the land-use scene classes listed in Fig. 6.

<table>
<thead>
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<th>TABLE IV. COMPARISON OF CLASSIFICATION ACCURACY (MEAN±STD) ON THE 19-CLASS SATELLITE SCENE DATASET</th>
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<tr>
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<tr>
<td>Bag of colors [26]</td>
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<td>Tree of e-shapes [26]</td>
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<tr>
<td>Bag of SIFT [26]</td>
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<td>Multifeature concatenation [26]</td>
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<td>Local Ternary Pattern Histogram Fourier (LTP-HF) [24]</td>
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<td>Ours (GCLBP)</td>
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Fig. 11. Confusion matrix of our method for the 19-class satellite scene dataset.

The dimensionality of the GCLBP features can be fairly high, e.g., it is 1080 for the 21-class land-use dataset, if a large $m$ is used for the CLBP operator. To gain computational efficiency, dimensionality reduction techniques such as principal component analysis (PCA) [28] can be applied to the GCLBP features to reduce the dimensionality.

V. CONCLUSION

In this paper, an effective image representation method for remote sensing land-use scene classification was introduced. This representation method was derived from the Gabor filters and the completed local binary patterns (CLBP) operator. Gabor filters were employed to capture the global texture information from different directions of an input image, whereas CLBP histogram features were extracted from the Gabor feature images to enhance the texture information (e.g., edges and corners). The combination of a global operator (Gabor filters) and a local operator (CLBP) greatly enhanced the representation power of the spatial histogram. The experimental results on two datasets demonstrated that our proposed Gabor-filtering-based CLBP (GCLBP) representation method achieved superior classification performance over the existing methods for land-use scene classification.

REFERENCES


