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The Detection of Ancient Dwellings Based on Gabor Histogram Features

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Abstract

In order to detect objects which may have features of different sizes and directions from satellite map, some bounding boxes which surround these objects are obtained, and convolve with multi-parameters Gabor wavelet to get multi-direction Gabor amplitudes. By computing the average of these Gabor amplitudes, the local texture features of bounding box can obtain, which are direction-invariant. By using histogram algorithm, these Gabor averages are projected onto a given base (some interval divisions) to get different projection coefficients, which can be combined into a feature vector. The vector combines local texture features and global statistic features to representative the texture features of the object. Recognition and Classification of ancient dwellings can be realized by using GLVQ. Experiments show, the vector can representative those irregular and low resolution ancient objects that are based on Gabor direction-invariant local texture features and histogram global features. The GLVQ classifier based the vector of histogram has a good robust, and obtains better detecting effect.

Keywords: *Gabor, Histogram, ancient dwelling, object detection, GLVQ*

1. Introduction

Huizhou in China has abundant ancient architectural resources, especially ancient dwellings and villages which have a long history of thousands of years [1]. Due to the influences of geographical environments, and the less are damaged by the war and natural disasters, the ancient architectures are preserved more completely. Ancient dwellings and villages deduce human architectural history, cultural characteristics, and living habits *etc*. It has some certain significance those in different studies of the deduction of ancient dwellings and villages.

Today, applications based on satellite map are becoming more and more popular. The satellite map can be used in urban monitoring, geological exploration, field detection, economic crops, environmental monitoring, forest monitoring and other fields [2-3]. According to the features of RGB and shapes, we can extract the corresponding target images from satellite map to identify and locate them accurately. It will greatly promote the protection and visualization of ancient buildings based on the identification and monitoring of satellite map.

Now, we design methods to detect targets from a satellite map. First of all, according to the size of targets, we use a detection box with fixed size, search in the corresponding map to obtain test some boxes, and then extract their RGB features, shape features, texture or global statistical features, and match templates of target by using similarity calculating methods and classification algorithms, finally complete the detection and recognition of targets.

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Current researches on texture features include local feature extraction (such as local binary pattern LBP transform [4], wavelet transform [5], Gabor transform [6], and convolution transform [7]), global feature extraction (histogram [8], the gray level co-occurrence matrix (GLCM) [9], mean and variance and other statistical values [10]) and combining with local and global features of them.

Due to the position and direction of the target in the satellite map are irregular, many of the extracted target image direction (the angle between the long side and horizontal direction) are different, and so the extraction of the direction- invariant feature is particularly important. In this paper, the amplitude of the target image is obtained by using Gabor multi-direction wavelet, and the mean value is invariable in direction. Then the Gabor magnitudes are projected onto the specified bases of histogram and get the projection coefficients in each base component, and concatenated them into a feature vector. It is used to characterize the target image texture features. Following, we will give some of the commonly used methods of texture feature extraction.

2. Research Statuses

The local texture features of image are mostly to convolute the image with a given operator (adjacency pixels matrix or transform, such as Gabor, wavelet, LBP, Laplace, *etc*.), then get different convolution coefficients. Those operators are used to characterize the image characteristics of local changes [2-7]. In [2], the authors utilize D-S evidence theory to fuse the focus point, highlight lines and shadow areas, and realize the building targets detection in SAR images. In [3], the authors use hyper-spectral image to calculate the normalized vegetation index by adopting object-oriented feature extraction method to achieve large commercial housing extraction. In [7], the authors aim at the detection of the saliency target in SAR images, and come up with the adaptive detection algorithm based on the multi-scale self-convolution variance. In [10], the authors analyze the image fusion effects of the multi-scale transformation to the combination of HIS transform with Laplace Pyramid transform and the lifting wavelet transform.

The extraction methods of texture features of images mainly include gray level co-occurrence matrix (GLCM) [9], some convolution processing (such as Local Binary Pattern (LBP) [4, 8], Wavelet [5], Gabor transform [6]), PCA [20], *etc*. In [12], the authors utilize energy value, entropy value and inertia moment of GLCM to provide qualitative information on the framework of visual change, and use kernel principal component analysis (KPCA) to reduce dimensionality and GLVQ neural network to classify them. In [14], the authors use rotation-invariant features of Gabor to classify texture characteristics. In [15], the authors utilize the Gabor wavelet and HMM to study the fatigue state recognition algorithm of eyes, and identify the normal, fatigue and doubt by learning three learning states. In [17], the authors come up with flame image state recognition method of KPCA based on Log-Gabor wavelet and fractional order polynomial. In [20], the authors propose a face recognition algorithm based on the combination of KPCA and canonical correlation analysis. Those face images are divided into several sub-modules. Thus, local features are extracted, meanwhile, they use KPCA to extract global features, and use CCA algorithm to fuse these features.

In [21], the authors use linguistic terms for retrieving images based texture image features, which include Contrast, Cluster shade, Homogeneity, and Entropy of GLCM. In [22], the authors propose a multiple kernel learning (MKL) algorithm for heterogeneous feature fusion and variable selection. In [23], the authors classify insects by analyzing color histogram and GLCM of ROI (Region of Interest). In [24], the authors use feature selection based on mutual information and fusion of features extracted from intensity, shape, texture, and form three different spatial scales by using minimum redundancy, maximal relevance, normalized mutual information feature selection (NMIFS), and conditional mutual information feature selection (CMIFS). In [25], the authors use GLCM, SIFT and moment invariant features to extract features from natural images, using SVM classifier to retrieval image based on Euclidean distance.

The common classification algorithms include decision tree [27], support vector machine SVM [26,28] and learning vector quantization (LVQ) [29, 30], *etc*. In [27], the authors use J48 decision tree and supervised classification algorithm to specify land us information by constructing land use type conversion matrix. In [28], the authors use multi-scale and multi-orientation features of Gabor filter of face image to fuse the features of different scales in the same direction based on KPCA selection. In [29], the authors utilize Gabor filter to extract the local features of the target satellite, and then use the histogram method to obtain the global features. A feature vector is generated representative of the target image texture feature, and they use the modified LVQ algorithm to achieve target detection of ancient buildings.

3. Multi-Directions and Multi-Scales Features of Gabor

Gabor is a wavelet transform of windowing (mother wavelet is Gauss function). Gabor filter (kernel) in the direction μ and scale v is defined as follows:

$$\psi_{\mu,v}(z) = \frac{\left\|k_{\mu,v}\right\|^2}{\sigma^2} e^{-\left\|k_{\mu,v}\right\|^2 \left\|z\right\|^2 / 2\sigma^2} (e^{ik_{\mu,v}z} - e^{-\sigma^2/2}) \tag{1}$$

Here, $z=(x,y)$ is a pixel point. $\|\cdot\|$ represents a norm operator .The wavelet vector $k_{\mu,v}$ is defined as: $k_{\mu,v} = k_v e^{i\phi_\mu}$, $k_v = k_{\max} / f^v$, $\phi_\mu = \pi\mu / 8$, where the maximum frequency is $k_{\max}$ ..The distance between the kernels in the frequency domain is f . The ratio of width of Gaussian window with the wavelength of wavelet is determined by σ .

Convoluting the target image img with a given Gabor core $\psi_{\mu,v}$, and the filter coefficients $G_{\mu,v}(z) = img * \psi_{\mu,v}(z)$ are obtained, where $*$ denotes the convolution operator. The Gabor filter coefficients $G_{\mu,v}(z)$ can be written as follows:

$$G_{\mu,v}(z) = M_{\mu,v}(z) e^{i\theta_{\mu,v}(z)} \tag{2}$$

$M_{\mu,v}$ is the amplitude and $\theta_{\mu,v}$ is the phase. The amplitude information characterizes the image changes of local energy.

As a multi-scales and multi-orientation features extracting technology, Gabor filter produces high redundant features. Thus, in time and space domains, we use reducing sampling filter output to reduce the dimension of Gabor feature.

The target of the dwellings extracted from the satellite map is mostly direction-invariable, so it is suitable to adopt the multi-direction Gabor. Here, we take the set $\mu = \{1, 2..., 8\}$, that is $\phi_\mu = \{\pi/8, \pi/4, 3\pi/8, .., \pi\}$, and then to get the average value of the corresponding Gabor coefficient and obtain the invariance direction features.

In order to solve the target extraction of size inconsistency, we set three standard template sizes respectively as (16×15, 32 ×30, and 64×60). According to the size of the target, we use bilinear interpolation function to expand the size of the target to the corresponding closest to the template size. Then, the Gabor scale parameter is $v = \{1, 2, 3\}$, their mean value after the convolution can obtain the scale-invariance property.

So for an image ($M \times N$), after the Gabor kernel processing, their dimensions did not change (still is $M \times N$) and still need to further reduce the dimensionality. We put Gabor coefficients projection to a given intervals and count them, and obtain its projection on each interval and the statistical feature are extracted.

4. Region Histogram Based on Gabor Features

The histogram method can extract the global features of targets. If the whole target or the global histogram distribution is calculated directly, the error can be generated. So, we often divide the whole detection boxes into several mutually disjoint sub regions and solve the histogram of each sub region. The histograms of all sub regions are concatenated to obtain the histogram vector of the target which can better reflect the global features and local features.

In this paper, the standard size of targets is 32×30. We first extract detection box of targets, and convolute them with Gabor multi-directions and multi-scales to get direction-invariable and scale-invariable features. The whole image of target is divide into *K1*× *K2* (*e.g.* 4×6, denoted as *K*), and every sub-region is 64/*k1*×48/*k2* (*e.g.* 16×8). The divided regions are convolute with Gabor filters, and get their Gabor image, which can be denoted as *RGr (z)* (*r*=1...*K*) (such as *Rg1*, *RG2*.., and *RG24*), the corresponding histogram distribution is defined as follows:

$$h_{r,i} = \sum_{z} IE(RG_r(z) = i),\ i = 1,...m \tag{3}$$

$IE(A)$ is a judge function, if *A* is true, then its value is 1, otherwise 0. Variable *m* is the number of histogram columns, default as 256.

Each histogram column represents the times of corresponding gray-scale value or texture features which appear in the corresponding regions. Each sub region has *m* column corresponding to the histogram which connecting all *k* sub-region of the histogram in the values of vertical direction can get a feature vector, denote as follows:

$$v\_img = h_{r,i} = (h_{1,1}, h_{1,2}, .., h_{1,m}, h_{2,1}, h_{2,1}, ..., h_{2,m}, ... \\ , h_{k,1}, h_{k,1}, ..., h_{k,m}) \quad (r = 1..k, i = 1..m) \tag{4}$$

Wherein *k* is the divided number of each target, *m* is the number of histogram column of each sub-region.

Tof feature vector is used to characterize the local texture feature and the global statistical feature of the targets, then use classification algorithm based on the feature vector to classify all detection boxes, we can achieve the precise classification and recognition goal of ancient dwellings.

5. GLVQ Classification Algorithm Based on Feature Vector of Target

Learning Vector Quantization (LVQ) and its Generalized LVQ (GLVQ) are a kind of unsupervised learning strategy [17]. LVQ algorithm has two drawbacks: 1) There are many underutilized neurons; 2) information of input layer and the competitive layer between neurons are some redundant. GLVQ algorithm is an improved version for the input vector, and update weights corresponding to all competitive layer neurons.

Supposed that given *n* samples is characterized as a *n*-dimensional input vector space, denoted $X=\{X_1, X2... Xn\}$, where *i* represents the best match neuron, the loss function L_x is defined as follows:

$$L_x = L(X; W_1, W_2, ..., W_c) = \sum_{r=1}^{c} g_{ir} \left\| X - W_r \right\|^2 \tag{5}$$

Where *c* is the label of classifications, the updated weights of input layer and competitive layer is defined as follows:

$$g_{ir} = \begin{cases} 1, & r = i \\ 1/\sum_{k=1}^{c} \left\| X - W_k \right\|^2, & r \neq j \end{cases} \tag{6}$$

GLVQ learning algorithm aim at finding categories center W_r. Then the set W={W_r}such that the expected value Γ(W) of the loss function L_x is defined as (7), the gradient descent method can be used to solve optimization problems:

$$\Gamma(W)=\sum_{j=1}^{n}\sum_{r=1}^{c}g_{ir}\left\|X_j-W_r\right\|^2/n \tag{7}$$

The process of GLVQ learning algorithm is as follows:

1) Given a set of data $X=\{X_1, X_2... X_n\}\in R^p$, classes number c, loop times T and the permissible error ε> 0

2) Initialize the weight vectors W_0= {W_{10}, W_{20}... W_{c0}} and the initial learning step α

3) For each loop t = 1, 2... T, calculate $\alpha_t=\alpha_0(1-t/T)$, for k = 1, 2... n, find X_k satisfy (8):

$$\left\|X_k-W_i(t)\right\|=\min_{j\in\{1..c\}}\{\left\|X_k-W_j(t)\right\|\} \tag{8}$$

Then c right value vector {$Wr\ (t + 1)$} is updated according to formula (9):

$$W_i(t+1)=W_i(t)+\alpha_t[X_k-W_i(t)]\eta_i \tag{9}$$

Where $D=\sum_{r=1}^{c}\left\|X_k-W_r(t)\right\|^2$, then learning rate is defined as follows:

$$\eta_i=\begin{cases}(D^2-D+\left\|X_k-W_i(t)\right\|^2)/D^2, & i=r\\ \left\|X_k-W_i(t)\right\|^2/D^2, & i\neq r\end{cases} \tag{10}$$

4) Calculate the following formula:

$$\begin{aligned}E_t&=\left\|W(t+1)-W(t)\right\|_1=\sum_{r=1}^{c}\left\|W_r(t+1)-W_r(t)\right\|_1\\&=\sum_{k=1}^{n}\sum_{r=1}^{c}|\,w_{rk}(t+1)-w_{rk}(t)\,|\end{aligned} \tag{11}$$

5) If $E_t\le\varepsilon$ exit loop t, otherwise t = t + 1, continue to the next loop

6) Calculate the data set X about c categories center division U = [u_{ik}] c × n:

$$u_{ik}=\begin{cases}1, & \left\|X_k-W_i\right\|\le\left\|X_k-W_j\right\|, 1\le j\le c, j\neq i\\ 0, & 1\le j\le c, 1\le k\le n, otherwise\end{cases} \tag{12}$$

From 3), GLVQ weights of all neurons in the competitive layer have been updated (formula (9)), where the winner will have larger weights (equation (10)). For any input vector, all weights neurons are dynamically updated on the basis of learning, avoiding neuronal part problem of low utilization. At the same time, information between the input layer and competitive layer will be used to avoid the efficiency of results.

6. Experiments and Analysis

The geographical domains of Huangshan City on Google Maps are ranged from (30.517700, 117.203300) to (29.393030118.902450) of longitude and latitude. By using distance measurement tools of Google, the total size of Huangshan City is 120.9245 km x 182.7043 km. Based on the basic layer of Google map (zoom to 18 levels), the space resolution is 0.5376 meters (each pixel represented by a distance of 0.5376 meters), the scale is (its unit is meter) 1976:1.

According to the latitude and longitude of the villages, the satellite map of the corresponding villages can be obtained. Choosing Nan-Xi-Nan Village (Millennium ancient village, located in Tun-Xi District, Tun-Guang Town, Xin-An-Jiang East) as a test set of dwelling target detection and part of the map as in Figure1.

Figure 1. Part Map of Nan-Xi-Nan

The size of the detection boxes is set as 32×30. Each detection target is bean partition into 4 sub-regions and their multi-scales and multi-directions features of Gabor are extracted. We use histogram algorithm to generate a statistic distribution values, which are representative the features of each region. These values of all sub-regions of target are combined into a vector which are representative the features of target. Based on the comparing of all detection targets with standard templates of ancient dwelling samples, we use GLVQ classification algorithm to classify and recognize them. The recognition results as shown in Figure2.

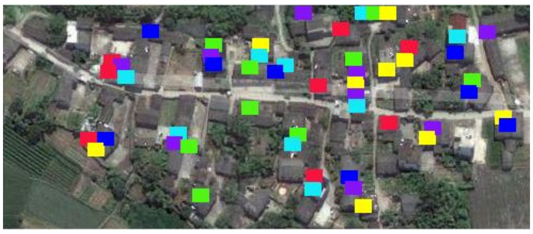

Figure 2. The Target Detection of Figure 1

After extracting the feature images of different Gabor features and histogram features, we can obtain their feature vector which characteristics their local features and global features. The classification is made to classify further their different types. The typical ancient dwellings are shown in Figure3.

Figure 3. Three Classes of Ancient Dwellings

Their feature vectors of Gabor histogram are shown in following. For the simple of expression, we only use 8 intervals.

The dimension of input layer of GLVQ classifier is $K \times M$, where K is the number of sub-regions of targets, and M is the bins of histogram. The dimension of output layer is 4 neurons corresponding to representative three types' dwellings and unrecognized targets. The dimension of competition layer can set as 10 neurons. The maximum number of loops is set to 5000. The minimum allowable error is 0.001, and the learning step is 0.5, *etc*.

At the same time, we use the LBP+HOG method [4] to extract the texture features of ancient dwellings, and make some partitions of targets. Using the same classification algorithm, with different partitions, the correct classification rate is shown in Figure4.

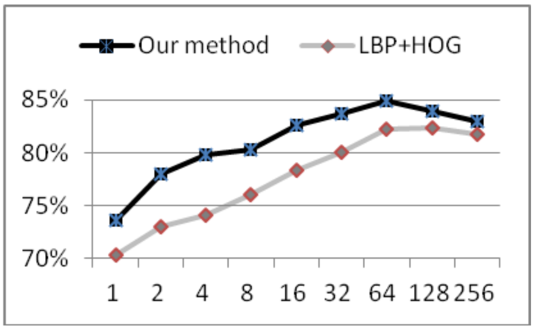

Figure 4. Correct Rate of Classification

In Figure 4, the classification correct rate of the Gabor histogram features is higher than LBP histogram feature. When the dimension of Gabor histogram increases, the classification correct rate is improved. The minimum interval of histogram is divided into 1. At this time, it is equally to directly use each pixel as a dimension, and the resolution is the lowest. However, when the dimension is too bigger, such as 256, the resolution will also fall, which belongs to over partitions.

We contrast our feature extraction methods respectively to paper [10], which views angular second moment, entropy, contrast and correlation of GLCM as their main features and the paper [23], which are based on the Gabor coefficients. Using the same classification algorithm, the dimensions of histogram is set to 64, and the target detection rate of ancient dwellings based on the three feature extraction methods are shown in in Table 1:

Table 1. The Classification Correct Rate with Different Methods

Method	classification rate
GLCM [10]	80.5%
Gabor [23]	81.3%
Our method	84.9%

7. Conclusions

Using the convolution operation between multi-parameter Gabor with the detection boxes, then the local feature of the targets can be obtained. Usually, in order to get the local features of targets, we can partition them into several sub-regions, and then use histogram method to statistic the Gabor coefficients of each sub-region. All histogram vectors are combined into a feature vector which can representative the local and global features of targets. Based these feature vectors of targets, GLVQ classification algorithm can achieve better classification results.

With the application of satellite images, the target of ancient dwellings can be easily detected from the village satellite map. According to the architectural features of ancient dwellings, it can effectively distinguish the ages of ancient dwellings and realize the classification of ancient dwellings. At the same time, we can use the same method to recognize the roads of village. We can generate the topology of the ancient village and get the historical deducting process of ancient villages, which has a certain practical application value for the protection of historical relics and cultural heritage.

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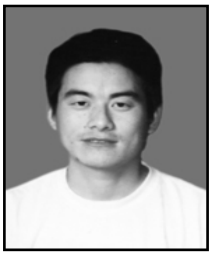

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