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Building Objects Extracting and Recognizing Methodology from Satellite Image based on the Feature Extraction Algorithms and Sliding Window Technique

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Abstract

Based on the gray features and shape features of objects, some satisfied objects are detected by using sliding window algorithm from satellite image. To further recognize their identification and classification, more texture features of them are needed to obtain to compare between them. GLCM (Gray-Level Co-occurrence Matrix) statistics are used to representative each partition of them. These PGLCM (Partition-GLCM) statistics can combine into a feature vector and those detected objects can be accurately recognized and classified by using GLVQ (Generalized Learning Vector Quantization) Neural Network algorithm. Experiments show when we choose those adapted parameters, such as the length and width of the window, and the threshold of difference of adjacent pixels, the extraction rate of building objects is up to 76.1%. Using the classification algorithm based on the feature vector generating by the statistics of PGLCM, the recognition rate of building is more than 88.9%.

Keywords: *GLCM, satellite image, window algorithm, GLVQ, building object*

1. Introduction

The object detection and recognition based on satellite image can make us obtain more comprehensive and abundant information, which will help us quickly position and recognize specified targets [1-3]. The applications of satellite objects include smart city, intelligent traffic, fine crop monitoring, precious species protection, field survey, ancient building recognition, and robot blind find, *et. al.* In China, there are many ancient dwellings including Beijing courtyard, Shan-xi cave, Hakka Earth, and Huizhou ancient dwelling, which have a thousand years of history. Because they distribute very wide areas, it is difficult to protect and monitor them in real time. For the Huizhou ancient dwellings, they reflect Huizhou mountain characteristics, geomantic ideas and regional gracefulness. They have a distinctive gray value distribution, patio structure and relatively fixed top graph area, which can separate and recognize from satellite image [4].

Now, we give the overall thoughts of objects extracting. Firstly, based on the longitude and latitude of the village, we can collect village satellite images of Huizhou area from 18-levels Google satellite Map by using the API function provided by Google Earth. Secondly, a preset sliding window will detect the village image to find possible dwelling objects based on the comparing to the given dwellings sample. In the comparing process, we design rectangle method, area method and GLCM texture method to find the true dwelling objects. Finally, diffident experiments will train the window algorithm to find the adapted parameters of each method.

The paper is expanded as following. Section 1 presents the research status of satellite image recognition and related technologies and problems. The window algorithm based

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on rectangle method, area method and GLCM texture method are given in Section 2. Section 3 is the experiments and analysis, and Section 4 is the conclusion and next work.

2. Research Statuses

Firstly, we give some research work on satellite image [1-6]. In [1], the authors proposed the pyramid model of parallel formation and use Hadoop cloud technology to establish the digital earth and achieve real time interactive roaming. In [2], the authors researched road extraction methods of remote sensing image, and then studied the automatic identification methods of remote sensing image of clouds in order to avoid clouds over the roads in the remote sensing image. In [3], the authors extract ship targets in remotely sensed images. They provided a comprehensive survey of recent developments on ship detection and recognition in optical remotely sensed imagery.

In the extracting process, the detecting window needs to compare with the given sample by using their shape features, gray features, texture features, et al. For texture features, there are local feature extracting method, global feature extracting method and fusion extracting method of local feature and global feature. Next, we first give the local features extracting methods.

Local features extracting methods usually filter an image with a given operator, such as Gabor [7-9], Fourier transforms [10], Hough transforms [11], self-feedback template [12], LBP (Local Binary Pattern) [13-14], Wavelet [15-16] and other filters [17-18], *etc.* In [7], the authors used Log-Gabor filter to detect the edge-oriented urban characteristics, and two Log-Gabor filter response images to suppress the noise and acquire a smooth spatial region. They used Otsu's method to extract residential areas of a set of smooth regions. In [10], the authors researched modulation transfer function (MTF) of the imaging system, and a series of processing technologies including sampling, curve fitting, Fourier transform and normalization were included. In [11], the authors used the Gabor wavelet transform to generate a texture feature matrix, and the mixture Gaussian model for the object is then trained. The rough extraction result of Hough transform counter clustering, incomplete lined in the image can be made up.

The global feature extracting methods include GLCM statistics [19-21], Histogram [22-24], and PCA [25-26], *etc.* In [19], the authors detected the forgeries in the image with the help of the GLCM Statistics and Bayesian classifier. In [20], the authors proposed a combustion working condition recognition method based on the GLVQ and extract GLCM statistics including energy, entropy and inertia. They used the kernel PCA method to deduct the input vector with high dimensionality so as to reduce the GLVQ target dimension and network scale greatly. In [22], the authors proposed a remote sensing image segmentation algorithm based on an improved 2D gradient histogram and minimum mean absolute deviation (MMAD) method, and extracted the global features as a 1-D histogram by diagonal projection. In [25], the paper present proposed methodology of global threshold technique, SIFT, PCA and SVM classify.

The fusion of local features and global features will become very popular [27-30]. In [27], the authors proposed the detection approaches based on structural feature description and query expansion, and the feature description combines both local and global information of objects. The image descriptor was constructed as a weighted frequency histogram of these SIFT descriptors, where the weights are determined by the spatial distribution of SIFT key points with respect to the image center. In [28], the edge-aware region growing and merging (EARGM) algorithm was developed for segmentation of SAR and optical data. Edge detection using a sobel filter was applied on SAR and optical data individually, and a majority voting approach was used to integrate all edge images. In [29], a wavelet based histogram of oriented gradients (WHOG) feature descriptors were proposed to represent shape information by storing local gradients in image.

The distance of these local or global features usually uses the computing mode of vector distance [30-33]. In [31], the authors suggest a linear time complexity method for computing a canonical form, using Euclidean distances between pairs of a small subset of vertices. This approach has comparable retrieval accuracy but lower time complexity than using global geodesic distances, allowing it to be used on higher resolution meshes. In [33], the authors located a dark circular object using two vectors including distance vectors and the other gradient vectors, the cross-correlation between these two vectors should be maximized at the center of a dark circle.

In the feature extracting process, we use the multi-partitions of a detection window to get its local feature, and use GLCM statistics to represent the global features of each partition. All the statistics of all partitions combine into a vector to represent the local features and global features of the detection window. Next, we'll give the sliding window detection process of buildings.

3. Building Extracting Algorithm based on Satellite Images

The extracting process mainly includes image preprocess and the fusion of window method, area method and Partition GLCM method. The mainly process is shown in Figure 1.

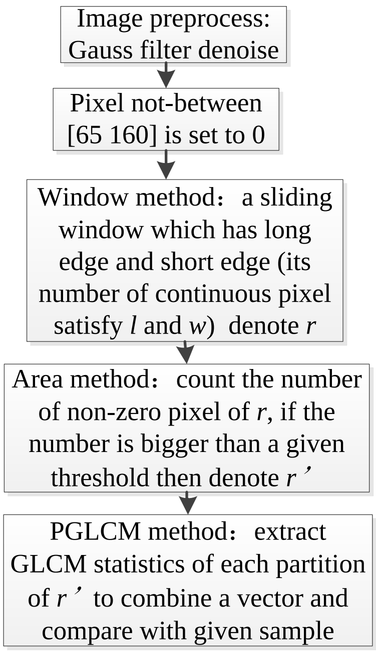

Figure 1. The Extracting Algorithm of Dwellings

The details of extracting algorithm are shown as following.

(1) Image preprocessing. The Gauss function is used to filter white noise of grayed images, that is $I(x,y) = rgb2gray(I(x,y) \otimes gauss(u,v,\sigma))$. *l*' and *w*' are pre-set length and width of sliding window. *l* and *w* are preset length and width of the dwelling. $l'=l\times1.2$ and $w'=w\times1.2$

(2) Window method. We design a sliding window of changeable size to judge whether there is an object. Here, we need to find long edge and vertical short edge of continuous pixels.

For a sliding window *r*, start from the first row to the last row, and for in each row, scan from the first column to the last column.

1 *r=1*;

for (*j=1, |Ii,j-Ii,j+1|<=m1, j<=l, j++*){//m1is the given threshold of adjacent pixel difference
m++; //count
if (*m==l*) //*l* is the given length
for (*i=1, |Ii+1,j0-Ii+2,j0|<=m1, i<=i+w, i++*){ //scan vertical of point *j0=j-h/2*
n++; //count
if (*n==w*){ //*w* is the given width
count0++; //denote it as *A(s, t)*
flag=1; //processed mark
}
}
}
r++; //
if *r>l'-l* then exit

(3) Area method： Count the number of not-zero pixels of *A(s, t)*

for (*s=a, s<=b; s++*) //*a* and *b* are the row' upper bound and lower bound of *A*
for (*t=c, t<=d; t++*) //*c* and *d* are the column' upper bound and lower bound of *A*
if (*As,t>0*)
count1++; //
if (*count1/s>= s0) //s=(b-a)*(d-c), s0* is preset threshold
count2++; //denote it as *B(s1,t1)*

(4) GLCM method. Partition each *B(s1,t1)* into several sub-region *ri (i=1..n)*.

for (*i=1, i<=n; i++*)
$f_i = (aut_i, ent_i, con_i, cs_i, im_i)$ //5-dimension features of each sub-region
$f = (f_1, f_2, ..., f_n)$ //vectors of all sub-regions combine into a vector

Compare f with the given samples, and judge whether it belong to the class of these samples. If the distance is less than a given threshold, B(s1,t1) is regarded as a dwelling object and is denoted as D(s1,t1). The detailed feature extracting and distance computing will introduce in Section 3.

(5) The length and width of detection object revise. For the obtained dwelling object D(s1,t1), based its long edge and short edge of having been found, if there are still non-zero pixels in their direction, their according size should add until its size is bigger the double of original size. When the size alters, the according rectangle will alter.

In the detection process, there are some thresholds such as length and width of sliding window, and adjacent pixel difference. Because these dwelling objects are irregular and their sizes are not same. Meanwhile, because of the shadow of light, aerial angle and irregular top graph, the pixels are not the same. We need to debug these parameters in the experiments.

(6) The dwelling object extracting result revise. Based on the dwelling object recognizing, we need to conduct field prospecting, and use GPS positing system to find the difference of sizes and positions of these dwellings in the village, finally we can revise their sizes and positions.

Because of the irregular of size, direction and pixels of dwellings, different dwelling reflect pixel matrixes of different dimensions or values. In order to realize accurate recognizing and classification of dwellings, the texture features need to extract and compare with the given dwelling samples. Next, we will introduce the partition process, GLCM statistics extracting method and the classification algorithm based on similarity measure of feature vectors.

4. GLCM Statistics Extracting and Classification Algorithm

(1) Partition process. An image can be averagely partitioned into several sub-regions by using regular row and column partition, such as 2×2, 3×3, *etc.* For different objects extracting process, the adapted partitions will debug in the experiments.

(2) GLCM statistics. Let a partition of the detection window is an $M \times N$ pixel matrix $I(M,N)$, its GLCM define as follows.

$$P(i,j,\theta,d) = \#(f(x_1,y_1,\theta,d) = i, f(x_2,y_2,\theta,d) = j \mid (x_1,y_1,\theta,d),(x_2,y_2,\theta,d) \in M \times N \tag{1}$$

Here, θ and d are any direction and distance of two pixels. θ usually can choose 0-degree, 45-degree and 90-degree, *etc.* d usually is a Integer, and it represents adjacent pixel values which distance is d. Function $\#(x)$ indicates the number of collection x. GLCM matrix represents the joint probability distribution of two pixels of θ distance and d distance, and it represents the local texture features of images.

GLCM generally usually has 17 statistics, whose correlations are quite different. For example, Energy and Entropy represent the same property of energy density of GLCM. Contrast and dissimilarity represent the same property of difference of values of GLCM. Cluster Shade and Cluster Significant character similar center clustering feature and their similarity are very high.

In the GLCM statistics choosing process, we try to choose those statistics with weak correlation or low similarity. Here, the five weak-correlation statistics are adopted to character each partition of objects, which include autocorrelation (*aut*), Entropy (*ent*), Contrast (*con*), Cluster Shade (*cs*), Information measure of correlation 2 (*im*) and their formula are shown in Formula (2)-(6).

$$aut = \sum_{i=1}^{n}\sum_{j=1}^{n} ijG(i,j) \tag{2}$$

$$ent = -\sum_{i=1}^{n}\sum_{j=1}^{n} G(i,j)\log G(i,j) \tag{3}$$

$$con = -\sum_{i=1}^{n}\sum_{j=1}^{n} (i-j)^2 G(i,j) \tag{4}$$

$$cs = \sum_{i=1}^{n}\sum_{j=1}^{n} (i+j-\mu_x-\mu_y)^3 G(i,j) \tag{5}$$

$$im = (1-\exp(-2(HXY_2 - HXY)))^{1/2} \tag{6}$$

Where n is the size of row and column of GLCM P, μ_x and μ_y are the mean of according row and column of GLCM. $\mu_x = \sum_i \sum_j i.G\ (i,j)$, $\mu_y = \sum_i \sum_j j.G\ (i,j)$, $G_x(i) = \sum_j G\ (i,j)$, $G_y(j) = \sum_i G\ (i,j)$ $HX = -\sum_i G_x(i)\log G_x(i)$, $HY = -\sum_j G_y(j)\log G_y(j)$, $HXY = -\sum_i \sum_j G(i,j)\log G(i,j)$, $HXY_2 = -\sum_i \sum_j G_x(i)G_y(j)\log(G_x(i)G_y(j))$.

(3) Feature vector generating

For each partition of the detection window, we use the five GLCM statistics $f_i = (aut, ent, con, cs, im)$ to present its texture features and all the vector of $r \times c$ partitions will combine into a vector with 5rc-dimensions, which can character the identification of the detection window object. For example, there are three class typical ancient dwellings with double-patios, single-patio and non-patio successively in Figure 2.

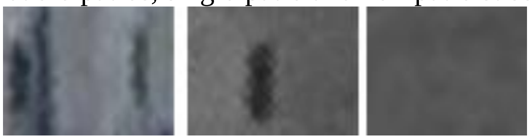

Figure 2. Three Classes Typical Ancient Dwelling

When the partition is 2×2, their 20-dimensions vector can be computed to obtain as follows.

Double-patios {27.7, 2.54, 0.43, -25.2, 0.92, 34.7, 2.68, 0.35, -35.6, 0.90, 31.4, 3.08, 0.67, -17.5, 0.92, 37.7, 2.70, 0.59, -37.7, 0.88}

Single-patio {44.7, 2.05, 0.31, -65.1, 0.87, 22.1, 2.29, 0.56, 3.04, 0.78, 43.7, 2.37, 0.43, -100.6, 0.91, 16.1, 2.54, 0.51, 4.49, 0.85}

Non-patio {18.9, 2.77, 0.36, 15.2, 0.94, 16.1, 2.67, 0.28, 17.9, 0.95, 26.2, 2.62, 0.39, -13.2, 0.91, 28.9, 2.58, 0.32, -12.9, 0.92}

For each dimension of the 5rc-dimensions vectors, there is large dispersion difference. We can use standard method to modify each dimension. The standard formula is shown in (7).

$$v_i^{'} = (v_i - \mu_i) / \sigma_i \, , i = 1..5rc \tag{7}$$

Where, m is the number of objects, $\mu_i = \sum_{l=1}^{m} v_i^l / m$ and $\sigma_i = \sum_{l=1}^{m} (v_i - \mu_i)^2 / m$

(4) Decision tree classification algorithm based vector distance

We use the binary decision tree to classify these detection objects. When the distances between detecting window with the given three classes typical samples exceed a pre-given threshold, we consider it not a dwelling object. According to the minimum distance principle, the detecting object belongs to the class, whose distance with the center of that class is smallest. The center vector of each class is representative by the mean vector of the given sample of the class. When a detecting object is classified into the class, the center vector will be updated by using weighted average method and the weight is becoming smaller as its distance with the center becoming large, such as Gauss Function weighted method. The classification algorithm is shown as follows.

```
for (i=1,i<4,i++)
  if (distance(test, ti)>d0){ //d0 is a given threshold
    test∈min(ti);  //classify test
    c=i;  //denote label
   }
else
  test is not a dwelling object;
end if
end for
```

For the given 3-classes typical dwelling samples and some detecting object, we can compute their feature vector by using partition and GLCM statistics. Therefore, all the objects can be compared by using their feature vector. When the detecting object is classified a certain class, the center vector of the class will update by using Gauss weighted method. A 3-layers classification tree can be constructed and the first layer can represents the true dwellings or not, and the second layer can represent different distinction dwellings such as double-patios, single-patio and non-patio. These different dwellings represent chronicle characteristics of the ancient dwellings.

5. Experiment Design and Analysis

Our experiment environments are listed as following. CPU is Inter(R) Core i5 3.10GHZ, RAM is 4GB size, Operation System is Win7-64, Programming Language is Matlab2013a, and the satellite data is 18-levels Google satellite Map.

The longitude and latitude of Huangshan city in the Google Map is from (30.517700, 117.203300) to (29.393030, 118.902450). The spatial resolution of 18-levels is 0.5376 meter. Plotting scale is 1976:1. We choose Nanxinan village to extract ancient dwelling. The village has thousands of history, which has 1100 population and 572 dwellings.

In the sliding window detecting process, we design different length and width parameters to extracting dwelling object. The threshold of difference of adjacent pixels is set to 3 and the area method threshold of similarity is set to 70%. Our methods compares with the rectangle extracting method in the paper [5] and the extracting results are shown in Figure 3.

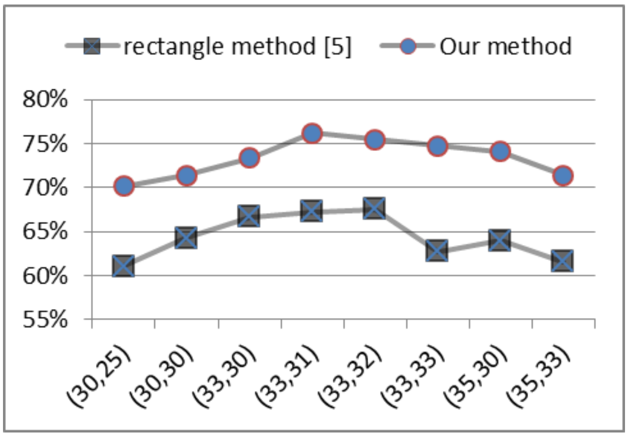

Figure 3. Extracting Result of Different Parameters

When the parameters of length and width are set to big numbers, some small dwelling will be omitted. On the contrary, if length and width are set to small numbers, some big dwelling may be consider two or multi-dwellings. As can be seen from Figure 3, the length and width is set to (33, 31), the extracting rate is highest, the recognizing result is shown in Figure 4.

Figure 4. Recognizing Result in (33, 31) Parameters

These extracting errors usually are reduced by those wrong recognizing areas, which include some withered grass, hillside and dry lakes, *etc.* We can use partition technology and GLCM statistics method to extract their further local and global texture features. Different partitions of objects will reduce different extracting efforts of local features. When we use these methods to compare with the rectangle method which mainly accords with 11-dimensions feature vector of gray value, the results are shown in Figure 5.

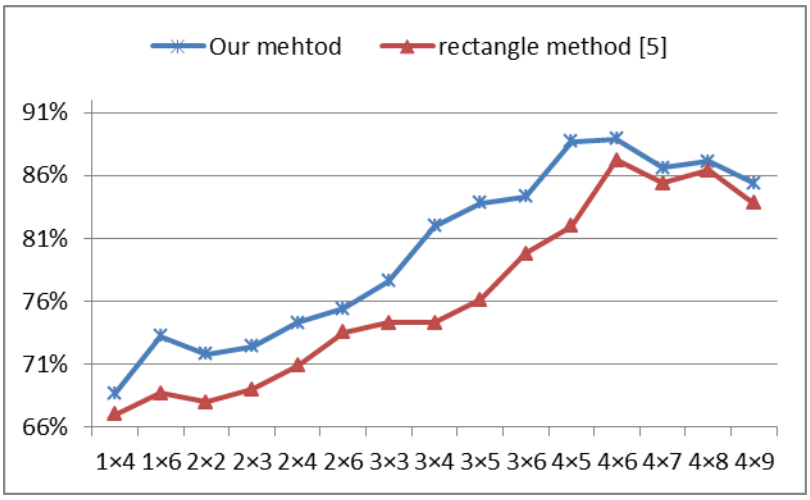

Figure 5. Recognition Rates of Different Partitions

In above Figure 5, we can see that the recognition rate adds with the size of partitions. The reason is that the local feature can character more accurate according to the addition of the partitions. When the partitions are smaller, the recognition rate is below because of under-partition, such as 1×4 and 2×2. The best partition is 4×6, and the according recognition rate is above 88.9%. When the partitions are bigger, such as 4×7, 4×8, the recognition rates drop because of over- partition.

We compare our method to other two methods to verify our methods effectiveness. In [5], the authors use rectangle method and four 11-dimensions vector of gray values to detect house from satellite. In [15], the authors use area method and five GLCM statistics including correction, contrast, energy, entropy and homogeneity to extract objects. The results are shown in Table 1.

Table 1. Recognizing Rate of Different Methods

Method	Correct Rate
Rectangle method [5]	75.6%
Area method [15]	81.8%
Our method	88.9%

6. Conclusions

In the texture feature process, we mainly combine the partition image idea with GLCM global statistics. Because of the irregular satellite objects, the partition efforts will change and possess those situations of below-partitions and over-partition, and those detection objects need to be standard into same size and direction.

Based on the recognition of dwellings and roads of villages, the topology of them can obtain. According to the chronology features of ancient dwellings and ancient villages, we can model and simulate the developments and evolutions process of ancients and villages. The ancient dwellings and villages of different chronology can be virtual reproduction and we can research their architecture history, living habits and cultural heritage of people.

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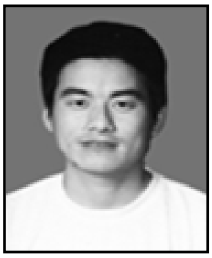

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