Airport Detection on Optical Satellite Images Using Machine Learning Method

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Abstract: A method for detecting airport on remote sensing images based on machine learning method is proposed. First, Canny operator and Hough Transform are applied on optical satellite images of Google Earth to detect edge and extract straight line. Using the character that airport regions are more likely to have parallel lines, the total length of parallel lines that are close enough are accumulated, and the region which has the longest total length of parallel lines is selected as an airport region. And the feature vectors of airports and non-airports are calculated respectively in the accumulating process. Finally, an airport detection model is learned from the features vectors with support vector machine learning method. The proposed method has been tested on remote sensing images and compared with other methods. The result shows that the method can generate a considerably high detection rate and low false alarm rate on optical satellite images in a reasonable time.

Key Words: Canny operator; Hough transform; SVM; Airport detection

1 INTRODUCTION

Airport detection on optical satellite images is essential targets for both military and civil applications. But it remains a difficult work due to the complex target structures with highly changing surroundings in airport region. Normally, airports are often located in urban or suburban regions in which roads, rivers and buildings sometimes share similar features with nearby airport. And optical satellite images usually have a large number of pixels; therefore algorithms that have high time complexity are not acceptable. Previous work on this field can be roughly classified into two groups: The first kind is based on edge detection and the other is built on image segmentation [1-3]. Since runways are the most remarkable feature in an airport, the former one put its focus on the runway, applies edge detection on the image and then uses Hough transform for extracting straight lines to locate airports [4]. In the meantime, the latter makes use of image segmentation to extract regions of interest (ROIs). These methods are feasible mainly based on the fact that airport regions are textural different from regions that contains buildings, roads or rivers. There are many typical works about the two groups. A linear time algorithm was proposed in 1986 by Burns [5]. An approach controls false alarms successfully in airport detection was discussed by Desolneux [6]. And Line segment detector (LSD) for finding line segments, and validates line segments discovered using a contrario model was proposed by R. Von Gioi [7]. These features retracted from images often represent targets infinite aspects. Machine learning approaches have been well known for their superior objects classification and shown great potentials to generate efficient image features by finding proper representations through uncertain experience and limited expert knowledge[8]. Thus, it could open up prospects for superior image classification and detection by using machine learning methods compared with the previous approaches.

An airport detection approach from optical satellite images using SVM with Canny edge detector and Hough transform for airport detection is proposed in the paper. By using Canny edge detector and Hough transform, features of airport in optical satellite images were abstract. Then features were learned and trained by SVM to obtain the model of airport detection that could classify the features of airport or non-airport two kinds.

2 THE MODEL OF AIRPORT DETECTION

The proposed method is formed by mainly four steps to reduce unnecessary computation cost and false alarm rate of airport detection. The first step is RGB image to gray scal, the second is fragmenting grayscale images with Canny edge operator, the third is extracting straight lines to locate airports with Hough transform, and the last is learning and training on the extracted lines of airports with SVM to obtain model. All the tested optical satellite images were collected from Google Earth with the resolution of 8m × 8m and the size of about 3000×3000.

2.1 Image gray processing

In RGB model, color represents a gray color where the value of R=G=B is called gray value. Therefore, each pixel of gray image only needs one byte to store the gray value (also called intensity value, brightness value)[9].The gray scale range is 0-255.

According to the importance and other indicators, the three components of R, G and B are weighted by different weights[10]. Since the human eye is the most sensitive to green and the least sensitive to blue, a reasonable gray level image can be obtained by weighted average of three

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components of RGB. By this way, it could reduce the original amount of image data and computation cost in the subsequent processing. The formula is as follows:

$$f(i,j)=0.30R(i,j)+0.59G(i,j)+0.11B(i,j) \quad (1)$$

By using the method of gray weighted mean, the accuracy of measurement can reach sub-pixel region.

2.2 Canny edge detector

The main purpose of image edge processing is to highlight the details in the image or to enhance the blurred details, so that the structure outline of the scene can be clearly displayed. The principle is that the edge and contour of the image are located in the place where the gray level changes, so the realization of edge detection is actually based on differential action [11].

Canny defines a target set for an edge detection algorithm and uses the optimization method to realize edge detection. He also proved that the first derivative of the Gaussian function is an effective approximation of the edge detection filter. Specific steps of the algorithm are:

Step 1. Use Gaussian filter to smooth the image.

Step 2. Calculate the amplitude and direction of the image gradient.

Step 3. The gradient amplitude is suppressed by non-maximum value.

Where the Gaussian function is as following:

$$G(x)=\frac{1}{\sqrt{2\pi}\delta}e^{-\frac{x^2}{2\delta^2}} \quad (2)$$

By this way, more important edge points in an image were extracted.

2.3 Hough transform for line detection

Hough transform is an effective method for detecting and locating straight lines and analytic curves. It transforms curves and lines of a given shape in the original image into a point in the parameter space. That is, all the points on a given curve or straight line are concentrated on a point in the parameter space to form a peak value, so that the detection problem on a given line or curve in the original image can be taken as the problem of seeking the peak value in the parameter space [12].

There is a corresponding relationship between collinear point in the digital image space and concurrent line in the parameter space. As long as the point of the concurrent curve in the parameter space is found, the straight line in the image space can be determined. In our experiment, the Hough transform maps every point in the image space to the Hoff parameter space, and then sets an accumulator at every point in the Hoff parameter space. Whenever a point in the parameter space satisfies a straight line, add 1 to the value of the accumulator. Here we set a threshold, and the function of this threshold is when the accumulator's value accumulates, we determine that the point corresponds to a straight line. If the maximum value is greater than the threshold, the line exists and is discarded if smaller. The parameters corresponding to the line can be determined by detecting the value of the in the parameter space, that is, the parameter of maximum value of concurrent lines in accumulator. Then the line can be detected out [13].The threshold of detection line segment has been set in the algorithm and can only be recognized as a line segment if it is greater than the threshold. Compared with the traditional methods of airport detection, Hough transform is only used to obtain features of airports and non-airports, not to detect them directly.

2.4 SVM learning algorithm in airport detection

Using SVM algorithm on the basis of edge extraction and line detection to learn airport detection model is introduced. Using the learning ability of SVM algorithm, the features of remote sensing images could be classified into non-airport and airport for recognition. It could effectively eliminate the problem of confusion features between the two group images. Here LIBSVM [14]is used, which is an integrated software for support vector classification, (C-SVC, nu-SVC), regression (epsilon-SVR, nu-SVR) and distribution estimation (one-class SVM). It supports multi-class classification. The classification function provided by LIBSVM is mainly used in this method. A classification task usually involves separating data into training and testing sets. Each instance in the training set contains one target value and several attributes. The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data given only the test data attributes.

Given a training set of instance-label pairs $(x_i, y_i), i=1,\ldots,l$ where $x_i \in R^N$ and $y_i \in \{1,-1\}^l$, the SVM requires the solution of the following optimization problem:

$$\min_{w,b,\varepsilon} \frac{1}{2}w^T w + C\sum\nolimits_{i=1}^{l}\varepsilon_i \quad (3)$$

Subject to

$$y_i(w^T\phi(x_i)+b)\geq 1+\varepsilon_i, \varepsilon_i \geq 0 \quad (4)$$

Here training vector x_i is mapped into a higher (maybe infinite) dimensional space by the function φ. SVM finds a linear separating hyper-plane with the maximal margin in this higher dimensional space. C> 0 is the penalty parameter of the error term. Furthermore, $K(x_i, y_i) \equiv \varphi(x_i)^T\varphi(x_j)$ is called the kernel function. When the sample dataset is linear, the kernel function f(x) can be represented as:

$$f(x)=(\omega,x)+b, \omega\in X^N, b\in R^N \quad (5)$$

The nonlinear regression function estimation decision function is:

$$f(x)=\sum\nolimits_{i=1}^{l}(a_i-a_i^{(*)})\phi(x_i,x)+b, b\in R^N \quad (6)$$

Using K-fold method, we divide the original data set into N parts: K as training set, and the other N-K as test set. Then we use training set to train and test set to verify. Interchange training sets and test sets for K iterations, and taking the error of K iterations as the prediction error of the total data, the results show that the recognition accuracy is higher than only using edge extraction and line detection under the same conditions. It can be seen that xi in the algorithm only represents the feature quantity extracted from the Hough transform, and y_i represents -1 and 1 we defined, and the two variables constitute the virtual points of the classification. The idea of the classification has something in common with the spatial transformation in the Hough transform. But in the Hough transform, the pair of xi and y_i denotes a real point in a position.

3 EXPERIMENT

The proposed method is tested with Google Earth images. The dataset contains most images of China civil airports, including many famous international airports. A total of 40 airport images and 40 non-airport images with 1:1 scale are collected. The computing platform used in the experiment consists of CPU of Intel i7-4790K and GPU of NVIDIA GTX780 with 3-GB video memory. The algorithm is compiled in MATLAB R2016a.In our experiment, the data set is used for SVM training, and then other airport and non-airport images are checked and predicted.

3.1 Effect of edge extraction with Canny operator

In order to illustrate the effect of the proposed Canny operator, it is compared with other methods used in detecting airport on remote sensing images. The result is shown in figure 1.

(a) Gray Image

（b）Results of Canny edge detection

(c) Results of Roberts operator detection

(d) Results of Sobel operator detection

(e) Results of Prewitt operator detection

(f) Results of Laplace operator detection

Fig. 1. Effect comparison of different edge detection operator

From the above comparison chart, using Canny operator to process the final image could detect clear edges of airport, a lot of details were to be marked. It is conducive to extract the features of airport and non airport image at later, and can greatly reduce the false alarm rate and improve the forecast accuracy. If other edge extraction methods were selected, some details in remote sensing images are easy to be overlooked. Features of the airport and non-airport were easy to be confused, and it is not conducive to airport images detection. Thus Canny operator for edge detection was adopted in our research.

3.2 Feature extraction using Hough transform

We choose Hough transform was picked up to extract features of images for its biggest advantage of strong anti-noise ability, not sensitive to the noise in the remote sensing image, and can detect the straight line or the certain regular curve under the condition of low signal to noise ratio.

The most important step in the realization of Hough transform is to set up accumulator in the parameter space and accumulate the accumulator according to the points of the original image space. Finally, a total numerical matrix of the parameter space accumulator is obtained. Then the maximum values of the matrix are taken to obtain the corresponding lines, and the parallel judgment of lines can be carried out.

In this algorithm, 80 sample images were used to process with Hough transform, and the matrix quantity representing the longest line segments in each image is selected as the feature quantity. This is based on the fact that the amount of the longest segment matrix of the airport image must be different from that of the non-airport image because of the existence of the airport runway. Tables 1 and 2 are feature quantities of airport images and non-airport images, respectively, as shown below.

Table 1 Extracted lines of 40 Airport

No	Start point of extracted (x,y)	End point of extracted (x,y)
1	(82,215)	(192,123)
2	(63,124)	(147,145)
3	(2,219)	(195,137)
4	(58,140)	(254,200)
5	(105,59)	(191,197)
6	(208,34)	(179,85)
7	(5,202)	(227,41)
8	(135,86)	(84,141)
9	(55,75)	(104,91)
10	(26,7)	(131,75)
11	(147,2)	(255,115)
12	(16,160)	(207,237)
13	(196,42)	(169,182)
14	(38,202)	(157,103)
15	(99,2)	(255,142)
16	(130,38)	(186,221)
17	(105,55)	(255,135)
18	(252,3)	(165,255)
19	(69,222)	(140,191)
20	(121,138)	(122,192)
21	(17,57)	(205,244)
22	(4,5)	(59,41)
23	(83,255)	(255,135)
24	(130,47)	(75,114)
25	(13,254)	(255,146)
26	(208,61)	(149,143)
27	(32,142)	(218,2)
28	(116,116)	(181,201)
29	(200,2)	(99,191)
30	(2,115)	(94,242)
31	(92,17)	(247,65)
32	(183,2)	(183,84)
33	(174,108)	(67,255)
34	(99,84)	(175,68)
35	(147,56)	(165,235)
36	(238,123)	(124,250)
37	(2,220)	(209,53)
38	(90,105)	(193,215)
39	(191,21)	(159,207)
40	(43,97)	(128,213)

Table 2 Extracted lines of 40 non-airport

No	Start point of extracted (x,y)	End point of extracted (x,y)
1	(162,154)	(214,130)
2	(12,38)	(25,84)
3	(244,62)	(247,121)
4	(211,199)	(232,220)
5	(150,141)	(156,172)
6	(34,46)	(66,78)
7	(168,122)	(189,102)
8	(50,137)	(73,177)
9	(83,179)	(118,191)
10	(80,139)	(92,158)
11	(42,121)	(86,149)
12	(44,226)	(88,224)
13	(83,98)	(112,123)
14	(175,178)	(207,177)
15	(74,144)	(39,180)
16	(32,17)	(62,32)
17	(107,147)	(165,193)

No	Start point of extracted (x,y)	End point of extracted (x,y)
18	(71,116)	(88,140)
19	(79,98)	(55,123)
20	(210,171)	(233,194)
21	(158,2)	(57,184)
22	(140,66)	(127,172)
23	(255,15)	(130,194)
24	(2,112)	(191,24)
25	(234,9)	(199,176)
26	(253,21)	(35,255)
27	(34,128)	(121,253)
28	(72,2)	(103,255)
29	(130,27)	(67,208)
30	(38,130)	(169,3)
31	(2,181)	(255,127)
32	(2,82)	(163,255)
33	(158,95)	(249,70)
34	(254,2)	(174,223)
35	(175,2)	(184,75)
36	(31,209)	(122,127)
37	(2,76)	(90,163)
38	(4,3)	(253,220)
39	(236,168)	(155,255)
40	(180,15)	(174,94)

where (x,y) is the first five peaks found in the Hough matrix that are greater than 0.3 times the maximum value, that is, the polar coordinates of the five points indicated in the Hough transform diagram. Fig. 2. shows the complete processing of the experiment.

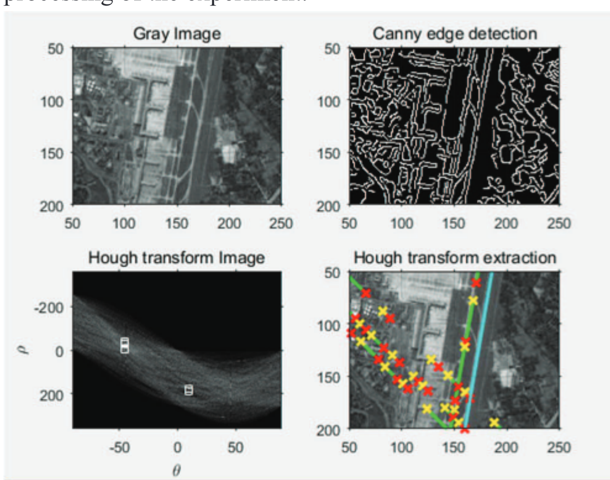

Fig. 2. The process of airport detection

3.3 The SVM machine learning algorithm

The software LibSVM of SVM is used to implement the SVM machine learning algorithm, which is developed by Chang and Lin to building model, training sample and predicting result [15].The first work needed to do is to build the SVM training set based on the 40 airport image features and 40 non-airport image features extracted previously. At the same time, predicted output of the image was defined in SVM, i.e., airport image is 1, non-airport image is -1. After the data set is fully trained and learned in the SVM algorithm, other non-sample images from the Google Earth were selected for experiment, and the prediction accuracy was observed. As shown in figure 2, it could be found that the proposed algorithm has less false alarm rate and higher accuracy than other similar algorithms under the same conditions.

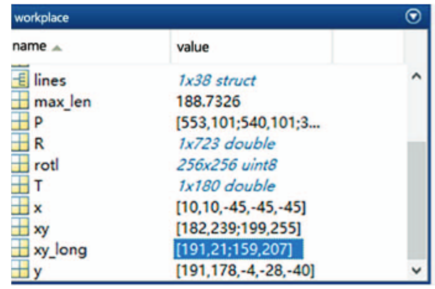

Fig.3 The verify of the proposed method with an airport image

Where xy represents the endpoint coordinates of the initial segment in the Cartesian coordinate system and xy_long represents the endpoint coordinates of the longest line segments in the Cartesian coordinate system, and the prediction result of the image is it is an airport. 20 untrained images from Google Earth satellite data are selected randomly, that is, as test set images, and test the accuracy of the proposed method. Two of the airport images are detected error, and the accuracy of this method is to be 90.

4 CONCLUSION

This paper presents an airport detection method SVM algorithm combined with Canny edge detection and Hough transform line detection. Because the efficiency of Canny edge detection and Hough transform line detection, SVM algorithm can greatly reduce the cost of learning. Based on transform and learning limited satellite samples, LibSVM algorithm can accurately identify the airport. The experimental results show that under the same conditions, compared with other similar methods, we proposed the method of airport detection has higher accuracy. We can find that the recognition ability of this method for non-airport images is much higher than that for airport images, which is due to the complexity of the regional environment of the airport, which is easy to be confused with the non-airport areas, resulting in the prediction errors. We can further improve the accuracy of this method by enhancing the learning of airport images in training set and eliminating obfuscation.

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