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RESEARCH ARTICLE

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One airport detection method based on support vector machine

Abstract This paper proposes a novel airport detection method, which integrates the texture features and shape features of the airport. Eight texture features, such as the mean of the region, the deviation of the region, the smoothness of the region, the skewness of a histogram, the uniformity of the region, the randomness of the region, the mean of the gradient image and the deviation of the gradient image, are used to represent the features of the region. In this method, first the long lines are detected and the regions where the lines locate are segmented. Second, support vector machine (SVM) based on Gaussian kernel is used as a classifier which discriminates the runway from other candidate regions. Experimental results show that the error rate of the proposed method is lower than those of conventional methods which detect airport only by the shape feature of runway. The detection accuracy of the proposed method is nearly ten times higher than that of Liu's methods, and the method has favorable speed for a real-time system.

Keywords airport detection, support vector machine, line detection

1 Introduction

Airport detection is one of the important application fields in target detection and pattern recognition. Also it is useful in navigation and military fields. Automatic airport detection is attracting more and more attention. Nonetheless, there are two difficulties in automatic airport detection. First, as airports are located in urban or suburban areas where the terrain is complex, it is often difficult to distinguish them from the natural background. Second, there are many objects similar to airport runways, such as roads and shorelines, which may result in confounding with airport runways. Previous works [1−6] are based on the analysis of the runway shape, and try to detect the lines in order to determine the airport runways. However, their methods can hardly distinguish the airport runways from roads and shorelines, because there are plenty of lines in the image such as the edges of buildings, roads, shorelines, and so on. The work in Ref. [7] first analyzed the texture of the airport runways, and used kernel matching pursuits to train a classifier in order to extract the region of interest (ROI), and then determined the airport runway by line analysis. However, if the regions of interest are wrongly classified, the airport would not be correctly detected. Moreover, the method requires the image to shot in certain range when estimating the width and length of the runway.

2 Long line detection

The runway is the salient character of the airport, which appears to be a long straight line with two parallel edges. The long lines are detected first. It is an important step to select edge detector, because images have noises and some are blurred and some have low contrast. Canny edge detector is adopted, which has the advantages [8] as follows. First, its error rate is low and it can detect most of the edges. Second, it can locate the edge with high accuracy. And third the edge precision is one pixel. Thereafter, two results can be got by Canny operator, one of which is the gradient magnitude denoted by M and the other is the gradient direction denoted by θ.

The result of the line detection is shown in Fig. 1. The binary image is cluttered, and it needs preprocessing before Hough transformation. The binary image can be cleaned by removing the pixels lying on short lines and little curves. The preprocessing step can reduce Hough transformation's computation and detect the meaningful lines. Figure 1(b) shows that the two lines detected by Hough transform are

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wrong without the preprocessing step. In the binary image, the edges are white and the background should be black. Two stacks are used to save the searched edges pixels. One is for the searched white pixels denoted by S^A, and the other is for the pixels having the same gradient direction denoted by S^B. An array flag is used to sign the searched pixel, that is, if one white pixel is searched, its flag value is set to 0. Otherwise, it is set to 1. The searching algorithm is presented as follows.

Step 1 For the white pixel P, if there are white pixels in its 8-neighbor area, then the white pixels are saved in the stack S^A and their flag values are set to 0.

Step 2 For the pixels in stack S^A, determine if

$$\left|\theta(S^A(l)) - \theta(P)\right| < \sigma \tag{1}$$

where $S^A(l)$ is the lth element saving the location of the lth pixel. Then save the pixels that satisfy Eq. (1) in stack S^B and in the mean while the last saved pixels in S^B are set as the point P, and then loop to Steps 1 and 2.

Step 3 If no points in the neighbor of P satisfy Eq. (1), count the points in S^B as N. If N is smaller than the setting threshold, the value of the points in S^B is set to 0.

Step 4 Extract the main long lines and remove the cluttered curves and short lines, as shown in Fig. 1(c), and set $\sigma = 0.25$ rad, $N = 20$.

After the preprocessing step, the white pixels are lined in some order in the binary image. Then Hough transformation is used to link the white pixels with a meaningful line.

A point (x, y) and all the lines that pass through it are considered. The line can be represented normally as $x\cos\theta + y\sin\theta = \rho$. The $\rho\theta$ parameter space is formed and subdivided into so-called accumulator cells. If the points are lying on the same line, each of them will put a toll in the same accumulator cell. It is challenging to find a meaningful set of distinct peaks in Hough transform. Because of the quantization in space of the digital image as well as the fact that edges in typical images are not perfectly straight, Hough transform peaks tend to lie in more than one accumulator cell. To overcome the problem, the highest value is found in the accumulator cell and its location is recorded, then the cells in the immediate neighborhood of the maximum just found are suppressed. Once a set of candidate peaks has been identified, it remains to be determined if there are line segments associated with those peaks, as well as where they start and end. The region which has any of the n longest lines will be segmented in sequence. The result by Hough transformation on the preprocessed image is shown in Fig. 1(d), and there are two lone lines.

The direction of the line as well as the line can be detected by Hough transformation. In general, there lie two parallel runways in the airport, so the parallel lines can be determined by the directions of the detected lines. However, the two runways are seldom detected because of the illumination and the viewing perspective. Moreover, one runway is relatively easier to detect. Therefore, it is not suitable to take parallel lines or the longest line as the only criteria to judge the airport condition.

3 Classification of texture feature by support vector machine (SVM)

From the analysis above, it is difficult to determine the airport runway only by the geometric shape of it. In this section, the texture features of runways are analyzed. Because runways turn into lines in the image and their gray values are relative consistent which are different from the background. Thus, the texture feature in the gray image is considered and the well performed SVM is utilized as the classifier.

3.1 Texture features of airport runways

The eight features are taken as the feature vector which is as follows.

The first feature is the mean of ROI.

$$m = \sum_{i=1}^{L-1} z_i p(z_i)$$

where z_i denotes the gray values, and $p(z_i)$ is the frequency of the gray value in the histogram of the sample region, and L is the number of the gray level.

The second: deviation

$$\sigma^2 = \sum_{i=1}^{L-1} (z_i - m)^2 p(z_i)\,.$$

The third: smoothness

$$R = 1 - 1/(1 + \sigma^2).$$

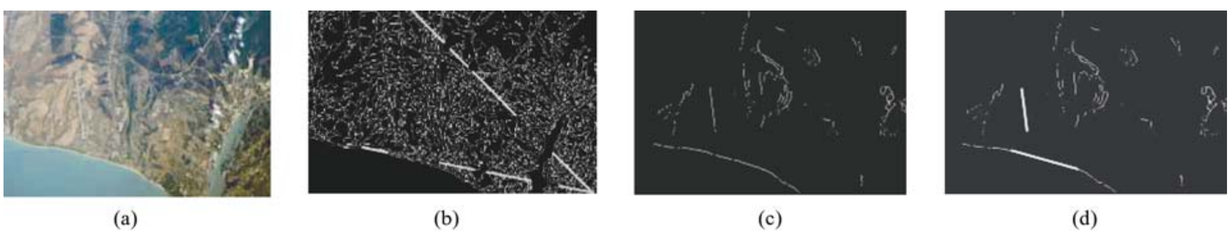

Fig. 1 Line detection results
(a) The original image; (b) the result after Hough transformation; (c) preprocessing result after edge detection; (d) the result after Hough transform on the image of (c)

The fourth: three order moment that stands for the slope of the histogram

$$\mu_3(z)=\sum_{i=1}^{L-1}(z_i-m)^3 p(z_i)\,.$$

The fifth: consistency of ROI

$$U=\sum_{i=0}^{L-1}p^2(z_i)\,.$$

The sixth: the random

$$e=-\sum_{i=0}^{L-1}p(z_i)\log_2 p(z_i)\cdot$$

The seventh: the gradient mean of ROI

$$M_1=\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}g(x,y)$$

where $g(x, y)$ is the binary image after the edges detection.

The eighth feature is the gradient deviation

$$M_2=\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}(g(x,y)-M_1)^2\,.$$

The eight features are taken as the texture feature vector, $\boldsymbol{x}'=[m, \sigma^2, R, \mu_3, U, e, M_1, M_2]$. The first six features are the gray level features of the runway regions which have consistent gray level and the last two are gradient features of the runway.

3.2 Discriminate airport runways by SVM

Support vector machine proposed by Vapnik [9] is an efficient method for pattern recognition. It discovers the classification function to separate the two classes. And it is a convex quadratic optimization problem that has the optimal solution [10]. In this paper, the following classical kernel functions are considered, one is the polynomial kernel function $K(\boldsymbol{x}, \boldsymbol{x}_i)=[\langle \boldsymbol{x}, \boldsymbol{x}_i\rangle+\beta]^d$, and the other is Gaussian kernel function $K(\boldsymbol{x},\boldsymbol{x}_i)=\mathrm{e}^{-\|\boldsymbol{x}-\boldsymbol{x}_i\|^2/(2\delta^2)}$, where δ is a parameter.

One hundred images were collected as airport images set, which include the aerial optical images and images from ground. And 59 images were selected for training. In the training set, 151 positive sub-images which contain airport runways, and 122 negative sub-images which do not include airport runways but buildings, bridges, roads, vegetation, etc. were sampled.

In order to show that the proposed feature vector is prior to the common features such as the geometric invariant moment, and texture statistic features [11] which are based on the gray level histogram, polynomial kernel SVM and Gaussian kernel SVM [12] are used respectively on the three feature vectors of the training images and the results are shown in Table 1. It can be found that Gaussian kernel SVM on the proposed features has higher performance of classification, so in this experiment it is adopted and the parameter δ is set to 2.

4 Experimental results

The proposed algorithm is shown in Fig. 2. The algorithm was tested by 100 images collected in MATLAB6.5. The airport is determined by the shape of runways combined with texture features. First, parallel lines are used as the criteria. If the parallel ones are detected, the algorithm signs the airport runways. Otherwise, the algorithm applies SVM to ROI and determines the airport.

Experimental results show that the proposed algorithm can detect airport runways exactly in over 70 images. Some of the results are shown in Fig. 3. The algorithm can eliminate the interference of lines, such as shorelines, roads and so on to a large degree. Compared with the algorithm in Ref. [7], the proposed algorithm can successfully detect more airport runways by ten times, and the computing time is similar to that in Ref. [7]. Figure 4 shows that the algorithm can detect airport runways correctly while the algorithm in Ref. [7] indicates that there are two lines, one of which is right and the other is wrong. In the collected images, there are only several images that the algorithm in Ref. [7] can detect exactly, but the proposed algorithm did fail, and one example is shown in Fig. 5. The reason why the algorithm wrongly detected runways or neglected airport runways was also investigated.

Table 1 Comparison between two SVMs on three kinds of features

		Gaussian kernel					Polynomial kernel			
		$\delta=0.5$	$\delta=1$	$\delta=2$	$\delta=5$	$\delta=10$	$p=2$	$p=3$	$p=4$	$p=10$
s	The margin/10^{-6}	1	1	1	1	1	1	1	1	1
	The ratio of the support vector in the training vectors /%	92.4	94.2	95.3	96.4	97.5	93.5	93.1	92.7	91.6
t	The margin/10^{-6}	1	1	1	1	1	1	1	1	1
	The ratio of the support vector in the training vectors /%	96.0	95.6	96.7	97.1	97.1	94.2	95.6	96.0	94.2
c	The margin /10^{-3}	94.995	54.307	11.938	0.038	0.002	0.000	0.000	0.000	0.000
	The ratio of the support vector in the training vectors /%	98.9	87.3	61.8	46.2	57.8	100	100	100	100

Note: s denotes the geometric invariant moment, t denotes texture statistic features, c denotes the proposed features.

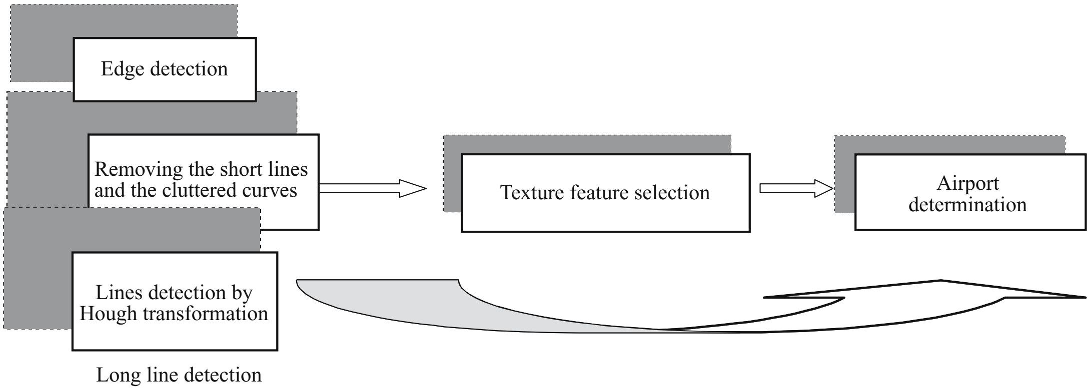

Fig. 2 Block diagram of airport detection

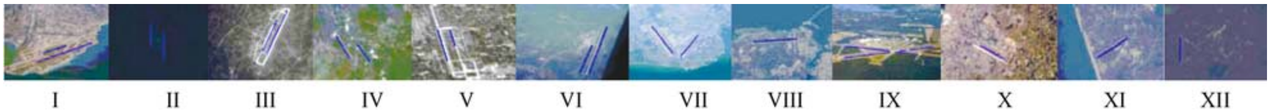

Fig. 3 Results obtained by the algorithm proposed in this paper
The detected results by parallel lines (I–VI); the results detected by SVM (VII–XII)

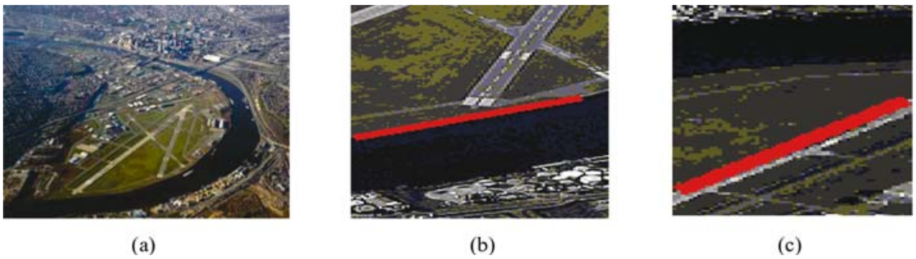

Fig. 4 Results of the two algorithms
(a) The original aerial airport image; (b) the wrong result by algorithm in Ref. [7]; (c) the correct result by the algorithm in this paper

Fig. 5 Results obtained from algorithm in Ref. [7]
(a) The original aerial airport image; (b) the correct result by the algorithm in Ref. [7]

First, the short lines which may be runways could have possibly been wrongly removed due to Step 2. The second is that the roads or the shorelines are incorrectly classified as runways, due to small training set used in this paper.

5 Conclusion

In this paper, an approach is proposed to detect the airport which not only analyzes the shape but also considers the texture features. The approach adopts support vector machine as the classification function. The algorithm first utilizes Canny operator to detect edges, then removes the short lines and curves, assembles the points to a meaningful line by Hough transform, and selects the regions of interest via the longest lines, and finally discriminates runways according to two rules. First come parallel lines and otherwise, by SVM. Experimental results demonstrate that the algorithm can detect most of the airport in the image set. It also shows its superiority compared with the algorithm mentioned in

Ref. [7] as well as other algorithms which use shape feature as the airport feature only.

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