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Detection Algorithm of Airport Runway in Remote Sensing Images

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Abstract

This article describes a rapid detection method of the airport runway for remote sensing images. The specific algorithm implementation steps are: Firstly, we use the Otsu's method to separate the runway from the images. Then we use the fractional differential gradient operator, which has good anti-noise performance and effective edge extraction ability, to extract the edge information of image, and use automatic threshold to distinguish the edge of runway and other objects. Finally, we use the Hough algorithm to calculate the runway. This detection method of the airport runway, which greatly reduces the data operation and greatly enhances the computing speed, has advantage of good test results and fast speed. This paper shows that, as the study of fractional differential, the application of fractional calculus in a wider area will be successful.

Keywords*: edge detection, OTSU, fractional differential operator, Hough transform*

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1. Introduction

Target detection in remote sensing image, the airport is a typical linear target. Airports are important military targets, in order to paralyze airport, the runway needs to be damaged continuous. There are some literatures about remote-sensing image detection and identification of airport runway in domestic and foreign [1-3]. In main features of the runway, the most obvious feature is a straight line, so the runway target detection problem turns into how to detect straight lines in the image. Generally Hough transform was used to detect airport runway. The main advantage of the Hough transform is not sensitive to noise, better able to handle partial occlusion in the image and covering other issues. However, because it is a type of exhaustive search, so its computational complexity and space complexity is very high [4, 5], which can not meet the requirements of real-time systems. Over the years a large number of researchers conducted a lot of study [6, 7], proposed various algorithms to significantly increase Hough operation speed. However, these algorithms are mostly application-specific.

There are three main issues of runway detection: Firstly, different remote sensing images with different brightness and contrast, runway is easy to be confused with other targets, which makes more difficult to separate of the runway from the background. Secondly, noise intensity of the airport runway is relatively large in the remote sensing images, making the accurate extraction of the edges of objects in the image becomes more difficult. Finally, Hough transform calculation, decided by its characteristics, is too slow. For large-scale remote sensing images is the computing process takes a long time, it is difficult to meet real-time remote sensing image target detection requirements. To solve these problems, this paper presents an improved airport runway detection algorithm. Firstly, we use Otsu's method (OTSU) to separate airport runway area from the images. Then we use the fractional differential gradient operator to extract image edge information, and use automatic threshold to extract edge, which significantly reduces the need to deal with image information. Finally, we use Hough calculation to extract the runway.

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2. Algorithm and Implementation

2.1. OSTU Threshold Segmentation Algorithm

Airport runway detection in the remote sensing image, we first deal with the image segmentation. Typically, different remote sensing images have different brightness, contrast and resolution, and also accompanied by high noise, which makes it difficult to automatic segmentation of the airport runway. These often make the area containing the runway can not be successfully extracted, or together with other objectives. Although there are many image segmentation methods [8], but they are powerless for runway recognition in remote sensing images. For example, iterative threshold segmentation, mathematical morphology segmentation. Therefore, we propose algorithms for remote sensing image using OTSU threshold segmentation algorithm, which makes the brightness and contrast of the runway relative to the background has been significantly enhanced.

OTSU algorithm was proposed by Japanese scholars Otsu in 1979 [9]. We use OTSU algorithm to extract the interesting region, which contains the runway. The method is defined as:

$$f(x,y)=\begin{cases}\text{s(x,y)} & \text{if} \quad \text{s(x,y)} \geq T \\ 0 & \text{Otherwise}\end{cases} \tag{1}$$

Where s(x, y) is the original image, f(x, y) is the segmented image, T is the threshold which divides source image pixels into two categories, and makes the between-class variance to maximum. It is determined by:

$$T=t \mid \delta_B(t)=\max\{\delta_B(k)\}, t\in k, k=0,1,2...255 \tag{2}$$

Where $\delta_B(k)$ is the between-class variance, given by:

$$\delta_B(k)=\omega_0(k)(\mu_0(k)-\mu_r(k))^2+\omega_1(k)(\mu_1(k)-\mu_r(k))^2 \tag{3}$$

$$\mu_r(k)=\sum_{i=1}^{L} iP(i)=\omega_0(k)\mu_0(k)+\omega_1(k)\mu_1(k) \tag{4}$$

$$\begin{cases}\mu_0(k)=\sum_{i=1}^{k}\dfrac{iP(i)}{\omega_0} \\ \mu_1(k)=\sum_{i=k+1}^{L}\dfrac{iP(i)}{\omega_1}\end{cases} \tag{5}$$

$$\begin{cases}\omega_0(k)=\sum_{i=1}^{k}P(i) \\ \omega_1(k)=\sum_{i=k+1}^{L}P(i)\end{cases} \tag{6}$$

$$p(i)=\frac{n(i)}{N} \tag{7}$$

Where L is the number of gray levels; *n(i))* is the sum of i-th pixel gray level; N is the total number of pixels the image; *p(i)* is the probability of gray level i; ω_0 andω_1 are the probability of the first class (for example: region of interest ROI) and the second category (for example: background); μ_0,μ_1,μ_r are the means of first, second and image respectively; δ_r is the image variance. OTSU advantage is that it is an optimal algorithm to distinguish between two types, which can easily obtain the regions of interesting (ROI) from the image. But it does not apply to many different targets, because in the final analysis it is only a single threshold segmentation method.

2.2. Using Fractional Differential Gradient Operator to Extract Edge

Edges of the object are the important features of target detection and identification, which is an important clue to visual perception. The edge of the target is gray-scale changes in the image, gray-scale changes have many forms, and the most basic form is the idealized model. The ideal edge is a set of connected pixels, which is generated on idealized model, each pixel is on a gray-scale vertical jumped step. In practice, the multiplicative noise blurs the contrast of adjacent areas in remote sensing images, that making changes in adjacent areas to flatten, there appears a transition zone at the edge areas, there no longer is a single pixel edge of ideal condition, it is difficult to determine the exact location of the edge. Remote sensing image background is more uniform and contains higher noise, the classical gradient-based edge detection algorithm is very sensitive to noise, so that classical edge detection methods are not suitable for the remote sensing images. To solve this problem, we use fractional differential gradient operator to extract edge of image. Fractional differential filter can be deduced from the integer-order differentiation filter [10, 11]. Fractional differential finite impulse (FIR) filter transfer function as follows:

$$D^v(z) = \left(\frac{1-z^{-1}}{T}\right)^v \tag{8}$$

Referencing the binomial series expansion $(1+x)^v = 1 + vx + \sum_{k=2}^{\infty} \frac{v(v-1)\cdots(v-k+1)}{k!} x^k$, and using $-z^{-1}$ instead of x , the Equation (8) can be written as:

$$D^v(z) = \frac{1}{T^v}\left(1 - vz^{-1} + \sum_{i=2}^{\infty} \frac{v(v-1)\cdots(v-i+1)}{i!}(-z^{-1})^{-i}\right) = \frac{1}{T^v}\sum_{i=0}^{\infty}(-1)^i \frac{\Gamma(v+1)}{\Gamma(i+1)\Gamma(v-i+1)} z^{-i} \tag{9}$$

Where: T is sampling period, z is the displacement operator and $\Gamma(\cdot)$ is the Gamma function. According to the limited impact of fractional differential (FIR) filter transfer function, selecting the suitable N , obtained approximate first-order backward finite difference formula.

$$D^v(z) = \left(\frac{1-z^{-1}}{T}\right)^v \approx \frac{1}{T^v}\sum_{i=0}^{N}(-1)^i \frac{\Gamma(v+1)}{\Gamma(i+1)\Gamma(v-i+1)} z^{-i} \tag{10}$$

It can get a signal differential equation:

$$\frac{d^v f(t)}{dt^v} \approx f(t) + (-v)f(t-1) + \frac{v(v-1)}{2} f(t-2) + \cdots + (-1)^n \frac{\Gamma(v+1)}{n!\Gamma(v-n+1)} f(t-n) \tag{11}$$

For digital images, based on the signal difference equation, fractional differential gradient formula can be obtained in different directions.

Horizontal direction:

$$D^v_{XL\leftrightarrow XR} = D^v_{XL} - D^v_{XR} = a_1 I(x-1,y) - a_1 I(x+1,y) + \cdots + a_n I(x-n,y) - a_n I(x+n,y) \tag{12}$$

Vertical direction:

$$D^v_{YU\leftrightarrow YD} = D^v_{YU} - D^v_{YD} = a_1 I(x,y-1) - a_1 I(x,y+1) + \cdots + a_n I(x,y-n) - a_n I(x,y+n) \tag{13}$$

135° direction:

$$D^v_{LU\leftrightarrow RD} = D^v_{LU} - D^v_{RD} = a_1 I(x-1,y-1) - a_1 I(x+1,y+1) + \cdots + a_n I(x-n,y-n) - a_n I(x+n,y+n) \tag{14}$$

45° direction:

$$D^v_{RU\leftrightarrow LD} = D^v_{RU} - D^v_{LD} = a_1 I(x+1, y-1) - a_1 I(x-1, y+1) + \cdots + a_n I(x+n, y-n) - a_n I(x-n, y+n) \quad (15)$$

Where $a_1 = -v$, $a_2 = \frac{v(v-1)}{2}$, $a_3 = \frac{-v(v-1)(v-2)}{6}$, $a_4 = \frac{v(v-1)(v-2)(v-3)}{24}$,…, $a_n = (-1)^n \frac{\Gamma(v+1)}{n!\Gamma(v-n+1)}$

Selecting the previous items n, the four directions of the gradient of fractional differential mask can be achieved by the truncated. To not make filter errors too large, we choose the previous three items of fractional order difference definition to construct the following 5×5 different directions fractional differential gradient mask.

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0	0	0	0	0
0	0	0	0	0
$(v^2-v)/2$	-v	0	v	$(v-v^2)/2$
0	0	0	0	0
0	0	0	0	0

(a) Horizontal direction

0	0	$(v^2-v)/2$	0	0
0	0	-v	0	0
0	0	0	0	0
0	0	v	0	0
0	0	$(v-v^2)/2$	0	0

(b) Vertical direction

$(v^2-v)/2$	0	0	0	0
0	-v	0	0	0
0	0	0	0	0
0	0	0	v	0
0	0	0	0	$(v-v^2)/2$

(c) 135° direction

0	0	0	0	$(v^2-v)/2$
0	0	0	-v	0
0	0	0	0	0
0	v	0	0	0
$(v-v^2)/2$	0	0	0	0

(d) 45° direction

Figure 1. 5×5 Different Directions Fractional Differential Gradient Mask

Referring the first derivative Sobel gradient operator and highlighting the role of the central row and column mask by weighted, we can construct the Tiansi fractional differential gradient mask as follow:

$(v^2-v)/2$	-v	0	v	$(v-v^2)/2$
(v^2-v)	-2v	0	2v	$(v-v^2)$
$3(v^2-v)/2$	-3v	0	3v	$3(v-v^2)/2$
(v^2-v)	-2v	0	2v	$(v-v^2)$
$(v^2-v)/2$	-v	0	v	$(v-v^2)/2$

(a) X direction fractional differential gradient mask

$(v^2-v)/2$	(v^2-v)	$3(v^2-v)/2$	(v^2-v)	$(v^2-v)/2$
-v	-2v	-3v	-2v	-v
0	0	0	0	0
v	2v	3v	2v	v
$(v-v^2)/2$	$(v-v^2)$	$3(v-v^2)/2$	$(v-v^2)$	$(v-v^2)/2$

(b) Y direction fractional differential gradient mask

Figure 2. Tiansi Fractional Differential Gradient Mask

Fractional differential operator realization and a detailed description of the anti-noise performance, see the article [12]. Remote sensing image contains the airport runway, of course, which also includes some other goals, such as buildings, streets, noise and so on. Plus, the length, width and structure of airport runway are different in remote sensing images. If the linear matching, Hough transform is directly applied to the image, each pixel needs to be detected the directions and angles. As a result, the required time is too long, and some non-linear objectives have been detected. Therefore, we use automatic threshold to extract image edge information. After the automatic threshold operation, the output is a binary image, which can reduce computation time and increase accuracy of detection of the airport runway. Comparing to the traditional methods, the directions and angles of the each pixel can be reduced effectively in binary image. Computing time will also be greatly reduced. Meanwhile, those non-straight edge and noise will not be false detected.

Automatic threshold is defined as:

$$b(x,y)=\begin{cases}1 & \text{if} \quad g(x,y)\geq\beta \\ 0 & \text{Otherwise}\end{cases} \tag{16}$$

Where *b(x,y)* is the output image, which is after automatic threshold operation. Note that, the definition of automatic threshold segmentation is under the assumption that the brightness of the target is greater than the background brightness. If on the opposite case, the operator Symbol ≥ should change to ≤.Threshold β is automatically calculated from the source image *f(x,y)* and low-pass filter *m(x,y)*.

2.3. Using Hough Calculation to Extract the Airport Runway

Hough transform was proposed by Paul Hough in 1962 [13]. Hough transform was originally defined as:

$$b=-ax+y \tag{17}$$

Where x and y is 2-dimensional space coordinates of a point set. For example, in two-dimensional images, a and b are respectively the slope and intercept of a straight line parameters. Thus, for each point (x,y), this set of parameters {(a,b)} can be obtained by Equation (17). If there is a group of coordinates {(x,y)} in the same line, they must have the same parameters (a,b). Hough transform is actually created an accumulator of these points. Searching local maxima of the accumulator, If the maximum value is approximately equal to the number of points, which indicates these points in the same line, otherwise not in the same line. Mapping at the local maximum of the parameters (a,b) is the set of points of a straight line slope and intercept. However, due to features of slope and intercept, parameters (a,b) may be infinite. This creates accumulator becomes impossible. Therefore, Hough transform is defined as:

$$\rho=x\cos\theta+y\sin\theta \tag{18}$$

Where ρ is the straight distance which is form the origin point to the line, and θ is the angle which is from the origin point to perpendicular line of the line. In this definition, ρ and θ are limited, ρ is from 0 to the image diagonal length; θ from 0 ° to 360 °

In Hough transform, there are three values need to accumulate, respectively, , x, y, θ (orρ). Obviously, the calculation is usually very complicated and slow. To solve this problem, we use the Hough transform which based on directional mask. Defined as:

$$A(\rho,\theta)=\begin{cases}\sum 1 \quad \text{if} \quad \theta\neq flag \quad \text{and} \\ \qquad\qquad O_m(x,y)-\Delta\theta\leq\theta\leq O_m(x,y)+\Delta\theta \\ \qquad\qquad \rho=x\cos(\theta)+y\sin(\theta) \\ 0 \quad \text{Otherwise}\end{cases} \tag{19}$$

Where A(ρ, θ)is the accumulator of□ρ andθ , Om (x, y) is the directional mask. Δθ is the angle of an acceptable offset, ∑1 indicates plus one.

Be noted that in the traditional Hough transform, the angle θ range is 0°-360°. Hough transform of an image, the origin point is set to the upper left point or lower left point, the angle range is -90°-+180°. But the directional mask angle range is -90° - +90°, therefore, the directional mask angle needs to be converted to a Hough transform angle. There directional mask angle is $O_m(x, y)$,, after converted Hough transform angle range is $O_m'(x, y)$, the conversion formula is as follows:

$$O_m'(x,y) = \begin{cases} O_m(x,y) + 180^\circ & \text{if} \quad O_m(x,y) < 0 \quad \text{and} \quad \delta(x,y) > 0 \\ O_m(x,y) & \text{Otherwise} \end{cases} \tag{20}$$

$$\delta(x,y) = \begin{cases} -x\tan(O_m(x,y) + 90^\circ) + y & \text{if} \quad O_m(x,y) < 0 \\ \text{skip} & \text{Otherwise} \end{cases} \tag{21}$$

Accordingly, Equation (19) is replaced by:

$$A(\rho,\theta) = \begin{cases} \sum 1 \quad \text{if} \quad \theta \neq flag \quad \text{and} \\ \qquad O_m'(x,y) - \Delta\theta \leq \theta \leq O_m'(x,y) + \Delta\theta \quad \text{and} \\ \qquad \rho = x\cos(\theta) + y\sin(\theta) \\ 0 \quad \text{Otherwise} \end{cases} \tag{22}$$

Once the Hough transform was completed, you can search for accumulator $A(\rho, \theta)$ to find a local maximum. Search can use any search method. Traditional search algorithms known as exhaustive search, is defined as:

$$A_m(\rho,\theta) = \max\{A(\rho_i,\theta_i)\} \tag{23}$$

Where $\rho i=\rho-K, \rho-K+1,\ldots, \rho, \rho+1,\ldots, \rho+K;\theta i=\theta-K, \theta-K+1,\ldots, \theta, \theta+1,\ldots, \theta+K$. (2K +1) × (2K +1) is the nuclear size of search. K value was determined by the maximum distribution. In our experience, 1<K<3 is appropriate. The line will be detected which corresponds to the maximum value of parameters ρ and θ.

3. Experimental Results and Analysis

In order to test the feasibility of the proposed method and results, experiments are as follows: Remote sensing images used for the test shown in Figure 3. The figure shows that the runway has different brightness, contrast, and width in comparison with other regions. Figure 4 shows the results of typical threshold OTSU segmentation algorithm. By fractional differential gradient operator to extract the edge image was shown in Figure 5. Next, we use the automatic linear threshold algorithm to detect edge. Then, using Equation (22) of the Hough transform method to construct a straight line, reconstructed straight line was shown in Figure 7.

Figure 7 shows, the runways were successfully detected. From the experimental results, the method proposed in this paper better than the traditional method of image segmentation, which reduce the amount computation of Hough transform and greatly improve the operation speed.

Figure 3. The Original Image

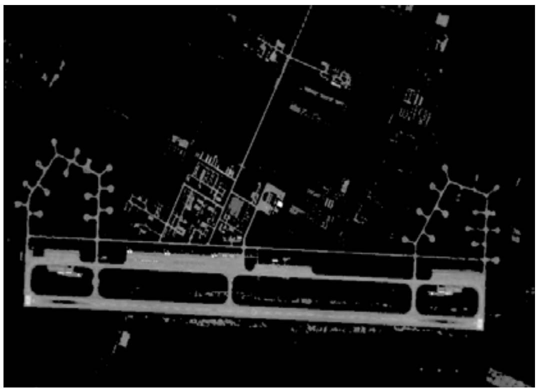

Figure 4. The Results of Processed by OTSU Algorithm

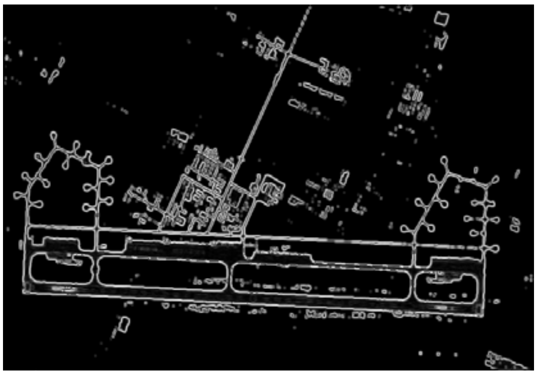

Figure 5. The Results of Operated by Fractional Differential Gradient

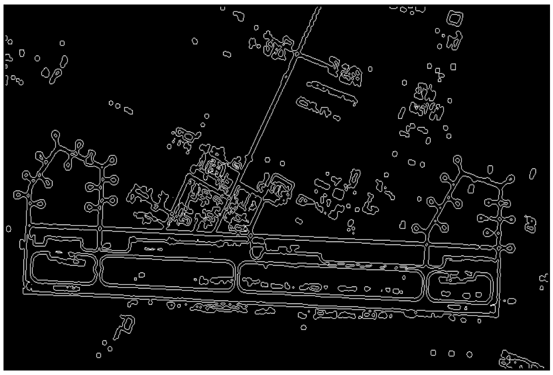

Figure 6. The Results of Detected by Automatic Threshold

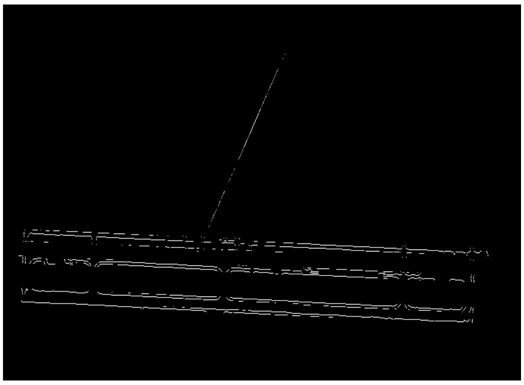

Figure 7. The Result of Hough Transform

4. Conclusion

HONG algorithm is very suitable for the detection of straight lines in the image, and has good anti-noise performance, but its calculation amount is huge. If only processing the edges of image, can greatly reduce the computation time, but the traditional edge detection algorithms are sensitive to noise. This article was based on fractional differential edge detection operator which can improve its noise immunity.The proposed algorithm is not only insensitive to noise, but also greatly reduces the computation time. Meanwhile this algorithm can meet the large-scale and real-time remote sensing image processing.

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