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Research on the edge extraction algorithm for pollution clouds based on wavelet transform

Shunhua Liu[1], Jin Gu[1], Xun Sun[1], Zhizhen Zhu[2]

[1]Institute of Chemical defense, [2]The Military Representative Office of Chemical defense in Kunming

liu_shun_hua@sohu.com

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Abstract. According to the high requirement for time efficiency of monitoring on pollution clouds, based on the modern infrared telemetry technology and spectral imaging technology, the edge extraction algorithm for pollution clouds is established by using the wavelet transform principle, and the damage range of pollution clouds can be calculated quickly after proper expansion and the superposition with original images. In this paper, this algorithm is verified scientific and has a good processing effect by simulating smoke screen instead of pollution clouds, which can provide effective means for the real-time and accurate monitoring of pollution clouds.

Introduction

A larger pollution area came into being for a certain scale of pollution clouds caused by chemical accidents diffusing to the downwind direction with air. One of the main tasks of chemical accidents emergency rescue is to monitor the scope and diffusion trend of pollution clouds and provide key information for the commander's decision on defense policies. The pollution clouds are mixed up with smoke of gunpowder and dust, some toxic agents are colorless, which are usually difficult to observe and monitor with naked eyes.

In recent years, with the development of the method of reconnaissance and monitoring, the infrared telemetry technology and spectral imaging technology are mature gradually, they can obtain the image information of pollution clouds through remote telemetering, which laid the foundation for edge extraction of pollution clouds. The pollution hazard area can be calculated quickly after extracting the edge of pollution clouds, which provides the real-time information for commander's scientific decision-making and personnel protection. At present, there are lots of algorithms for edge extraction, but the algorithms which can be applied in the edge extraction of pollution clouds with typical Gaussian diffusion model are less. The research in this paper can provide a reference for the accurate monitoring of pollution clouds and the decision-making on personnel protection.

Requirements for the Edge Extraction of Pollution Clouds

Image contains a wealth of information, distinguishing the target objects with the background is the main task of image analysis. In order to extract the outline of pollution clouds in the images, the edge of pollution clouds must be detected firstly. According to the characteristic, the edges are usually divided into: step edge, pulse edge and roof edge, the first or second order derivative can be used to complete the edge detection.

The image of pollution clouds is usually generated by the visible light imaging or infrared imaging, which has the characteristics of complex background, heavy noise and difficulty in interpretation, as well as possessing the typical features of Gaussian diffusion. The edge of pollution clouds is the direct basis to delimit chemical hazard area, more attentions should be paid for the following points when extracting the edge of pollution clouds in the images:

(1) The edge of pollution clouds is generally consistent with the Gaussian diffusion model, namely: the upwind is the step edge, the crosswind is the pulse edge and the downwind is the roof edge.

(2) The pollution clouds affect the safety of the personnel and equipment, the edge position of

pollution clouds can be properly expanded outward, but which cannot be overlooked;

(3) The diffusion mechanism of pollution clouds is complex and which involves a relatively large calculation errors, therefore, the accuracy of edge extraction is not required, but the extraction speed must be fast, in order to provide adequate pre-warning time for personnel protection.

Wavelet Transform Principles and Edge Detection Ideas

At present, the typical edge detection operators involve: Sobel operator, Roberts operator, Prewitt operator, GaussLaplace operator and Canny operator, etc.[3] This kind of operators own the advantages of simple algorithm, fast operation and so on, but they are easy to be disturbed by the noise, the accuracy of edge positions are not enough, which leads to the edges of adjacent areas overlap easily . The modern edge extraction methods include: morphology, wavelet transform, fuzzy theory and neural network, etc.[4].

Wavelet transform has become a popular image processing method because of its good characteristic of local time-frequency, many of its features, such as multi-resolution analysis, are not available in the traditional image processing methods. Compared with Fourier transform, wavelet transform is very useful for the analysis of transient time-varying signals.

Images can be expressed by two-dimensional function, the Fourier transform can be used to processing the stable image signals (invariant over time). However, wavelet transform is suitable for processing the unstable image signals, such as video, smoke screen, explosion, clouds, waves and jitters, etc[5].

Wavelet transform can adjust the time and frequency window area according to the demand analysis, with a zoom capability, which can achieve the aim of not only seeing the trees, but also seeing the forest, and the basis function of wavelet transform can also be designed according to the needs[6]. Therefore, wavelet transform is very suitable for processing image signals. The traditional edge detection operators mentioned above, such as Sobel, Prewitt and so on, all don't possess the idea of automatic zoom[7].

Edge extraction is actually a process of finding the edge points whose grayscale or brightness changes sharply in the images. Those edge points are usually regarded as singular points, and through the function, which can be described as the discontinuous points with a slope tending to infinity. In effect, the pixels of the input images in image processing are discrete, so the edge is often defined as the local gradient maximum.

With the natural characteristic of multi-scale, wavelet transform analyzes the signals in detail through the operation of expansion and translation, which can achieve time subdivision at high frequency points and frequency subdivision at low frequency points. By applying the multi-resolution analysis of the wavelet into the edge extraction of pollution clouds, decomposing the images with multi-resolution method, the edges with subtle changes can be obtained at small scale, and the stable image edges can be obtained at large scale[8-9]. Extracting the edges of the low frequency images at each scale, and then fusing the different edge images, which can not only improve the anti-noise ability, but also maximize the extraction of the images' edge information. Therefore, wavelet transform is more suitable for detecting the edges of pollution clouds.

Edge Detection Algorithm based on Wavelet Analysis

Suppose that the image signal of the two-dimensional pollution clouds $f(x,y)$, $\theta(x,y)$ is a smooth two-dimensional function, which meets:

$$\iint \theta(x,y)\,dxdy = 1$$

$$\lim_{x,y\to\infty} \theta(x,y) = 0$$

After introducing the scale parameter α , the convolution of the smooth function

$\theta_\alpha(x,y)=\frac{1}{\alpha^2}\theta\left(\frac{x}{\alpha},\frac{y}{\alpha}\right)$ in image $f(x,y)$ and α makes the image $f(x,y)$ smooth, the smoothed image is:

$$g(x,y)=\theta_\alpha(x,y)*f(x,y)$$

The partial derivatives of the smoothed images are:

$$\frac{\partial g(x,y)}{\partial x}=\frac{\partial}{\partial x}\left[\theta(x,y)*f(x,y)\right]=f(x,y)*\frac{\partial\theta(x,y)}{\partial x}$$

$$\frac{\partial g(x,y)}{\partial y}=\frac{\partial}{\partial x}\left[\theta(x,y)*f(x,y)\right]=f(x,y)*\frac{\partial\theta(x,y)}{\partial y}$$

We can see that the right sides of the two formulas above are actually two wavelet transforms of the function $f(x,y)$.

The two-dimensional wavelet function defined under the scale parameter α :

$$\begin{cases}\psi^x(x,y)=\frac{\partial\theta(x,y)}{\partial x}\\ \psi^y(x,y)=\frac{\partial\theta(x,y)}{\partial y}\end{cases} \tag{1}$$

Namely:

$$\frac{\partial g(x,y)}{\partial x}=W^x f(x,y)=f(x,y)*\psi^x(x,y)$$

$$\frac{\partial g(x,y)}{\partial y}=W^y f(x,y)=f(x,y)*\psi^y(x,y)$$

The two-dimensional wavelet transform expressed by vector form is as follows:

$$\begin{aligned}&\alpha\left[\frac{\partial(f*\theta_\alpha)(x,y)}{\partial x}\vec{i}+\frac{\partial(f*\theta_\alpha)(x,y)}{\partial y}\vec{j}\right]=\alpha\left[\left(f*\frac{\partial\theta_\alpha}{\partial x}\right)(x,y)\vec{i}+\left(f*\frac{\partial\theta_\alpha}{\partial y}\right)(x,y)\vec{j}\right]\\&=\alpha f(x,y)*\left[\psi^x(x,y)\vec{i}+\psi^y(x,y)\vec{j}\right]\\&=\alpha\left[\left(f*\psi^x\right)(x,y)\vec{i}+\left(f*\psi^y\right)(x,y)\vec{j}\right]\\&=W_\alpha^x f(x,y)\vec{i}+W_\alpha^y f(x,y)\vec{j}\\&=\alpha\nabla(f*\theta_\alpha)(x,y)\end{aligned} \tag{2}$$

The modulus of this gradient vector is $Mod\left[W_\alpha f(x,y)\right]=\sqrt{\left|W_\alpha^x f(x,y)\right|^2+\left|W_\alpha^y f(x,y)\right|^2}$, the included angle between the gradient vector and the horizontal axis X is : $A=Arg\left[W_\alpha f(x,y)\right]=arctg\left[\frac{W_\alpha^y f(x,y)}{W_\alpha^x f(x,y)}\right]$.

From the previous analysis we can see, the image edges are corresponding to the modulus maxima points of first-order derivatives, the two wavelet transforms of $f(x,y)$ are namely two first-order derivatives, therefore, the modulus maxima of the two wavelet transforms of $f(x,y)$ are namely corresponding to the edge points of this image.

In generally, the scale is set to 2^j, the binary dilation for the wavelet $\psi^x(x,y)$ and $\psi^y(x,y)$ is conducted to obtain $\left\{\psi_{2^j}^1(x,y),j\in Z\right\}$, $\left\{\psi_{2^j}^2(x,y),j\in Z\right\}$, so

The binary wavelet transform of $f(x,y)$ is:

$$W_{2^j}^x(x,y)=f(x,y)*\psi_{2^j}^1(x,y)$$

$$W_{2^j}^y(x,y)=f(x,y)*\psi_{2^j}^2(x,y)$$

$W_{2^j}^x$ and $W_{2^j}^y$ refer to the partial derivatives of the image in the direction of x,y respectively. Selecting the scale 2^j, the modulus and phase angle of the wavelet respectively are:

$$M_{2^j} f(x,y) = \sqrt{\left|W_{2^j}^x(x,y)\right|^2 + \left|W_{2^j}^y(x,y)\right|^2}$$

$$A_{2^j} f(x,y) = \arctan \frac{W_{2^j}^y(x,y)}{W_{2^j}^x(x,y)}$$

The positions of image signal mutation points are corresponding to the local maximum points of modulus $M_{2^j} f(x,y)$ in the direction of $A_{2^j} f(x,y)$, those points namely are the edge points of image.

The edge is corresponding to the extreme value point of $Mod\left[W_\alpha f(x,y)\right]$,the multi-scale edge extraction can be realized through changing α.

The wavelet transform of arbitrary direction is defined as:

$$W_\alpha^\theta f(x,y) = f(x,y) * g(x,y,\theta) = f(x,y) * \left[\psi^x(x,y)\cos\theta + \psi^y(x,y)\sin\theta\right]$$

$$= W_\alpha^x f(x,y)\cdot\cos\theta + W_\alpha^y f(x,y)\cdot\sin\theta = \left\|W_\alpha f(x,y)\right\|\cdot\left(\frac{W_\alpha^x f(x,y)}{\left\|W_\alpha f(x,y)\right\|}\cdot\cos\theta + \frac{W_\alpha^y f(x,y)}{\left\|W_\alpha f(x,y)\right\|}\cdot\sin\theta\right)$$

$$= \left\|W_\alpha f(x,y)\right\|\cdot\left(\cos\left(Arg\left[W_\alpha f(x,y)\right]\right)\cdot\cos\theta + \sin\left(Arg\left[W_\alpha f(x,y)\right]\right)\cdot\sin\theta\right)$$

$$= \left\|W_\alpha f(x,y)\right\|\cdot(\cos\alpha\cdot\cos\theta + \sin\alpha\cdot\sin\theta) = \left\|W_\alpha f(x,y)\right\|\cdot\cos(\alpha-\theta) \quad (3)$$

So,

$$Mod\left[W_\alpha f(x,y)\right] = \max\left[W_\alpha^\theta f(x,y)\right] \quad (4)$$

This shows that the square of the directional wavelet transform value is just proportional to that of the gradient modulus value with the smoothed function, the calculation for gradient modulus value can be replaced by the calculation for the value of directional wavelet transform. According to the relation between the gradient value and the wavelet transform value of functions, we can find the maximum value along the direction of the wavelet transform, and the calculation for the gradient direction and the gradient modulus value is not necessary.

The Gaussian Function symmetric to the 2-D rotation with the variance σ^2 is:

$$\theta_\alpha(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \quad (5)$$

The two directional derivatives of Gaussian Function are:

$$\begin{cases} \theta_\alpha^x(x,y) = -\dfrac{x}{2\pi\sigma^4}\exp\left(-\dfrac{x^2+y^2}{2\sigma^2}\right) \\ \theta_\alpha^y(x,y) = -\dfrac{y}{2\pi\sigma^4}\exp\left(-\dfrac{x^2+y^2}{2\sigma^2}\right) \end{cases} \quad (6)$$

If the scale is 2^j, the 2-D dyadic wavelet transform in the direction of x and y is:

$$\begin{cases} \psi_{2^j}^x(x,y) = -\dfrac{1}{4^j}\theta^x\left(\dfrac{x}{2^j},\dfrac{y}{2^j}\right) \\ \psi_{2^j}^y(x,y) = -\dfrac{1}{4^j}\theta^y\left(\dfrac{x}{2^j},\dfrac{y}{2^j}\right) \end{cases} \quad (7)$$

$$\begin{cases} W_\alpha^x f(x,y) = f(x,y) * \psi_\alpha^x(x,y) \\ W_\alpha^y f(x,y) = f(x,y) * \psi_\alpha^y(x,y) \end{cases} \quad (8)$$

$$W_{2^j}^x f(x,y) = f(x,y) * \frac{1}{4^j}\theta^x\left(\frac{x}{2^j},\frac{y}{2^j}\right) = \frac{1}{4^j}\left(-\frac{1}{2\pi\sigma^4}\right) f(x,y) * x\cdot\exp\left(-\frac{x^2+y^2}{4^j 2\sigma^2}\right) \quad (9)$$

Let $K = -4^j 2\sigma^2$, so the formula(3-9)is:

$$W_{2^j}^x f(x,y) = \frac{1}{K\pi\sigma^2}\cdot f(x,y) * x\cdot\exp\left(\frac{x^2+y^2}{K}\right)$$

$$= \sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} f(x-m,y-n)\cdot m\cdot\exp\left(\frac{m^2+n^2}{K}\right)\Big/ K\pi\sigma^2 \quad (10)$$

Due to the influence of the image noise, the correlation among the neighborhoods are relatively

low, so that the directional filter can't accurately locate the boundary state of the pixel point (x, y). Because of the arbitrary directions of image boundary, the calculation for responses of multidirectional wavelet transforms is conducted to search the image boundaries in all possible directions, the transform window is 5×5, as shown in Figure 1.The final edge detection result is the average of the multidirectional filtered images.

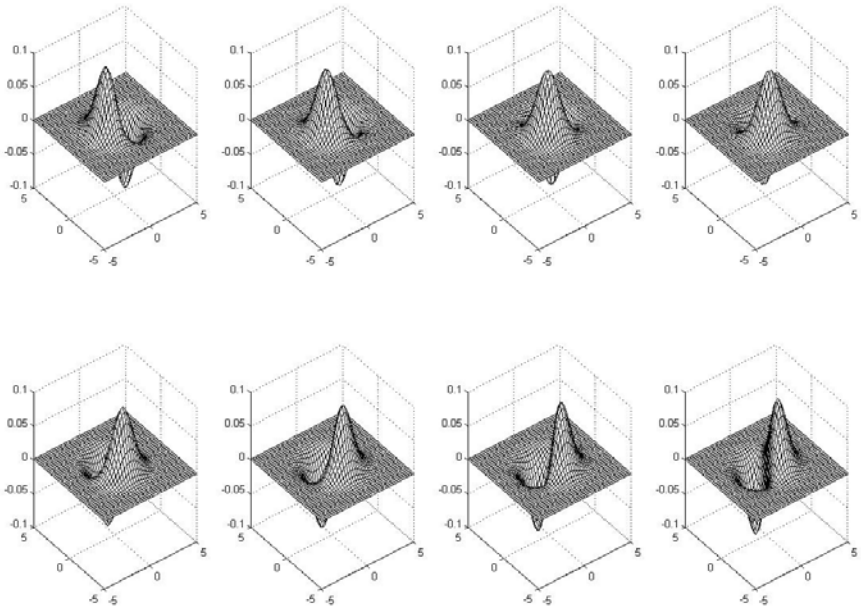


Figure 1. The 8 direction adjustable wavelets with the transform window of 5×5

Detection-- Simulation Tests and Results

The smoke screen is used to simulate the diffusion of pollution clouds, the picture taken by model airplane from the air is shown in figure 2, and the histogram of grayscale image for the pollution clouds' diffusion map is shown in figure 3.

Figure 2. Simulation on the Diffusion of Pollution Clouds

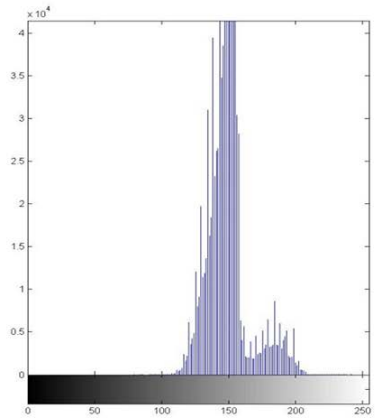
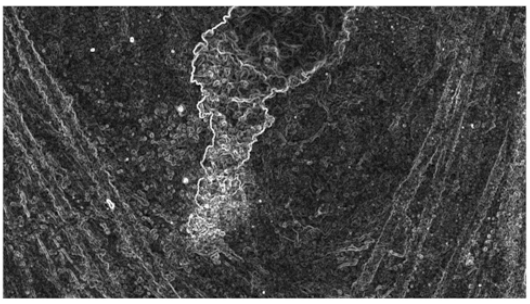


Figure 3. Image Histogram

Based on wavelet transform, figure 4 is obtained by detecting the image edge of smoke screen; figure 5 is obtained by detecting the image edge of the filtered smoke screen; from Figure 5 and figure 4 we can see, the edges obtained through wavelet transform are graceful, many of its transition points can be detected, whose continuity and smoothness are also good.

In many edge detection algorithms, Canny algorithm is wildly used for its simple arithmetic and high efficiency in operation. Because the Canny operator uses a fixed threshold for edge detection, the interference of local noise can't be eliminated, which leads to the loss of local edge. The

detection result is not ideal when the distribution for the brightness and contrast ratio of the pollution clouds' image is not uniform, although the edge detection of different images can be carried out by changing the threshold, the choice for threshold has a great influence on the test results, usually, we can't get the ideal results. From figure 6,7 and 8 we can see, the inappropriate choice for threshold will lead to many false edges or missed edges and affect the results of edge detection.



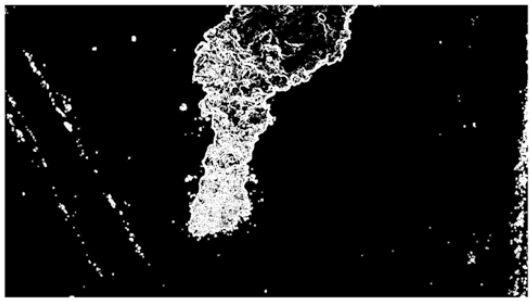


Figure 4. The edge obtained by 8 direction adjustable wavelets

Figure 5. The edge obtained by 8 filtered direction adjustable wavelets

Figure 6.The edges obtained by the Canny operator before (left) and after filtering (right) (threshold 0.25)

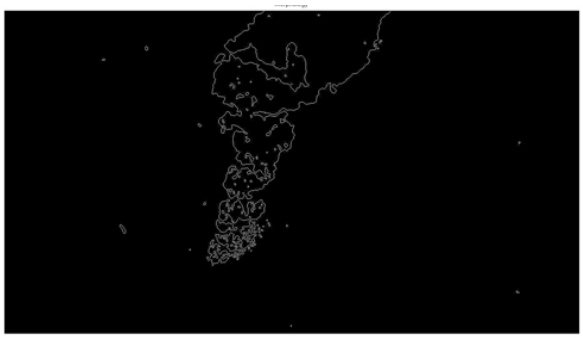


Figure 7. The edges obtained by the Canny operator before (left) and after filtering (right) (threshold 0.50)

Figure 8. The edges obtained by the Canny operator before (left) and after filtering (right) (threshold 0.65)

The edge of smoke screen detected based on wavelet transform algorithm, after extracting, which can be expanded along with the wind direction according to the Gaussian diffusion model,

superimposing the extracted edge on the original image of smoke screen directly (as shown in Figure 9 and 10), it can realize real-time display and quantitative calculation and dynamically identify the pollution clouds hazard area, which is convenient for the commanders' decision-making.

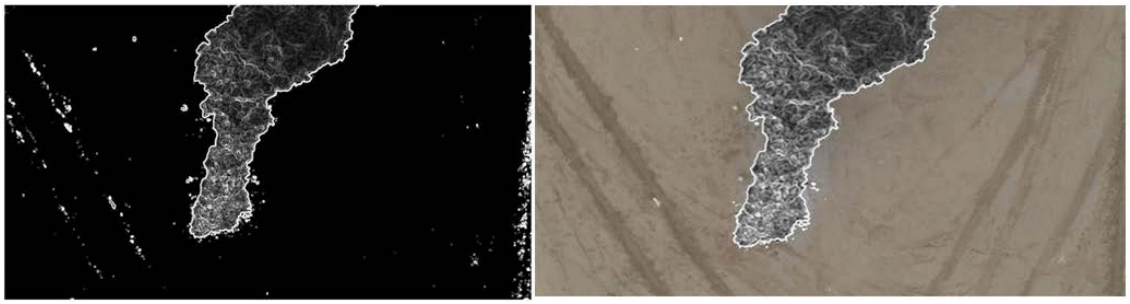


Figure 9. The edge obtained by 8 filtered direction adjustable wavelets
Figure 10. Superimposing the extracted edge on the original image

Conclusion

Edge exists in the grayscale mutation points of the image, which is a place with greatest uncertainty in the image, and contains a wealth of image information. However, because of the contradiction between the anti-noise ability and the detected precision, edge detection is still one of the classic technical problems currently. In the actual imaging process, the problems of the image features of pollution clouds, such as fuzziness, deformation and so on, will be caused by the projection, mixing, distortion and noise, etc. And the particularity of grayscale images leads to the difficulties in the edge detection of pollution clouds. Compared with the traditional algorithms, wavelet transform algorithm has a unique advantage in the image edge detection of pollution clouds, which can reflect the characteristic of image collection in edge detection, detect the image edge efficiently and obtain the clear, accurate and complete edge images of pollution clouds. The image edge detection of pollution clouds plays a key role in image processing, its solution has a great significance to describe, recognize and understand the high level features of the image of pollution clouds.

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