Detection of High Resolution Remote Sensing Imagery Using Wavelet

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ABSTRACT:

In this paper, The 3-.level B-Spline wavelet transform is applied to extract different types of edges, according to the singularity exponent of edges from high resolution remote sensing imagery. Gradient algorithm, Laplacian algorithm, Robert algorithm are classic linear algorithms. However these algorithms have an acute function on edges and are vulnerable to noise. In the process of edge detection using wavelet, edge information at different scales is obtained according to wavelet multi-scale's character. We may integrate multi-scale edge information to create high accuracy and different types of edges with a pixel width. In this paper, I take over 3-level B-Spline wavelet function. We also verify the 3-level B-Spline wavelet transform being asymptotically optimum in the practical application such as feature extraction. This paper gives out its fast algorithm in decomposition, response in time and frequency analyze. More importantly, in this paper, the algorithm can also be used to determinate the singularity exponent of edges so as to identify different types of edges. According to the different needs, we can output the different types of edges that serve as a more effective representation on which subsequent localization and recognition tasks are based.

1. INTRODUTION

In the process of remote sensing imagery comprehension, there are three levels: low-comprehension, middle-comprehension, high-comprehension. In the process of low-comprehension, all kinds of feature are extracted, for example, point, line, region and more image feature that was composed of it. The edge of image is the most important feature of high-resolution remote sensing imagery, because edge can delineate shape of object and contain most of information. Edges of images are characterized by sharp variations in intensity values. Edges are among objects, regions, between objects and backgrounds. Edges are presented by object's geometric edge, shape, object's surface grain and so on. On ground of different needs, different edges should be extracted. These factors make edge detection difficult. Up to now, edge detection is still a difficult problem.

Gradient algorithm, Laplacian algorithm, Robert algorithm are classic linear algorithms. However these algorithms have an acute function on edges and are vulnerable to noise. To remote sensing imagery in which there are many complicate surface features, the effect of edge detection is not good. Multi scales method is an effective method. Wavelet is a developing branch of applied math since the middle-eighties. Because of perfection in math and comprehensiveness in application, wavelet is studied in depth in many fields. In the process of edge detection using wavelet, edge information at different scales is obtained according to wavelet multi-scale's character. We may integrate multi-scale edge information to create high accuracy and different types of edges with a pixel width

2. FUNDAMENT OF EDGE DETECTION

2.1 Dyadic Wavelet Transform and Edge Detection

Definition 1: If there are invariables $0 < A \le B < \infty$ to function $\Psi \in L^1 \cap L^2$,

$$A \le \sum_{k \in z} \left| \hat{\Psi}(2^k w) \right|^2 \le B, \qquad (2\text{-}1)$$

then ? is a dyadic wavelet, condition (2-1) is stability condition. If A=B, it is the most stable condition. Meanwhile, function sequence $\{W_{2^k} f\}_{k \in z}$ is dyadic wavelet transform. Thereamong

$$W_{2^k} f(x) = f * \Psi_{2^k}(x)$$

$$= \frac{1}{2^k} \int_R f(t) \Psi(\frac{x-t}{2^k}) dt, \qquad (2\text{-}2)$$

Because dyadic wavelet transform have translation invariance in the time domain. It is important to signal singularity detection and image edge detection.

In the two dimensional image edge detection, $q(x, y)$ is smooth function that match criteria as follows:

$\int_{R^2} q(x, y) dxdx = 1$ and if $x^2 + y^2 \to \infty$, $q(x, y) \to 0$; meanwhile, $q(x, y)$ is differential.

$$q_{2^j}(x, y) = 2^{-2j} q(2^{-j} x, 2^{-j} y) \qquad (2\text{-}3)$$

$$y^1(x, y) = \frac{\partial q(x, y)}{\partial x} \qquad (2\text{-}4)$$

$$y^2(x, y) = \frac{\partial q(x, y)}{\partial y} \qquad (2\text{-}5)$$

Wavelet transform of the two dimensional signal $f(x, y) \in L^2(R^2)$ have two amounts in the 2^j scale. They are defined as follows:

$$W^1_{2^j} f(x, y) = f * y^1_{2^j}(x, y) \qquad (2\text{-}6)$$

$$W^2_{2^j} f(x, y) = f * y^2_{2^j}(x, y) \qquad (2\text{-}7)$$

Then

$Wf = \left[W^1_{2^j} f(x, y) \quad W^2_{2^j} f(x, y) \right]^T$ is two dimensional dyadic wavelet transform of f(x,y).

through (2-3) ——(2-7),

$$\begin{bmatrix} W^1_{2^j} f(x, y) \\ W^2_{2^j} f(x, y) \end{bmatrix} = 2^j \begin{bmatrix} \frac{\partial}{\partial x}(f * q_{2^j}) \\ \frac{\partial}{\partial y}(f * q_{2^j}) \end{bmatrix} = 2^j \nabla (f * q_{2^j})(x, y) \qquad (2\text{-}8)$$

The Formula Illustrate: The two amounts of two-dimensional dyadic wavelet transform in the 2^j scale are in proportional to the two amounts of gradient vector that f(x, y) are smoothing by $q(x,y)$. Then magnitude of gradient vector is in proportional to

$$M_{2^j} f(x,y) = \sqrt{\left|W_{2^j}^1 f(x,y)\right|^2 + \left|W_{2^j}^2 f(x,y)\right|^2} \tag{2-9}$$

and angle between gradient vector and x orientation is the angle of $W_{2^j}^1 f(x,y) + i \cdot W_{2^j}^2 f(x,y)$, is denote as

$A_{2^j} f(x,y)$. as a result, image edge points are local maximum of $M_{2^j} f(x,y)$ in the direction of vertical $A_{2^j} f(x,y)$.

2.2 Wavelet transform and edge singularity

Image edges are counterpart to image gray singularity, a different type of edge have a different singularity. A parameter that depicts singularity is Lipschitz exponent. However, $M_{2^J} f(x,y)$ check with Lipschitz exponent a closely. In other words, exponent a is solved by maximum of wavelet transform .Lipschitz exponent a is definited as follow:

Definition 2 : signal x(t) have the following characteristic in the vicinity of t_0

$$\left|x(t_0 \pm h) - P_n(t_0 \pm h)\right| \le A\left|h\right|^a, \qquad n < a < n+1 \tag{2-10}$$

in the formula, h is abundant bitsy amount; $P_n(t)$ is polynomial. Then a is Lipschitz at t_0. Edge points magnitude have relational with Lipschitz exponent a as follows:

$$\left|M_{2^j} f(x,y)\right| \le k\left(2^j\right)^a \tag{2-11}$$

In the other words,

$$\log_2\left|M_{2^J} f(x,y)\right| \le \log_2 k + ja \ \log_2\left|M_{2^J} f(x,y)\right| \le \log_2 k + ja \tag{2-12}$$

Commonly, adjacent domains of local shakeup points are not singularity. It is important that we assess smooth of smooth edge. Smooth factor s is another parameter that symptom edge characteristic. Edge image may think that original edge image (Lipchitsz exponent= a) are smoothed by Gauss function(mean square deviation= s).as a result , $M_{2^J} f(x,y)$ have relation with Lipschitz exponent a , smooth factor s as follows:

$$\left|M_{2^j} f(x,y)\right| \le k 2^j s_0^{a-1} \tag{2-13}$$

In the fulmar,

$$s_0 = \left[\left(2^j\right)^2 + s^2\right]^{\frac{1}{2}} \tag{2-14}$$

accordingly, the a that symptom edge singularity is solved by wavelet transform at a good three scales. Then according to a , a different type of edge are represented in terms of image analysis demand.

3. EDGE DETECTION ALGORITHM

3.1 Wavelet Function Select and Filter Design

We also verify the 3-level B-Spline wavelet transform being asymptotically optimum in the practical application such as feature extraction. Unser have demonstrated that if exponent count $n \to \infty$, $B-Spline$ and its founier transform converge to Gauss function. Their approximate relation is as follows:

$$b^n(x) \approx \sqrt{\frac{6}{p(n+1)}} \exp\left(-\frac{6x^2}{n+1}\right) \tag{3-1}$$

$$b^n(x) = b^0 * b^{n-1} = \underbrace{b^0 * b^0 * \cdots * b^0}_{n+1} \tag{3-2}$$

$$b^0 = x\left[-\frac{1}{2} \quad \frac{1}{2}\right]$$

If $b_{2^{-1}}^{n+1}(x)$ are smooth function, then

$$\begin{aligned} y^n(x) &= \frac{d}{dx} b_{2^{-1}}^{n+1}(x) = 4b'^{n+1}(x) \\ &= 4\left[b^n\left(2x+\frac{1}{2}\right) - b^n\left(2x-\frac{1}{2}\right)\right] \end{aligned} \tag{3-3}$$

As a result,

$$\hat{y}^n(w) = iw\left(\sin c\frac{w}{4}\right)^{n+2} \tag{3-4}$$

if $b^n(x)$ is scale function, according to two-scale equation

$$\begin{aligned} \frac{1}{2} b^n\left(\frac{x}{2}\right) &= \sum_{k=-\infty}^{\infty} h_k b^n(x-k) \\ \hat{b}^n(2w) &= H\left(e^{iw}\right)\hat{b}^n(w) \end{aligned} \tag{3-5}$$

$$H\left(e^{iw}\right)=\sum_{k=-\infty}^{\infty}h_k e^{-ikw}=\frac{\hat{b}^n(2w)}{\hat{b}^n(w)}=\frac{2\sin c^{n+1}(2w)}{\sin c^n(w)}$$

$$\begin{aligned}&\frac{1}{2}y^n\left(\frac{x}{2}\right)=\sum_{k=-\infty}^{\infty}g_k b^n(x-k)\\&\hat{y}(2w)=G(w)b^n(w)\\&G(w)=\sum_{k=-\infty}^{\infty}g_k e^{-ikw}=\frac{\hat{y}(2w)}{b^n(w)}\end{aligned} \tag{3-6}$$

In the time domain:

$$h_k=\begin{cases}\frac{1}{2^{n+1}}\begin{pmatrix}n+1\\ \frac{n+1}{2}+k\end{pmatrix} & |k|\le\frac{n+1}{2}(n\ is\ odd)\\ 0 & other\end{cases} \tag{3-7}$$

$$\begin{pmatrix}n\\k\end{pmatrix}=\frac{n!}{k!(n-k)!}$$

$$\begin{cases}g_0=-2, \quad g_1=2\\ g_k=0, \quad (k\neq 0 \quad k\neq 1)\end{cases} \tag{3-8}$$

3.2 Discrete wavelet transform fast algorithm

In edge detection using wavelet, It is a primary demerit that wavelet transform have fast algorithm.

j=0;

If(j<J){

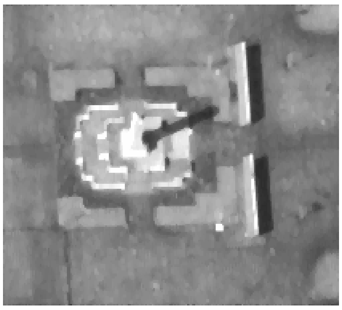
$$\begin{aligned}&W_{2^j}^1 f=S_{2^j}*(G_j,D);\\&W_{2^j}^2 f=S_{2^f}*(D,G_j);\\&S_{2^{j+1}}=S_{2^j}*(H_j,H_j);\\&j=j+1;\end{aligned}$$

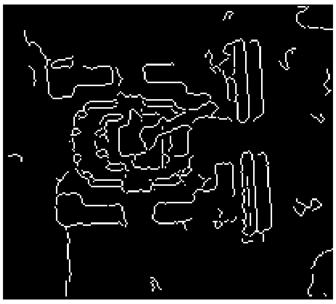
}

End

D is Dirac filter.

4 EXPERIMENT AND COMCLUSION





Original image edge image

Top left image is original image (iknos, 1m, 2000). The image picked off is in Tian An mern square. Because of the image revolution is 1m, it is a important significance that all kinds of objects are automatically recognized. The first step of object recognition is edge detection and image segmentation. As a result, the effect of edge detection influence on object recognition. Top right image is edge image. In the edge image, the Lipstchz exponents of edge points exceed 0.56. Experiment prove that We may integrate multi-scale edge information to create high accuracy and different types of edges that serve as a more effective representation on which subsequent localization and recognition tasks are based.

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