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Framelet transform based edge detection for straight line detection from remote sensing images

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Abstract

Edge detection has been widely used as a pre-processing step for image processing applications such as region segmentation, feature extraction and object boundary description. Classical edge detection operators available in literature are easy to implement, but not all the edge detection operators is suitable for remote sensing images in terms of selecting threshold and kernel function. There is no acceptable method to select the parameters in classical edge detection methods. Multiresolution analysis such as wavelet transform has been shown to have advantages over classical edge detection techniques, as it is less sensitive to noise. The discrete wavelet transform (DWT) is shift variant, due to critical subsampling. The DWT is not capable of capturing edges, which are not aligned in horizontal and vertical directions. In this paper, we focus beyond DWT, framelet transform used to detect edges from LISS III and Cartosat images. The proficiency of the proposed method is evaluated by comparing the results of DWT, dual tree complex wavelet transform (DTCWT), curvelet transform (CUT), contourlet transform (CT) and non subsampled contourlet transform (NSCT) based edge detection methods. Rosenfeld evaluation metric is used to measure the quality of the edge detection methods, which shows the framelet based edge detection produce sound results than other methods. Principal component analysis (PCA) and singular value decomposition (SVD) methods are used to remove the correlation among the multispectral bands and selected maximum information bands for edge detection, instead of using one particular band because each band in multispectral image is suitable for specific applications. The detected edges are further subjected to line detection algorithms such as standard Hough transform, small eigenvalue analysis and principal component analysis. The outcomes are compared in terms of complexity measurements. Framelet transform along with principal component analysis based line detection algorithm perform better than other two methods.

Keywords: Discrete wavelet transforms (DWT); principal component analysis (PCA); singular value decomposition (SVD).

1. Introduction

Due to increasing availability of remote sensing data of various spatial, temporal, radiometric and spectral resolutions, new methods are developed to analyze and understand the collected data more effectively. The delineation and extraction of features from remote sensing images is widely used in image segmentation and information extraction. Detection and extraction of straight lines in an image has been a challenging problem for automatic extraction of particular features in remote sensing images. There are different methodologies in literature for straight line detection. The most commonly used techniques are pixel connectivity, edge linking (Nevatia & Ramesh Babu, 1980), Hough transform (Duda & Hart, 1972), Principal component analysis (Lee *et al*., 2006) and small eigen value analysis (Guru *et al.,* 2003). Line detection algorithms follow edge detection, which is a pre-processing step for feature extraction. Edges can be considered as pixel intensity discontinuities within an image. An edge is a curve that follows a path of rapid change in image intensity. Edge detection is a process of identifying and locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity, which characterize boundaries of objects in a scene. Edge pixels are grouped into features such as lines or boundaries of objects in the image. An important property of the edge detection method is its ability to extract the accurate edge line with good orientation, which leads to easy measurement of all the basic characteristics of the objects for further feature extraction. Numerous edge detection methods have been proposed in the last decade.

Classical edge extraction is usually based on a variety of differential algorithms, combined use of templates, threshold and smoothing. The most commonly used edge detection (Gonzalez & Woods, 2002; Marr & Hildreth, 1980) algorithms are Robert (Gonzalez & Woods, 2002), Sobel (Gonzalez &Woods 2002), Prewitt (Gonzalez & Woods, 2002), Laplacian (Gonzalez & Woods, 2002), LoG (Gonzalez & Woods, 2002) and Canny algorithm (Gonzalez & Woods, 2002). Robert method calculates the difference between adjacent pixels to detect edge which is sensitive to noise. Sobel and Prewitt are weighted average operators, which give weight to the centre pixel for detecting edges. This can smoothen the noise, but with more calculation and its position accuracy is not well. Laplace operator is invariable in different directions. LoG is the second order differential algorithm, which uses pre smoothing of the image. The main drawback of LoG operator is that it filters the noise and also smoothen the edge. Canny edge detector (Canny, 1986) is a commonly used tool in edge detection. This method blurs the input image and then finds the gradient of the blurred image. Edges can be affected by finding local maxima of the magnitude of gradient image. This measure has high de-noising ability. Both suffer from some practical limitations, such as complex programming and slower computing work. Rothwell edge detection algorithm (Rothwell *et al.*, 1995) is similar to canny edge detection. Edge thinning followed by dynamic thresholding is used instead of hysteresis and non-maximal suppression. Susan operator (Smith & Brady, 1995) uses circular mask of defined size positioned over each pixel in the original image. Susan operator is much faster than canny edge detector. Selecting the size of the mask is critical in high level image processing. Edison operator (Meer & Georgescu, 2001) employs two confidence measures for each detected edge. Template matching approach is used to derive edge confidence. Though these edge detection methods give better outcome, finding which edge detector with which parameters like kernel size and thresholding provides good quality edges for feature extraction is a challenging problem for researchers in remote sensing images. With the growth of wavelet theory, the wavelet transforms (Soman *et al.*, 2010) have been found to be important mathematical tools to analyze the singularities including edges and contours of the earth surface features. Discrete wavelet transform (DWT) is the failure to capture directional features, which is not adjusted in horizontal and vertical directions. The discrete wavelet transform is shift variant due to critical sub sampling. This can lead to small shifts in the input waveform, causing large changes in the wavelet coefficients, large variations in the distribution of energy at different scales and possibly large changes in reconstructing waveforms. Recently number of approaches are used, which can provide sound directional features. The dual tree complex wavelet transform (DTCWT) (Selesnick *et al.*, 2005) has been used to find an important tool to overcome the drawbacks of discrete wavelet transform (DWT). Real and imaginary parts of the wavelet coefficients are generated by two trees of filters. During reconstruction, summing of the output of the two trees can suppress the aliased components and provide approximate shift invariance.

Curvelet transform (Candes & Donoho, 2000) was introduced as another multiresolution transform. This provides more edge information which represents the edges and singularities along curves and much more effective than discrete wavelet transform, which can identify only horizontal, vertical and diagonal edge image, ignoring smoothness along curves. Computational complexity is more while applying real time imagery. Contourlet transform (Do & Vetterli, 2003) was proposed as a multiscale and directional image representation (Do & Vetterli, 2005) that uses a wavelet like structure for edge. Contourlet transform can perform better in representing lines, edges, contours and curves of images due to the characteristics of its directionality and anisotropy. Laplacian pyramid is used to extract point discontinuities, then directional filter banks link point discontinuities into lines. Contourlet transform is also not shift invariant due to down sampling and up sampling in both Laplacian pyramid and directional filter banks. (Cunha *et al.*, 2006) proposed a modified version of contourlet transform, which was made by combing a non subsampled Laplacian pyramid and non sub sampled directional filter banks known as non subsampled contourlet transform. Though much development is made in wavelet theory, each wavelet transform has its own filter banks and computational complexity. Remote sensing images are frequently tempted by low resolution, blurry quality and distortion, due to camera view points. Edge detection is difficult in noisy images, since both the noise and edges have a high frequency. So the detection of edges in noisy images sometimes leads to missing true edges, false edge detection and localization. Due to the large number of edge detection methods, applying and finding an efficient method for edge detection of remote sensing images is a major challenge for researchers in the field of satellite image processing. Even though these techniques bring about good results, application of wavelets in remote sensing image edge extraction is limited. In this study, we have focused framelet based edge detection for extracting straight line features from remote sensing imagery. Due to accessibility of different imageries, data reduction is necessary before edge detection .The work flow is as follows, 1. Band selection, 2. Framelet transform based edge detection, 3. Line detection

2. Band selection analysis

Two kinds of the sensors that are used for remote sensing in the past are panchromatic sensor and multispectral sensor. Panchromatic in general refers to broad spectral range having one band, which generally shows black and white image. A multispectral sensor captures the image data at specific frequencies across the electromagnetic spectrum. For visual display, each band of the image may be displayed, one band at a time as a gray scale image or in combination of three bands at a time as a color composite image. Not all the bands are equally useful for specific applications. There are difficulties in processing more than single band in images. Data reduction is necessary for compacting redundant data into smaller dimensions. The dimension of the data may be reduced by transforming the original space into lower dimension. In this report, we have used singular value decomposition (SVD) (Golub & Loan 1996) and Principal component analysis (PCA) to reduce high dimensional data into fewer dimensions, to retain important information.

PCA (Jolliffe, 2002) transform the high dimensional data to lower dimension, for removing correlation among bands. Most of the information is contained in the first few bands. The information content of the PCA bands reduces, when the number of PCA bands increases.PCA transforms an image into a new coordinate space without considering the noise impact.

The procedure for computing PCA is:

1. Mean centre the data. 2. Compute covariance matrix of the dimension. 3. Find eigenvectors of the covariance matrix. 4. Sort the eigenvectors in decreasing order of eigenvalue and project eigenvectors in to data.

Singular value decomposition (SVD) is also similar to PCA. SVD is directly applied to an MxN matrix, but in PCA, it is applied to a covariance matrix. The important property of SVD is that the given data is subjected to scaling, transpose, flipping, rotation and translation of the singular values that still remain the same as that of the given data. It is also a low dimensional matrix with the main characteristics of the original data without loss of information.

Let A be an m x n matrix, singular value decomposition of A is $A = U\sum V^T$, U is the m x m matrix and V is the n x n matrix. The columns of U and V are the left and right singular vectors. $\sum$ is m x n matrix whose diagonal entries are singular values of A. Left singular vectors of A are the eigen vectors of AA^T . Right singular vectors of A are the eigenvectors of A^TA.

3. Edge detection with framelet transform

To rule out the impacts on satellite images with classical edge detection algorithms and improve precision of edge locating, an effective edge extracting algorithm based on framelet transform is proposed for straight line detection from satellite images. Framelet transform (Hadeel & Taai, 2008) is similar to wavelets but has some differences. Framelet transform (Selesnick & Abdelnour, 2004; Selesnick, 2004) has two or more high frequency filter banks, which produces more subbands in decomposition. This can achieve better time and frequency localization ability in image processing. There is redundancy between the framelet subbands, which means a change in coefficients of one band, can be compensated by other subbands coefficients. After framelet decomposition, the coefficient in one subband has correlation with coefficients in the other subband. This signifies that alterations on one coefficient can be counterbalanced by its related coefficient in the reconstruction stage, which produces less noise in the original image. A tight frame filter bank provides symmetry and has a redundancy that allows for approximate shift invariance. This leads to clear edges with effective denoising which is lacking in other wavelet transform.

The image is decomposed into one approximation and eight detailed subbands. Approximation and detailed subbands of framelet coefficients will be further used for edge detection as follows,

The edges of approximation subband are extracted by canny algorithm. The gradient magnitude of each pixel in high frequency subband is calculated by the following equation.

$$G[F(x,y) = \sqrt{|G_x|^2 + }\left|G_y\right|^2 \qquad (1)$$

G_y, G_x - Represent the partial derivative of vertical and horizontal direction respectively.

Then divide each gradient magnitude image into overlapping square windows. After subdividing the image, the pixel with large magnitude in gradient magnitude image is likely to be an edge point, while pixel with small magnitude may be background noise point. Otsu's algorithm (Gonzalez & Woods, 2002) is used to find the optimal threshold (T). T>=G is an edge point and make T<G is a noise point.

Inverse transform of edge extracted subbands gives better high quality edge images.

4. Line detection and experimental results

The algorithm is implemented in Matlab platform. LISS III, and Cartosat images were used to test our proposed method. LISS III image 4-MSS bands with 23.3m resolution, image 4-MSS with 2.4m resolution and PAN with 1m resolution of Chennai Mambalam area and Cartosat image of 2.5m resolution of small areas of Karanja District, Karnataka were selected. Rectification was carried out through latitude and longitude from survey of India toposheets using ArcGIS. In multispectral images, all the bands are not equally useful for specific applications. In this paper, PCA and SVD methods are used for band selection. SVD1 and PCA1 bands were selected, which contain maximum information of the original image. The quality of images was measured using no reference image quality metrics. No reference image quality is a process of predicting the visual quality of image without using any reference image. The quality of the SVD1 and PCA1 component images are calculated using two no reference quality metrics. Entropy (Mohsin, 2013) is a measure of information in a source image. Entropy can be represented as a measurement of the sharpness of the edge details, which is directly related with better defined structural information. Quality score (Zhou Wang *et al.*,2002) is a no reference scalar measure that estimates the horizontal and vertical blocking artifacts in images. The overall image quality of the given image is the arithmetic mean of two estimates. The results are shown in Table 1. The results of the proposed method were compared with DWT, DTCWT, CUT, CT and NSCT based edge detection methods. The quality of the detected edges was evaluated in terms of visual quality and Rosenfeld evaluation metric (Kitchen & Rosenfeld, 1981). This evaluation method is founded on the criteria of good edge formation without requiring ground truth information. Continuation and thinness are two desired qualities considered, when the central pixel in 3x3 widow is an edge of the detected edge map. Readers refer the algorithm (Kitchen & Rosenfeld, 1981) and the results are shown in Table 2. The edges extracted from proposed method were overlaid with actual satellite images using ArcGIS. Edges were checked randomly and there were no broken edges. An extracted edge matches with the edges in actual satellite images. Three features such as tanks, river and roads having a typical geometry were tested with original satellite images. This analysis also proves the validity and feasibility of the framelet transform based edge detection. This new approach will be useful for further image processing applications.

Table 1. No reference quality metrics

Image	PCA1		SVD1	
	Entropy	Quality_Score	Entropy	Quality Score
LISS III	5.215	6.367	6.129	7.205
	6.724	7.356	7.518	8.234

Table 2. Rosenfeld evaluation metric

S.No	Edge detection method	Rosenfeld edge evaluation metric
1	DWT	0.532
2	DTCWT	0.589
3	CUT	0.643
4	CT	0.675
5	NSCT	0.723
6	Framelet transform	0.783

With availability of large number of geometrical features in satellite images, extraction of lines and shapes is an essential task for further applications. After framelet based edge detection, LISS III and Cartosat images were subjected to the line detection methods. We have employed three methods for straight line detection as follows,

1. Standard Hough transform (Duda & Hart, 1972)

2. Small eigenvalue analysis (Guru *et al*., 2003)

3. Principal component analysis (Lee *et al.*, 2006).

The results are shown in Figures.1, 2 & 3.

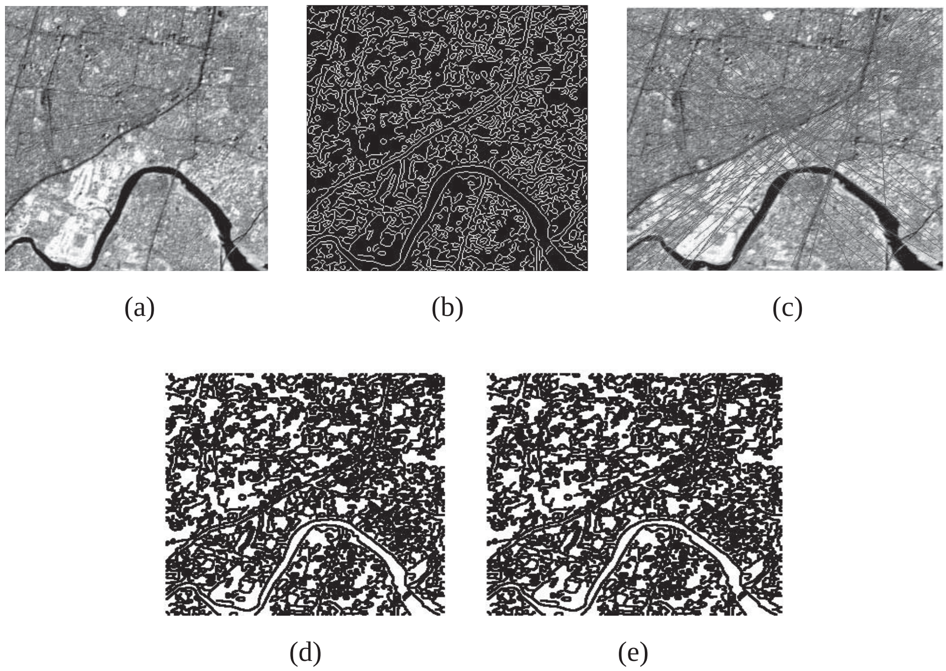

Fig. 1. LISS III (23.5m Resolution) (a) SVD component image (b) Framelet based edge detection (c) Line detection - Hough transform (d) Line detection- mall eigenvalue analysis (e) Line detection- principal component analysis.

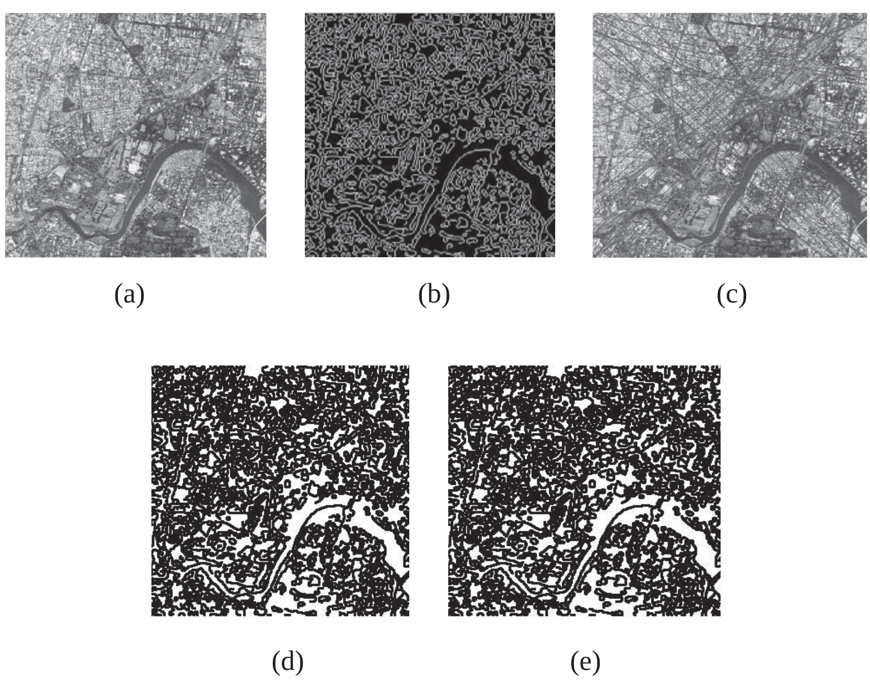

Fig. 2. (2.4m Resolution) (a) SVD component image (b) Framelet based edge detection (c) Line detection -Hough transform (d) Line detection-small eigenvalue analysis (e) Line detection- principal component analysis

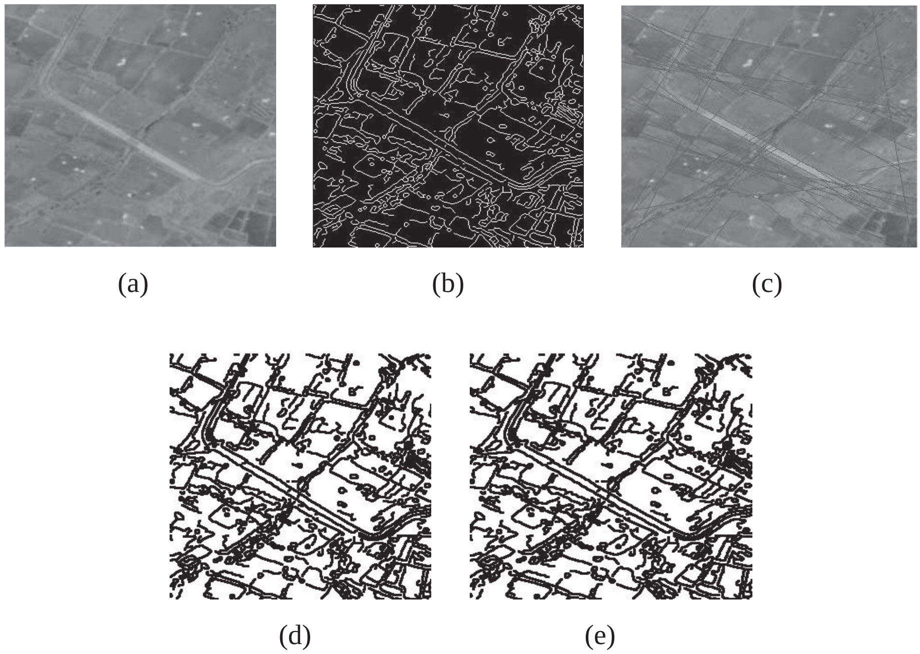

Fig. 3. Cartosat (2.3m Resolution) (a) SVD component image (b) Framelet based edge detection (c) Line Detection -Hough transform (d) Line detection-small eigenvalue analysis (e) Line detection- principal component analysis.

Hough transform is used to detect lines, curves and objects in an image using the concept of parameter space. This technique takes a binary edge image as an input. Each edge point is transformed from image space to parameter space by increasing the elements of an array called accumulation, using the line parameters as array indices. The cells of the array, which have the largest values indicate the possible location of lines in the given image. In Lee *et al* method, the row and column edges are labelled from the edge detected image. PCA is performed for each labelled edge. With the eigenvalue, the straight lines and their orientations are calculated. In Guru *et al* algorithm, the edge map is obtained by employing an edge detector on gray scale image. The window is placed at each edge pixel and computes the small eigenvalue of the covariance matrix of the set of all edge pixels covered by the selected window.If the small eigenvalue is less than a predicted threshold value, then the pixels are said to be linear edge pixels.

Classical edge detection operators produce acceptable solutions, but for finding optimum parameters like threshold and kernel size for edge detection is a complex problem with satellite images due to geometric characteristics of different land use ground features. Some edges are not distinguishable or vanished, based on threshold and kernel size. 2D Discrete wavelet transform capture only point singularities. It is not efficient to capture 1-D singularities such as edges and contours, due to horizontal and vertical sampling. 2D-DWT cannot provide a good approximation for directional features, which are not aligned in horizontal and vertical direction. Symmetry and directional properties of framelet transform captures line singularities such as lines and contours in satellite images, which is used for automatic feature extraction. Most of the human made features that exist in satellite images are straight line segments. Edge detection is a pre-processing step for linear feature extraction. In this experiment, roads and buildings of straight line segments are extracted in LISS III and Cartosat images are using these three methods. More number of line segments detected in image, compared to LISS III image and manmade irrigation canals of straight line segments are extracted in Cartosat image. In the time complexity of the straight line extraction algorithm using framelet based edge detection with the Hough transform, eigenvalue analysis and Principal component analysis are also evaluated with Matlab (tic) and (tac) comments shown in Table.3. Hough transform has high computing time compared to (Guru *et al*., 2003) and (Lee *et al*., 2006) methods. Guru algorithm eliminates the drawback of the standard Hough transform in which accumulator cells are divided by user defined angle and distance. Guru algorithm is easy to implement, but selecting kernel size and threshold for line detection depends on the objects in the images. Lee method avoids mask processing, the edges are labelled separately and then the small eigenvalue of labelled edge is used to identify the straight line segments.

Table 3. (Elapsed time in seconds)

S.No	Line detection method	Elapsed time in (Sec)
1	Framelet transform+ Hough transform	2.504
2	Framelet transform+ (Guru et al algorithm)	2.423
3	Framelet transform+(Lee et al algorithm)	2.356

5. Conclusion

Edge detection is an important task in remote sensing applications. Edges in an image provide a representation of object boundaries within that image. Classical edge detection operators are simple in computation and are capable to detect the edges and their orientation, but due to lack of smoothing stage, they are very sensitive to noise and are inaccurate. Wavelet transform has been applied for the edge detection. The discrete wavelet transform can capture only point singularities, due to subsampling process. In this paper, we have used framelet transform based edge detection. Good localisation and anti noise property of framelet transform leads to exact lines and contours in satellite images. PCA and SVD were used for feature reduction and no reference quality metrics is used to evaluate the quality of these methods. Higher values were obtained for SVD component image, which was input to framelet based edge detection. The proposed edge detection was compared with DWT, DTCWT, CUT, CT and NSCT based edge detection methods. The quality of these edge detection methods was evaluated in terms of the Rosenfeld evaluation metric and visual interpretation. Higher values were obtained for framelet based edge detection. The edges obtained through the framelet transform were subjected to line detection algorithms such as Hough transform (Duda & Hart, 1972), small eigenvalue analysis (Guru *et al*., 2003) and principal component analysis (Lee *et al*., 2006) to extract the straight line segments. Time complexity of the framelet transform +PCA based line detection was found to be less compared to framelet transform + Hough transform and framelet transform + small eigenvalue analysis. The proposed edge detection method will be suitable for remote sensing applications such as image segmentation and information extraction.

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التعرف على الحافة باستخدام تحويل الأطير للتعرف على الخط المستقيم من صور الاستشعار عن بعد.

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خلاصة

يتم استخدام التعرف على الحافة على نطاق واسع كخطوة مسبقة للتطبيقات المعتمدة على استخدام الصور مثل تقسيم الأقاليم واستنباط الخصائص وتوصيف حدود الأشياء. الوسائل التقليدية للتعرف على الحواف المتاحة سهلة الاستخدام لكن ليست كلها مناسبة لصور الاستشعار عن بعد اعتماداً على اختيار العتبة ودالة الجوهر. لا توجد طرق مقبولة لاختيار المعلمات في الوسائل التقليدية للتعرف على الحواف. التحليل المتعدد الدقة مثل تحويل المويجات (wavelet) له مميزات مقارنة مع الطرق التقليدية للتعرف على الحواف، لأنه أقل حساسية للضوضاء. تحويل المويجات المتقطع (DWT) يتغير بالإزاحة نتيجة لجزء من العينات الحرجة. تحويل المويجات المتقطع ليس له إمكانية التعرف على الحواف التي ليست متوافقة مع اتجاهات أفقية ورئيسية. في هذا البحث نركز أبعد من تحويل المويجات المتقطع، تحويل الأطيرات تُستخدم للتعرف على الحواف من LISS II وصور كارتوسات. تم تقييم الطريقة المقترحة بالمقارنة مع الطرق التالية للتعرف على الحواف. تحويل المويجات المتقطع، والتحويل ثنائي الشجرة المركب للمويجات وتحويل المنحنى وتحويل الإطار مع عينة وبدون عينة. باستخدام مقياس روزنفلد لقياس الجودة لطرق التعرف على الحافة، تم الوصول إلى الاستنتاج بأن تحويل الأطير أسفر عن نتائج أفضل من الطرق الأخرى. تم استخدام طريقة تحليل المكون الرئيسي وطريقة التفكيك أحادي القيمة لحذف الارتباط بين الحلقات الطيفية المتعددة وبعض حلقات المعلومات العظمى للتعرف على الحواف بدلاً من استخدام حلقة معينة وذلك لأن كل حلقة من الحلقات الطيفية المتعددة تتناسب مع أحد التطبيقات. الحواف التي تم التعرف عليها تم إخضاعها لنظام حسابي للتعرف على الخطوط مثل تحويل هونج وتحليل القيم الذاتية وتحليل المكون الرئيسي. تم مقارنة هذه النتائج من حيث القياسات المركبة. طرق التعرف على الحواف باستخدام تحويل الأطير مع تحليل المكون الرئيسي أفضل من الطريقتين الأخيرين.