Extraction of Edge-type and Anomaly-type Lineaments Based on Directional Continuous Wavelet Transform

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ABSTRACT

Background

Lineaments can be expressed as linear features which are notably brighter or darker than background (anomaly-type) and suddenly changed in brightness (edge-type) in the remote sensing (RS) and digital elevation model (DEM) images. A new method is proposed to extract both types of lineaments from RS and DEM images based on directional continuous wavelet transform (CWT).

The method consists of three steps: (i) determination of omni-directional CWT coefficient concerned with image gradient magnitude and omni-direction image reflecting image gradient direction using multi-directional CWT coefficients, (ii) extraction of image features such as extrema and edges using CWT modulus maxima line and (iii) detection of lineaments through segmentation and linkage of image features and linearization of image feature segments. The omni-directional CWT and omni-direction image determined from multi-directional CWT coefficients are associated with image gradient to be applied to image feature extraction, segmentation and linkage. The positive and negative lineaments can also be detected by the method.

The proposed method is tested using a simple example image and compared with the Hough transform (HT) method and applied to real RS and DEM images to extract both types of lineaments, which are compared with real geological structures including faults. The results show the proposed method is superior to the HT method and effective in detection of lineaments reflecting geological structures which are roughly rectilinear and expressed at multiple scales and directions.

Keywords: Directional continuous wavelet transform, Omni-direction, Lineament extraction, Digital elevation model, Image gradient

INTRODUCTION

Lineaments are closely associated with geological features including geological structures, lithological boundaries and stream networks. Therefore, lineament extraction is important in geological studies (1~3). Lineaments have been differently defined by many researchers for many decades, but their definition can be classified into two types: linear features which are abnormally brighter and darker than background (4,5) and those associated with sudden changes in brightness. In the view of image process, the sudden changes in image intensity correspond to image edge and lighter or darker pixels correspond to anomalies.

Most studies in lineament detection have been based on image edges (2, 6, 7). These methods generally consist of two steps: edge detection and lineament extraction. Image edges have been mainly detected using the convolution with derivative masks including the Roberts, Sobel, Prewitt, and Canny methods. In special, the Canny method has been widely applied to edge detection as it can detect edges more exactly using image gradients than other methods. Image gradients are determined by horizontal and vertical derivatives based on Gaussian filters. However, both derivatives can lead exact gradients about continuous and differentiable images which do not always agree with real images. Although images are smoothed, there can exist some line

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singularities like corners where images are not continuous and differentiable. Some researchers have used directional first derivative operators to overcome these shortcomings (8). Such methods can determine directly image gradients from multi-directional convolutions of images with directional derivative masks. These masks are usually constructed at specific scales and can hardly possible at any scales. Moreover, some researchers used four directional masks, which cannot provide exact image gradients. Other researchers used two-dimensional continuous wavelet transform (2D CWT) and its multi-directional characters to detect image edges more exactly near line singularities such as corners (9,10). However, their methods have not been applied to lineament extraction.

Another important issue in detecting and mapping lineaments is to enhance linearity of edges. Lineaments have to be image edges and straight lines. Therefore, methods have been proposed to select linear pixel group or detect lines including possible edge pixels from image edges. The typical methods used by most studies on lineament detection are Hough transform (HT) and its variations (11). They convert a pixel group laid in a straight line into a point in another parameter space of polar coordinates to detect the lineament including the pixel group. As many points included in a straight line in image domain are expressed as a point in the parameter space called Hough space, HT can easily detect the line by detecting only one point in Hough space instead of many points in image space. Although it is recognized to be a useful tool for pattern recognition including lineament detection, its lineament detection ability is low in noisy images including lineaments that are roughly rectilinear (12). Edges detected using image gradients contain information on their directions which can be helpful in lineament detection. The HT and its variations can hardly use this information.

Some lineaments are not related with image edges, but with anomalies or extrema in image intensity. Most morpholineaments such as valleys and ridges in a digital elevation model (DEM) are anomaly-type. Such lineaments are usually extracted from derived images, e.g. shaded relief (hillshade) or from second derivatives of images (5). As anomaly-type lineaments in an image can be converted with edge-type one in its hillshade, they can be extracted using lineament detection based on image edges from the hillshade. However, the hillshade is not unique for an image, but a little changed relying on the illumination altitude and azimuth. It can lead to different responses for a lineament. Šilhavý et al. tried to extract unique lineament by clustering of different lineaments detected from multiple hillshades. Other studies have applied second derivative operators such as Laplacian filter to detect anomaly-type lineaments. Mallast et al. introduced omni-directional image from four directional images convolved with directional Laplacian filters. Extrema in a DEM can preserve as extrema in the omni-directional image of the DEM. Both methods using first derivative and second derivative masks detect lineaments based on extrema detection. The former detects exact lineaments easily through comparing gradient magnitude along gradient direction, whereas the latter cannot do so and should use some thresholds and thinning.

This work aims to propose the method to detect lineaments associated with edges and anomalies based on directional CWT. Omni-directional CWT coefficient which can reflect gradient magnitude and be used as derived image for detecting anomaly-type lineaments is determined from multiple directional CWT coefficients based on the Gaus1 wavelet which is the first derivative of the 2D Gaussian function. Image edges are detected using the omni-directional CWT coefficient and omni-direction image. Edges are also segmented into several parts and the parts with similar direction are linked each other using them. Finally, every edge segment object is transformed into a lineament based on regression analysis.

METHOD

Omni-directional CWT and image gradient

2D wavelet function $\psi_{\boldsymbol{u},\alpha,s}(\boldsymbol{x})$, where $\boldsymbol{x}=(x, y)$ is the spatial variable vector, can be obtained from mother wavelet $\psi(\boldsymbol{x})$ by dilation, translation and rotation as follows.

$$\psi_{\boldsymbol{u},\alpha,s}(\boldsymbol{x}) = \frac{1}{s}\psi\left(\boldsymbol{R}^{-\alpha}\,\frac{\boldsymbol{x}-\boldsymbol{u}}{s}\right), \tag{1}$$

where $\boldsymbol{u}=(u_x, u_y)$ is the translation parameter vector, s is the scale parameter, α is the rotation angle and $\boldsymbol{R}$

is the rotation matrix.

The 2D directional CWT of a 2D signal $f(\boldsymbol{x})$ with respected to the wavelet □□□at scale s is defined as

$$WT_{\psi s}(\boldsymbol{u},\alpha) = \int_{R^2} f(\boldsymbol{x}) \frac{1}{s} \psi\left(\boldsymbol{R}^{-\alpha} \frac{\boldsymbol{x}-\boldsymbol{u}}{s} \right) d\boldsymbol{x}\,. \tag{2}$$

The space parameter vector $\boldsymbol{x}$ is eliminated after CWT and the translation parameter vector $\boldsymbol{u}$ is the same as $\boldsymbol{x}$ in essence. For convenience, we replace $\boldsymbol{u}$ with $\boldsymbol{x}$ to express the CWT as a function of the space parameter vector and rotation angle.

The omni-directional CWT, $WT_{\psi s}^{OD}(\boldsymbol{x})$, is given from multi-directional CWTs and defined as

$$WT_{\psi s}^{OD}(\boldsymbol{x}) = WT_{\psi s}(\boldsymbol{x}, \alpha^{OD}(\boldsymbol{x}))\,, \tag{3}$$

where $\left|WT_{\psi s}(\boldsymbol{x}, \alpha^{OD}(\boldsymbol{x}))\right| = \max_{\alpha} \left|WT_{\psi s}(\boldsymbol{x},\alpha)\right|$, □^{OD}($\boldsymbol{x}$) is omni-direction function. That is, the omni-directional CWT means the modulus maximum of directional CWT at $\boldsymbol{x}$ with respect to □□and the omni-direction function is the direction of the omni-directional CWT at $\boldsymbol{x}$. The directional CWT of $f(\boldsymbol{x})$ with Gaus1 wavelet is the same as the first derivative of the function smoothed with 2D Gaussian function. Therefore, the omni-directional CWT is proportional to image gradient magnitude and the omni-direction function reflects gradient direction. This means we can detect lineaments using the omni-directional CWT and omni-direction function instead of image gradient.

Convert of extremum points into edge points using omni-directional CWT

In the view of mathematics, anomaly-type lineaments such as ridges and valleys are associated with lines consisting of extremum points, which seem to be detected more hardly than edges. Derived image where edges correspond to extremum points in source image is necessary to detect anomaly-type lineaments using edge-based lineament detection method. Here, the omni-directional CWT of the source image is supposed to be used as the derived image. In general, if a 2D function has an extremum along the direction □ at the point x, the directional derivative of the function along the direction at the point is to be zero. This is certainly possible along the gradient direction. For convenience, let’s consider 1D function along the gradient direction (Fig. 1).

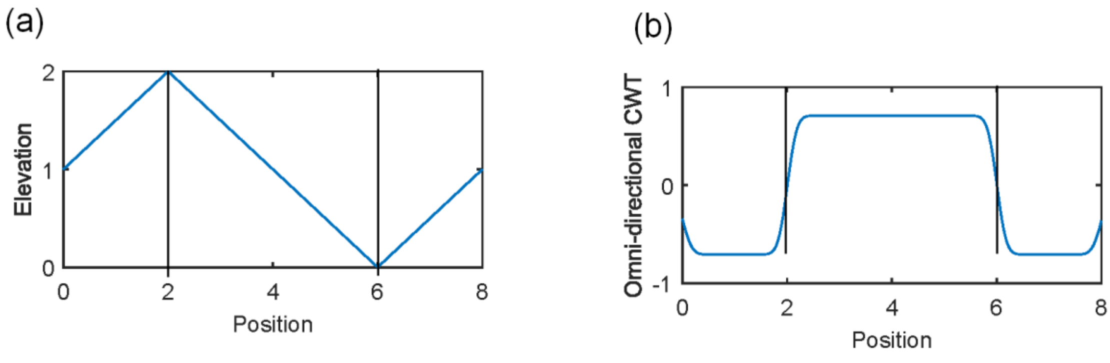

Fig.1 Principle of conversion of extreme points such as peaks and valleys into edges using the omni-directional CWT

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As shown in Fig. 1a, the peak and valley are expressed as extrema in the section along the gradient direction. They exist at extremum points where the dip tendency is changed from increase to decrease or from decrease to increase, which leads to sudden change in gradient magnitude (Fig. 1b). The extremum points in primary image are changed into edges in its omni-directional CWT. Therefore, edge-type lineaments detected from the omni-directional CWT are the same as anomaly-type lineaments of the primary image.

Edge detection using the omni-directional CWT and omni-direction

Omni-directional CWT is proportional to the gradient magnitude and omni-direction reflects the gradient direction. Therefore, edges can be detected using them.

An edge point at scale s is a point $\boldsymbol{x}_f$ satisfying the condition given as

$$\left|WT_{\psi_s}^{OD}(\boldsymbol{x}_f)\right| = \max_{x}\left|WT_{\psi_s}^{OD}(\boldsymbol{x})\right|, \tag{4}$$

where $\boldsymbol{x} = \boldsymbol{x}_f + \lambda \boldsymbol{n}_{\alpha^{OD}(x_f)}$ for $|\lambda|$ small enough to keep the omni-direction □$^{OD}(\boldsymbol{x})$ unchanged to be the same as □$^{OD}(\boldsymbol{x}_f)$, $\boldsymbol{n}$□ is an unit vector along the direction □□.

The edge function $E(\boldsymbol{x})$ is determined based on this condition. Its value is one for points where Eq. 4 is satisfied and zero for other points. In order to detect the positive and negative lineaments respectively, the positive and negative edge functions $E^+(x)$ and $E^-(x)$ can be determined as follows.

$$E^+(\boldsymbol{x}) = E(\boldsymbol{x}) \wedge (WT_{\psi_s}^{OD}(\boldsymbol{x}) > 0)\,, \quad E^-(\boldsymbol{x}) = E(\boldsymbol{x}) \wedge (WT_{\psi_s}^{OD}(\boldsymbol{x}) < 0)\,. \tag{5}$$

Edge segmentation and linkage

An edge can be partly rectilinear or curvilinear and lineaments correspond to rectilinear edge parts. Most lineaments reflecting geological structures are not strictly rectilinear, but roughly rectilinear and the criterion to evaluate whether an edge part is rectilinear or not is relative. HT uses too strict criterion for straight lines to detect such roughly rectilinear lineaments.

As an edge is perpendicular to gradient direction, omni-direction can reflect edge direction. In this paper a lineament is supposed to be a group of linked edge points with similar direction. Edges are segmented into nearly rectilinear parts with similar direction using omni-direction. Edge part image EP(x) consisting of nearly rectilinear edge part objects can be defined as follows.

$$EP(\boldsymbol{x}) = \begin{cases} 1, & if\ E(\boldsymbol{x}) = 1\ and\ \alpha^{OD}(\boldsymbol{x}) \in (\frac{\pi}{n}i - \frac{\pi}{2n}, \frac{\pi}{n}i + \frac{\pi}{2n}), i = 0,1,\ldots,n-1, \\ 0, & otherwise \end{cases} \tag{6}$$

where n is a number of divisions of omni-direction which defines how rectilinear each edge part is. Each object direction can be determined using mean of omni-direction values of edge points of the object or regression coefficient with respect to their positions. If neighboring objects have similar direction, they are linked to be an object. This is achieved by changing the value of edge part image from zero to one for the boundary points of object to be linked.

Linearization of edge part objects

Each edge part object has to be transformed into a straight line. This can be realized using regression analysis with respect to positions of edge points belonging to an object. The regression model is supposed as $y^{ou}=l(x)=ax^{o}+b$□ for the edge points of the object, $\boldsymbol{x}^{o}=(x^{o}, y^{o})$. The regression coefficients a and b are determined by regression analysis. The starting point $\boldsymbol{x}^{l}_{s}$ and end point $\boldsymbol{x}^{l}_{e}$ of the lineament corresponding to the object are set from the regression coefficient of the object, $\boldsymbol{x}^{o}_{s}$ and $\boldsymbol{x}^{o}_{e}$, as

$$\boldsymbol{x}_s^l = (x_s^o + (y_s^o - l(x_s^o))\sin\alpha, l(x_s^o + (y_s^o - l(x_s^o))\sin\alpha)), \tag{7}$$

$$\boldsymbol{x}_e^l = (x_e^o + (y_e^o - l(x_e^o))\sin\alpha, l(x_e^o + (y_e^o - l(x_e^o))\sin\alpha)), \tag{8}$$

where □= arctan(a). Finally, the lineament is determined as

$$\boldsymbol{L} = \{\boldsymbol{x}^l = (x^l, l(x^l)),\ x \in [x_s^l, x_e^l]\}. \tag{9}$$

Examples

Here, the proposed method is tested and compared with the HT method using a simple example image to prove its accuracy and efficiency. The image includes an edge-type lineament which is a fault expressed as a lithological boundary and three anomaly-type lineaments which are faults expressed as valleys (Fig. 2a). The lineaments are not strictly rectilinear, but have linear tendency.

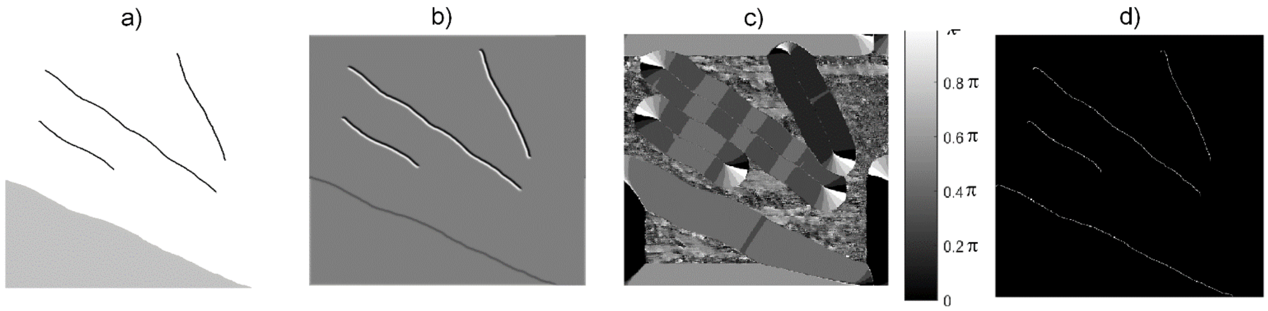

Fig.2 Example image including roughly rectilinear features (a), its omni-directional CWT (b) and omni-direction (c), detected edge image (d)

Firstly, the omni-directional CWT and omni-direction image are determined from eight directional CWT with the scale four (Fig. 2b, 2c). Edges are detected using the omni-directional CWT and omni-direction (Fig. 2d). The edges are segmented into nearly rectilinear parts using edges and omni-direction (Fig. 3a). The four edges are respectively segmented into four, four, seven and four edge parts. The segmented edge parts with similar direction are linked to form an object (Fig. 3b).

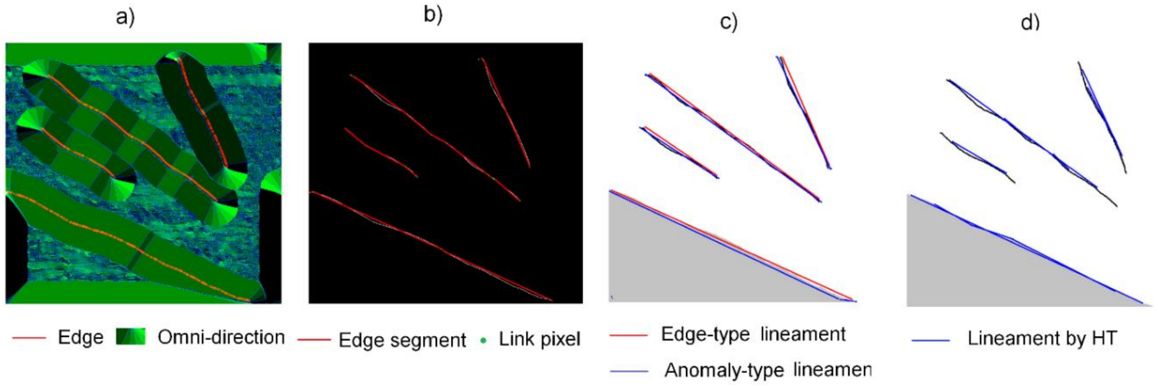

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Fig.3 Edge segmentation using omni-direction (a), linkage of edge parts with similar direction (b), lineaments detected by the proposed method (c) and those by the HT (d)

Every parts of each edge are evaluated to be similar in their direction and four edges correspond to four objects. Finally, they are linearized to form four lineaments (Fig. 3c, red line). Note that the edge-type lineament corresponding to the lithological boundary reflects it exactly, whereas other lineaments are a little deviated from the valleys corresponding to them. The anomaly-type lineaments are detected using the omni-directional CWT instead of the source image (Fig. 3c, blue line). In contrary to the edge-type lineaments, the anomaly-type lineaments exactly correspond to valleys, but not to rock facies boundary. Therefore, exact one among both types of lineaments should be selected relying on characters of geological features. The proposed method is compared with the HT. The lineaments detected by the HT (Fig. 3d) are more, but reflect the features less exactly and sufficiently than those by the proposed method. Lineaments detected by the HT are overlapped and grouped each other to reflect geological features, whereas those by the proposed method agree well with geological features and each lineament corresponds differently to each feature. This shows the proposed method can detect geological lineaments such as faults, lithological boundary and so on, which are roughly rectilinear, more easily and effectively than the HT method.

Applications

Here, the proposed method is applied to extraction of geological faults using RS and DEM data images. The first principal component image of the Landsat ETM+ data and the corresponding DEM data with spatial resolution of 30 m are used (Fig 4). Their size are all 1500×1500 pixels.

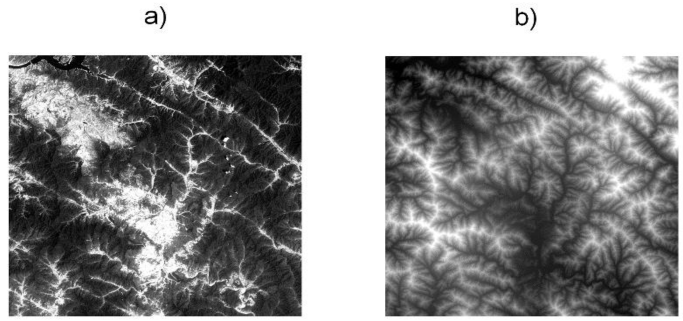

Fig.4 The primary component image of Landsat ETM+ data (a) and DEM image (b) of the study area.

Faults are generally expressed as lithological boundaries which can correspond to sudden changes in image intensity of RS data or valleys which are the morphometric features involved in DEM data. Therefore, edge-type lineaments corresponding to lithological boundaries are tried to be extracted from the RS data and negative anomaly-type lineaments corresponding to valleys are extracted from the DEM data. The first derivative of 2D Gaussian function is used as a mother wavelet and the scale is set as 2^4 which is similar to the width of the faults. The edges and edge-type lineaments extracted from the first principal component image of the Landsat ETM+ data are shown in Fig. 5a and 5b.

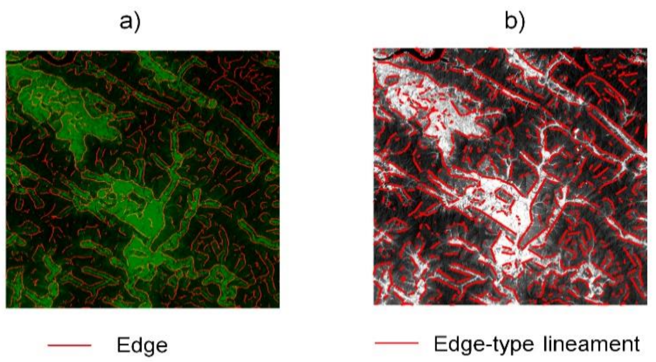

Fig.5 Edges (a) and edge-type lineaments (b) detected from the RS data (Fig. 4a) using the proposed method

Edges including lithological boundaries are exactly extracted, which provides the condition for detecting lineaments. Edges are segmented into several parts which are roughly rectilinear and the parts with similar direction are linked to form objects. The objects are linearized to be transformed into lineaments. These edge-type lineaments agree well with lithological boundaries which can be faults. The omni-directional CWT of the DEM data is determined (Fig. 6a) and its edges (extreme lines of the DEM data) are detected (Fig. 6b).

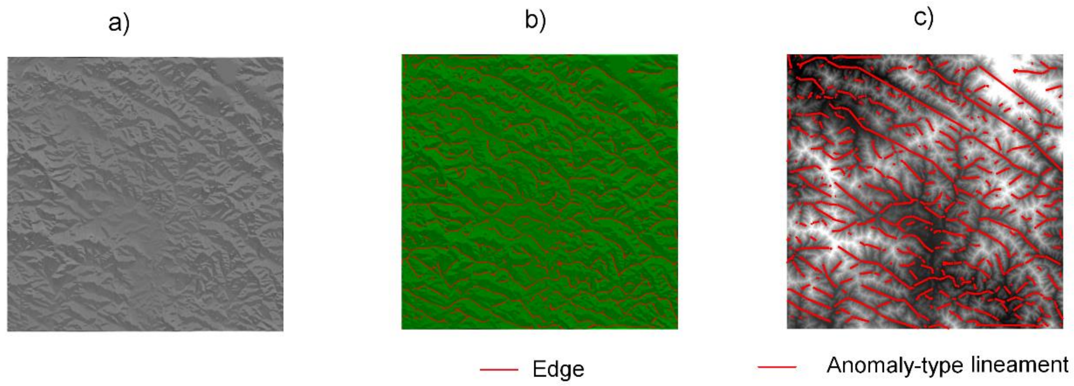

Fig. 6 The omni-directional CWT of the DEM data (Fig. 4b) (a), edges detected from the CWT (b) and anomaly-type lineaments detected from the DEM data by the proposed method

The negative anomaly-type lineaments corresponding to valleys are detected from the DEM data (Fig. 6c). The valleys in the DEM image are expressed as edges reflecting sudden changes in the omni-directional CWT image (Fig. 6a). This shows the omni-directional CWT can be used as a derived image for detecting anomaly-type lineaments instead of hillshades. Therefore, valleys can be detected by detecting edges from the omni-directional CWT (Fig. 6b). The lineaments lead from the edges are shown with the DEM data (Fig. 6c). The lineaments agree well with valleys. The NW-SE oriented valleys are specially rectilinear which are expressed as long lineaments.

Finally, the edge-type and anomaly-type lineaments are displayed together and compared with faults of the geological map of the study zone (Fig. 7a).

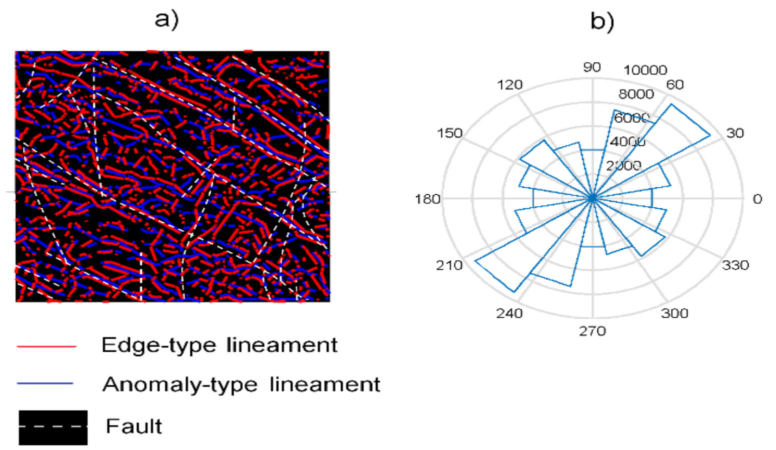

Fig. 7 Comparison of detected lineaments to faults (a) and rose diagram of lineaments azimuth (b)

As shown in the Fig. 7a, the NW-SE oriented strike-slip faults are mainly developed and NNW-SSE oriented and NNE-SSW oriented faults are additionally developed. Comparing detected lineaments with the faults (Fig. 7a), the lineaments correspond well with the NW-SE oriented strike-slip faults. These faults are nearly explained by detected long anomaly-type lineaments as they form roughly rectilinear anomaly-type lineaments such as valleys and narrow rectilinear bands. Other oriented faults are hardly detected as they do not form clear lineaments in the RS and DEM image. The result shows the anomaly-type and edge-type lineaments detected by the proposed method can express the faults and lithological boundaries well. The rose diagram made using the direction and length of detected lineaments reflects well the distribution of faults in study area.

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DISCUSSION AND CONCLUSION

This paper proposes the method to extract lineaments using directional 2D CWT. The omni-directional CWT and omni-direction determined from eight directional CWTs can be used as a tool to detect edges from RS and DEM data instead of image gradient. Moreover, the anomalies in the source image are converted into sudden changes in image intensity by the omni-directional CWT. Therefore, it can be used as drive image for detecting anomaly-type lineaments instead of hillshades which produce a little different lineament relying on the illumination altitude and azimuth. And edge detection of the omni-directional CWT seems to be superior to other methods using only the magnitude of the second derivative of the image, as the method uses the omni-direction. The omni-direction is used to segmentation of edges into roughly rectilinear parts. The neighbor edge parts with similar direction are linked to form an object. Roughly rectilinear objects are linearized to construct lineaments using regression analysis. Such segmentation, linkage and linearization are effectively used instead of the HT.

The examples show the method is more effective in detecting roughly rectilinear lineaments, which is the character of geological features, than the HT and the method using hillshades which lead several overlapped and colinear lineaments or false additional lineaments for a geological feature. The method has been applied to extraction of lineaments from the RS and DEM data for studying geological features including faults and lithological boundaries. The anomaly-type and edge-type lineaments extracted by the method agree well with most faults. However, both lineaments correspond to a geological feature. Therefore, lineament selection is necessary in order to express a geological feature using a proper lineament.

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