ISSN: 2664-9640

Overview of Automatic Fracture Recognition in Imaging Logging

Peng fei Wang

School of computer Science, Yangtze University, Jingzhou 434023, China

Abstract

The distribution of cracks in space is extremely non-uniform and diverse, with strong heterogeneity and anisotropy, and random in electro-imaging images. The formation bedding and fractures have a high similarity in the imaging map, which greatly interferes with the automatic identification of fractures. In this paper, the bedding extraction is firstly studied, and bedding information is extracted by the bedding extraction method based on the statistical method of electro-imaging, and then the interference in the imaging image is processed. First, the interference information is eliminated by filtering, then the crack information is enhanced, and finally the crack is extracted by edge tracking method.

Keywords

Electrical imaging logging data preprocessing, Bedding removal, Image enhancement, Automatic fracture picking.

1. Introduction

Fractures are post-depositional geological elements. They are not only important for understanding regional tectonic interpretation, but also restore the original depositional state and reconstruct the process of tectonic movement. In oil and gas exploitation, opening fractures is conducive to the flow of oil and gas, while filling fractures is just the opposite. In addition to cores, electrical imaging logging is currently the main method to obtain accurate wellbore fracture density and orientation. Considering that the imaged image has thousands of pixels, it is more efficient to use an automatic processing method to process the imaged image. Visually identifying geological planes is a very complex process. According to some specific criteria, geologists are able to distinguish depositional planes and fractures in electrical imaging images. Generally speaking, the depositional plane is the main heterogeneity plane, the depositional planes of the same type are all clustered closely, and there can only be one kind of deposition at the same depth. But cracks are more random, the cross-sections are often partially visible, and multiple types of cracks can appear at the same depth. This makes it very difficult to identify cracks using automatic identification methods. At present, the identification of fractures by most of the electrical imaging interpretation software is still based on human-computer interaction. Punctuation points, and then use the trajectory points to fit to obtain the fracture shape, or directly connect the trajectory points to pick the fracture segment. Manually picking up cracks requires high professional knowledge of the interpreter and requires some interpretation experience, so the interpretation efficiency of human-computer interaction is low.

2. Crack Identification Method

2.1. Crack Identification Based on Morphological Corrosion and Dilation

The term morphology generally refers to a branch of biology that studies the shape and structure of plants and animals. Erosion and dilation are for white parts (highlights), not black parts. Dilation is the expansion of the highlighted part of the image, "field expansion", and the rendering has a larger highlighted area than the original image. Corrosion means that the highlighted part of the original image is corroded, "the field is eroded", and the effect image has a smaller highlighted area than the original image.

Qin Wei et al. [1] proposed to use the dilatation and corrosion technology in morphology and the method of image recognition to realize the automatic identification of fractures in simple formations;

2.2. Recognition of cracks in a straight line on a plane

Because fitting a sine curve based on sample points is much more complicated than fitting a straight line, it will be much simpler if the crack identification problem can be reduced to a linear crack identification problem on a plane.

Xue Guoxin[2] et al. proposed a fracture identification method in imaging logging. It first finds a straight line with the largest number of possible fracture points in the image that passes through the wellbore, and then removes the noise points that are far away from the straight line. Then adjust the position of this straight line and repeat the above process to make up for the shortcomings of the traditional method.

2.3. Crack Recognition Based on Hough Transform

The Hough transform was proposed by Hough in 1962. Originally used to detect straight lines in images. Its basic idea is to transform a curve with an analytical representation in the image space into the parameter space.

For each black pixel in the image space, it becomes a curve or surface in the parameter space after transformation. All points are after this transformation. If these pixels have the shape of a known analytical curve in the parameter space, then the transformation curve or surface in the parameter space will most likely be clustered in a certain area. The parameter coordinates corresponding to this area are the characteristic parameters of the analytic curve corresponding to the pixels in the image space.

Since fractures appear as single-period sinusoids in imaging logs, Lu Jingan[3] et al. proposed a method and technology to automatically identify fractures by using Hough transform. By identifying sinusoidal images with known parameters. It is proved that the method has the ability to accurately identify the sine curve and its parameters. Even in the case of low signal-to-noise ratio of the original image, it can still give an ideal recognition effect.

3. Machine Learning Approaches for Crack Identification

3.1. Crack Recognition Based on DeepLabv3+ and Hough Transform

DeeplabV3+ is considered to be a new peak of semantic segmentation. In order to integrate multi-scale information, it introduces the encoder-decoder form commonly used in semantic segmentation. In the encoder-decoder architecture, the resolution of features extracted by the encoder can be arbitrarily controlled, and the accuracy and time-consuming are balanced by atrous convolution. Its biggest feature is the introduction of hole convolution, which increases the receptive field without losing information, so that each convolution output contains a larger range of information. Li Bingtao [4] et al. adopted DeepLabv3+, an image semantic segmentation model in the field of computer vision, to segment the crack region, and then used Hough transform to extract crack morphological parameters to identify cracks based on the segmentation results.

3.2. Crack Recognition Based on Conditional Generative Adversarial Networks

CGAN is to add conditional label images on the basis of GAN, and use the label image constraint generator to extract information from actual images, turning the GAN unsupervised training process into a supervised training process. At the same time, CGAN optimizes the judgment criteria of the discriminator, distinguishing false data + arbitrary labels and real data + wrong labels as false, and distinguishing true data + correct labels as true.

Wei Boyang [5] et al. proposed using conditional generative adversarial network (CGAN) to identify cracks in images. CGAN extracts the features in the training image and the label by training the given image and the corresponding label image, and uses the feature to identify the information in the image.

3.3. Crack identification combined with K-means clustering

The K-means clustering algorithm adopts the iterative idea, and its goal is to divide the sample data into k categories, by randomly initializing k sample center points, and continuously iteratively optimize the cluster center points, so that the k categories can ensure the smallest intra-class differences as much as possible. The largest difference between classes.

According to the difference between the gray value of cracks and background pixels, Tang Wei [6] used K-means clustering algorithm for image segmentation, and finally combined morphological methods and connected domain detection to achieve crack bridging and denoising.

Since the area of the connected domain in the fracture region is larger than that of the non-fracture noise point, the connected domain area constraint can be used to remove the noise point, and the fracture caused by the over-segmentation of the fracture feature can be repaired by the morphological method.

The specific process is as follows:

(1) First, the K-means segmented image is denoted as image D, and the inverse color is denoted as image D1.

(2) The image D1 is processed by the morphological dilation first and then erosion open operation, and the processed image is denoted as D2.

(3) Use connected domain detection to remove the impurity points in the eight-connected domain whose area is less than the threshold value, and calculate the number of all pixels in the eight-connected region S_i with each value of 255 in D2, denoted as Q_i, if Q_i is less than the threshold value T, then All pixels in the S_i area are assigned to 0, and the processed image is recorded as D3.

(4) Invert the D3 image to obtain the final crack extraction image D4.

3.4. Fracture Identification Based on BCEM Model

Zhang Zhenhai [7] and others proposed a bridge crack identification network based on the BCEM (Bridge crack extraction model) model. The network combines deep learning with traditional image processing methods. First, the crack image is preprocessed, and the data set preprocessing is divided into two steps: filtering and sliding window cropping. Before the image is cropped, the cracks are filtered bilaterally to make it easier for the network to learn the feature information of cracks, thereby improving the accuracy of surface identification and enhancing the expression of crack information; Based on the characteristics of meta-images, the improved BC-MobileNet lightweight model is used to classify the crack surface elements; finally, the false detection and missed detection surface elements are identified to realize the accurate identification of bridge cracks.

4. Crack Identification with Convolutional Neural Networks

4.1. Crack Recognition Based on Improved Convolutional Neural Network

Due to the characteristics of convolutional neural networks, different network structures are often required for different recognition targets. Zhang Zhenhua [8] and others proposed an image recognition method for concrete bridge cracks based on an improved convolutional neural network, using a dual-channel multi-size convolution kernel to perform convolution and feature extraction on bridge crack images, and with an improved activation function as the transfer function, using support vector machine (SVM) instead of Softmax classifier to improve recognition accuracy and efficiency.

4.2. A fast crack screening method

Du Jianchao [9] and others proposed a fast screening method for bridge crack images. The method first extracts the edge in the image, then obtains its minimum circumcircle by the end point coordinates of the longest edge, and then selects it based on the radius of the minimum circumcircle. Generally, the radius of the minimum circumscribed circle obtained from images with cracks is larger, and the radius of the minimum circumscribed circle obtained from images without cracks is smaller, which can be screened according to the set threshold. The threshold value used in the screening process is automatically determined by building an adaptive calculation model based on image resolution, that is, manually obtaining the best threshold value for different resolution image screening, and then fitting it with a function

The role of edge extraction is to find the longest edge in the image. The process is as follows: first, binarize the crack image, then detect all edges in the image and calculate their lengths, and find the one with the longest length as the longest edge.

In crack images, cracks usually have the following characteristics:

1) The gray value of the pixel point on the crack is low;

2) The number of pixels on the crack accounts for a small proportion of the total number of pixels in the image.

Based on the above characteristics, the P-quantile binarization algorithm is used to binarize the image; the principle of the P-quantile binarization algorithm is to select a threshold value according to the histogram of the image, so that the pixel whose gray value is less than the set threshold value The total does not exceed the set ratio.

After the image is binarized, the Canney edge extraction algorithm is used to extract the edge. First, the gradient of the image is calculated to obtain the set of all possible edge pixels; the gradient image is then subjected to non-maximum suppression, and the pixels with little local change are eliminated to further determine the position of the edge; finally, the obtained possible Pixels that are edges determine whether they are edges according to the threshold. The Canney edge extraction algorithm uses two thresholds to determine the edge, that is, a large threshold and a small threshold. If the gradient value of the pixel in the image is greater than the large threshold, it is considered to be a boundary, which is called a strong edge; if it is smaller than the small threshold, it is considered as a boundary. It must not be a boundary, which is called a weak edge; pixels larger than the small threshold and smaller than the large threshold need to be further judged. If there are strong edge pixels in its neighborhood, the pixel will be retained; otherwise, it will be eliminated. The two thresholds in the algorithm can take any value between 0 and 255, so the image is binarized before edge extraction, so that there are only two values 0 and 255 in the image.

After the edge points are extracted, the result of Canny edge extraction is searched for the longest edge. The specific process is: first determine whether an edge point has other edge points in its eight-neighborhood, if so, it is considered that two edge points are located on the same edge, and then continue to judge whether the next edge point exists in its eight-neighborhood Other edge points; otherwise, it is considered that there are no other points on the edge; after traversing all edge points in turn, several edges are obtained, and then the length of each edge is calculated to find the edge with the largest length. The edge length calculation method is to traverse the edge points contained in the edge in turn, calculate the Euclidean distance between the edge points, and then use the sum of all Euclidean distances as the edge length.

However, the length alone is not enough to effectively distinguish between cracked images and non-cracked images. For example, a circular-like edge appears in the image, which has a larger length but is usually not a crack. Therefore, according to the characteristics of relatively long and narrow cracks, a screening method based on the minimum circumscribed circle of the longest edge is proposed. The specific screening process is as follows: first, the minimum circumscribed circle is obtained according to the coordinates of the endpoints of the longest edge, and then the radius of the circumscribed circle is used as the screening method. Based on this, compare it with the screening threshold. If the radius of the circumscribed circle is greater than the threshold, it is judged as an image with cracks, and if it is less than the threshold, it is judged as an image without cracks.

4.3. Crack recognition based on atrous convolution and multi-feature fusion

DilatedConvolution enables ResNet to keep the parameters constant and the field of view of the convolutional layer in each stage unchanged. The convolutional layer at the back can also maintain a larger size of featuremaps, which is conducive to the detection of small targets and improves the overall model of the model. performance.

Qu Zhong [10] et al. proposed a concrete pavement crack detection network based on atrous convolution and multi-feature fusion, and the network adopted a U-Net-based encoder-decoder structure. In the encoding stage, the improved residual network Res2Net is used to improve the feature extraction ability; in the middle part of the network, the convolution of different hole rates combined in series and parallel is used, so as to increase the receptive field of feature points without The resolution of the feature map is reduced; in the decoding stage, multi-scale and multi-level features from low-level convolution to high-level convolution are fused, which improves the accuracy and precision of crack detection and has strong robustness.

4.4. Crack Recognition Based on Fully Convolutional Neural Network

The full convolutional neural network, as the name implies, is full of convolutional layer links in the network. The structure of the network is the same as that of the CNN in the first two steps, but when the CNN network is Flatten, the FCN network replaces it with a convolutional network. The kernel size is 5x5, the output channel is 50 convolutional layers, and the subsequent fully connected layers are replaced by 1x1 convolutional layers.

Deng Hui [11] and others proposed a BCI-AS (BridgeCrackImage-AutomaticSegmentation) bridge crack automatic segmentation model based on a fully convolutional neural network and a crack width measurement algorithm based on the least squares fitting centerline based on projection technology. The model based on BCI-AS performs accurate pixel-level segmentation on the bridge crack image dataset, and the segmentation accuracy reaches 94.45%. The algorithm of least square fitting center line based on projection technique measures the width of the segmented fracture binary image, and the result shows that the relative error is less than 7%.

4.5. Knowledge-based crack identification

Song Jinxiang [12] and others proposed an automatic picking and identification method, which combined the overall knowledge of fracture blocks and the manual picking knowledge of cracks by interpretation experts, and for the electro-imaging images of more complex situations, on the basis of image processing, through regular knowledge representation and analysis. Quantitative characterization, reverse knowledge reasoning technology and information fusion technology simulate and explain the manual picking process of experts, and automatically pick up cracks and determine their categories, and achieve the same recognition results as manual picking.

5. Automatic identification of cracks based on cellular automata

Cellular automata (CA) is a grid dynamics model in which time, space and state are discrete, and spatial interaction and time causality are local. It has the ability to simulate the spatiotemporal evolution of complex systems. Unlike general dynamic models, cellular automata are not determined by strictly defined physical equations or functions, but are constructed using a series of model-constructed rules. Any model that satisfies these rules can be regarded as a cellular automata model. Therefore, cellular automata is a general term for a class of models, or a method framework. Its characteristics are that time, space and state are discrete, each variable only takes a finite number of states, and the rules for changing its state are local in time and space.

Feng Lin[13] et al., based on the basic fact that the gray value of fractures in the acoustic imaging logging image is large and the fractures are continuous, using the local rules of cellular automata and the parallel computing mechanism, gave a A model for automatic fracture recognition in acoustic imaging logging images of cellular automata. Zhang Qunhui[14] and others proposed an image recognition algorithm based on cellular automata model for the task of automatic recognition of fractures in imaging logging. Based on the fact that the gray value of the fractures in the imaging logging images is large and the fractures are basically continuous, an automatic identification model of imaging logging fractures based on the cellular automata model is established by formulating immune rules. And its parallel computing mechanism to automatically identify fractures in imaging logging.

6. Crack Recognition Based on Transposed Convolutional Neural Network

Transposed Convolution is also known as Deconvolution. The reason why it is called transposed convolution is because it actually transposes the convolution kernel in the ordinary convolution operation we usually use, and then uses the output of the ordinary convolution as the input of the transposed convolution, and the transposed volume The output of the product is the input of the ordinary convolution.

In order to solve the problem of low recognition efficiency and low accuracy of convolutional neural network (CNN) in automatic detection of cracks in two-dimensional pavement grayscale images, Liu Qi [15] et al. first proposed a set of inter-layer feature fusion based on transposed CNN. The three-stage pavement crack extraction algorithm (the algorithm includes modules such as region determination, image segmentation, multi-layer feature fusion, etc.); then a classification-segmentation network is constructed, and the transposition of the intermediate layers of multiple fusion classification networks and the output layer of the segmentation network is trained. Convolutional network, and compared the running effect with CrackNet.

7. Conclusion

Electric imaging logging has been widely used in oil and gas exploration due to its features of visibility, intuition and high precision, and it is necessary to study it in detail. Using a fixed image processing algorithm to process the FMI image alone will inevitably contain noise in the obtained image. Using a certain learning algorithm to directly identify cracks will inevitably take a long time to process the FMI image using a certain image processing algorithm, and the obtained image will have both cracks and cracks. noise, and then use a certain learning algorithm to eliminate these noises to obtain accurate crack images.

ISSN: 2664-9640

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