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Deep learning approach to automatic detection of faults and fractures from magnetic data using the convolutional neural network (CNN)

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Summary

Magnetic data play a significant role in oil and gas exploration because they have the capability of detecting concealed geological structures, particularly faults and fractures, in sedimentary basins. Traditionally, faults and fractures are manually picked from a set of enhanced magnetic images that have been generated by applying derivative and gradient based edge filters to the magnetic image. However, some magnetic data especially those acquired from airborne platforms could be considered as 'big' data because they are huge in volume, accumulating rapidly at fast rates and exist in many varieties. Therefore, it would be very challenging to use traditional techniques to analyze big magnetic data for faults and fractures detection because they are, to some extent, limited in scope due to their subjectivity and for being slow. Consequently, traditional techniques are not suitable for analyzing big magnetic data since they can produce inaccurate results and also because they are time consuming. In response to these challenges, a new method based on deep learning artificial intelligence is proposed in this study to automatically detect faults and fractures in magnetic data. Deep learning is an advanced phase of machine learning within the field of artificial intelligence (AI). Machine learning attempts to build computer programs that are able to automatically learn and improve from experience without being explicitly programmed. It uses advanced statistical analysis techniques such as dimension reduction, linear regression, clustering and classification to analyze data, learn from that data, and utilize what they have learned to make predictions with minimum human intervention. In deep learning, a model learns directly from data and by which a computer can be trained to automate tasks that would be difficult to be performed by human. This new emerging technique owes its success to the use of powerful convolutional neural network (CNN) algorithms that perform a variety of image analysis tasks, so fast and so precise that in many cases surpasses human capabilities. Unlike conventional neural network, which has one or two hidden layers, deep learning CNN could have several hidden layers and each layer learns to detect different features of the input image, and it learns more features as it advances deeper into the network. For example, the first layer is able to recognize the boundaries or edges of the objects in the input image, and the last layer can recognize the full objects in the input image. Deep learning has already demonstrated its effectiveness in many image processing and interpretation applications such as clustering, classification, pattern recognition, and object detection. This study shows the results of the automatic detection of faults and fractures from magnetic data using deep learning CNN technique. The deep learning CNN technique was applied to a publicly available aeromagnetic image that covers part of the petroliferous Peace River Arch (PRA) structure in the Western Canada Sedimentary Basin (WCSB). The methodology used in this study involves two deep learning approaches. In the first approach, a supervised pre-trained Berkeley Segmentation Dataset (BSDS) benchmark learning algorithms was used. In the second approach unsupervised CNN learning algorithms was used with three hidden layers representing edge and line detectors



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along the north-south, east-west, and diagonal directions. Edge detectors are able to identify and locate abrupt discontinuities in the image pixels as indicated by sharp changes in the magnitude of their color or intensity gradients. Significant changes in the magnitude of the image's color or intensity gradients are identified as edges that are often linked to faults, fractures and other geological structures. Line detectors highlight the coherent alignments of image pixels with similar characteristics. The results obtained in this study are promising and they demonstrate the effectiveness of the deep learning technique in the automatic detection and mapping of faults, fractures, lithological boundaries, and other geological features from magnetic images.

Introduction

In recent years, deep learning convolutional neural networks (CNN) have achieved remarkable results in a wide range of applications, such as image classification, clustering, pattern recognition, and object detection. These achievements have inspired us to test deep learning CNN for the detection of faults, fractures and other structural and lithological discontinuities in magnetic data. Structural and lithological discontinuities, especially faults and fractures, are often displayed on magnetic images as sharp changes in pixel's color or intensity, and traditionally they are detected from a set of enhanced magnetic images using derivative and gradient based edge filters. However, traditional way of detecting faults and fractures is often carried out manually and thus they often produce inaccurate and subjective results. In addition, the traditional approach is usually slow and time consuming especially for analyzing big data where time is an important factor. In this study, we propose a novel approach to detect faults and fractures from magnetic data using the deep learning convolutional neural network (CNN). Deep learning is a subset of machine learning; a field of study that gives computers the ability to learn without being explicitly programmed (Samuel, 1959). Machine learning makes use of statistical techniques to construct a model from data, trains and learns from that data, and utilizes what it has learned to make accurate predictions. However, for big data, machine learning techniques are less efficient and less accurate than the deep learning techniques. There are two main types of machine learning; supervised learning and unsupervised learning. In supervised learning, training data are used to train the machine to produce a desired output that is closely related to the input data. In contrast, unsupervised learning does not use training data and it tries to find hidden features and patterns in the input data. Deep learning is able to teach computers to do what arises naturally to humans; learn by example and makes decisions with minimum human intervention. For example, train computers to learn statistical models such as classification directly from images. Deep learning models are very accurate and their performance, in many cases, exceed human level capabilities. They are also very effective in automatic detection and recognition of objects in images. Unlike machine learning, where the use of neural network is very limited, deep learning models are trained by neural networks with many layers. Deep learning is already proved to be more accurate and much faster than traditional approaches in many fields of interests including computer vision, remote sensing, medicine and geosciences.

The surge of interest in the deep learning started in 2012 following the release of AlexNet (Krizhevsky *et. al.*, 2012) at the **ImageNet Large Scale Visual Recognition Challenge 2012 (ILSVRC2012)** competition. At this annual competition, where research scientists compete to correctly identify and classify images, the AlexNet outperformed all competitors and won the



image classification challenge by a large margin. AlexNet is a deep learning CNN which is trained on more than a million images from the ImageNet datasets. As shown in Figure 1, the architecture of the AlexNet neural network is composed of five convolutional layers (C1 to C5) followed by two fully connected layers (FC6 and FC7), and a final softmax output layer (FC8). AlexNet is able to classify images into 1000 object categories. Each convolutional layer in AlexNet learns to produce a more detailed image representation than the previous convolutional layer. For example, the first layer (C1) is able to identify the major boundaries or edges of the object in an image, and the last layer (C5) shows the detailed structure of the object in the analyzed image (Fig. 1). Filters, or kernels, are applied to each training image on every layer at different resolutions, and the output of each convolved image is used as the input to the next layer. Since the release of AlexNet in 2012, several other popular CNN networks have been introduced, such as VGG Net, GoogLeNet and ResNet. In all these networks, CNN remains the center around which deep learning is built.

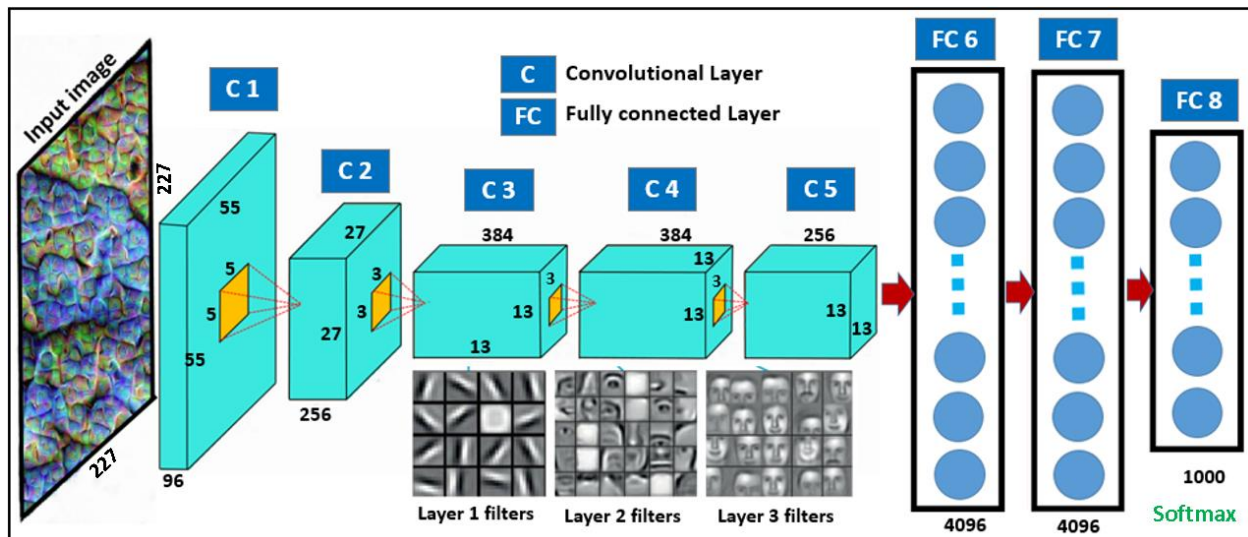


Figure 1. Alexnet architecture (modified after Krizhevsky *et. al.*, 2012).

In order to test the power of deep learning CNN in automatically mapping faults and fractures in magnetic data, a publicly available aeromagnetic grid (Fig. 2) was downloaded from Canada Natural Resources Geoscience Data Repository website and used as input for in this study. Prior to using the magnetic grid for the test, it was carefully inspected and any suspected cultural noise found in the data, which may interfere with the results, were removed from the data. Afterward, the magnetic grid was reduced to the pole (RTP) in order to center the magnetic anomalies over their causative sources. The RTP magnetic test grid covers part of the Peace River Arch (PRA) in the Western Canada Sedimentary Basin (WCSB). The Peace River Arch is a large E-NE trending basement structure which extends beyond the study area and runs from the northeast British Columbia into northwest Alberta for approximately 750 km (O'Connell, 1994). The overlying Middle Devonian to Upper Cretaceous sedimentary rocks have been a focus of an extensive oil and gas exploration campaign since 1949. Many of the discovered oil and gas traps over the PRA structure are fault controlled. The Precambrian core of the PRA consists mainly of granites that have been subjected to multiple tectonic episodes over the past 400 million years. Each tectonic episode created its own set of faults and fractures that could have been propagated into the overlying sedimentary cover and eventually became components of structural traps for



oil and gas accumulation. The main structural elements of the study area along with seismically mapped faults are plotted in Figure 2 over the input RTP magnetic image.

Methodology

Initially, our goal was to test one of the pre-trained deep learning CNN networks such as the AlexNet (Fig. 1), to detect faults and fractures from the input RTP magnetic image. However, we were unable to achieve this goal at this phase of the study because these pre-trained CNN networks are not trained for detection of edges in large size images. To make these networks more suitable for faults and fractures detection, they need some tuning, especially with regard to the size of the input image. For example, the size of the input image in AlexNet is set at 227 by 227 pixels which is too small for our purpose. Instead, we decided to use the Berkeley Segmentation Dataset (BSDS) benchmark which is adaptable to large size images and it is used extensively for detecting boundaries and edges in images. This benchmark dataset has been trained on a smaller set of test images; 200 for training and 100 for validation (Arbelaez *et al.*, 2011). The training images consist of a set of machine generated boundaries and edges whereas the validation images consist of human generated boundaries and edges.

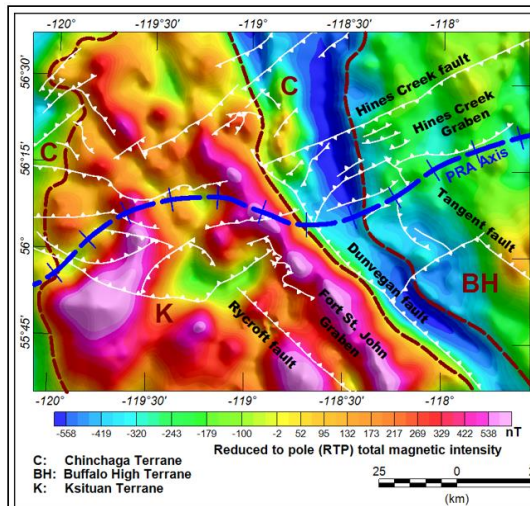


Figure 2. Input magnetic grid overlay part of the Peace River Arch structure.

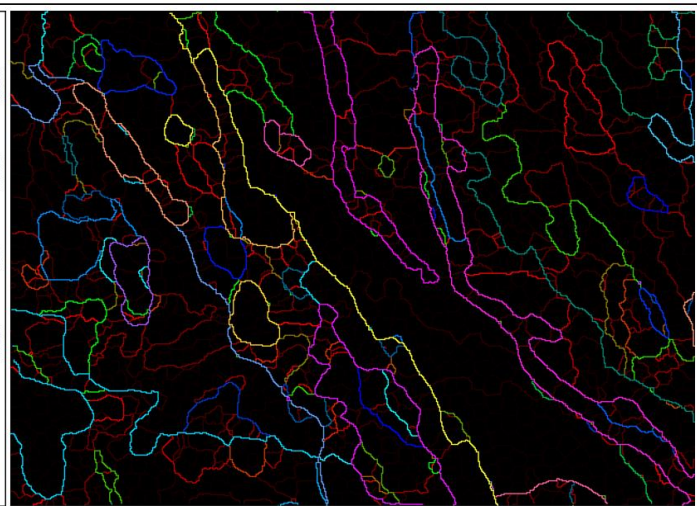


Figure 3. Edges detected using pre-trained Berkeley Segmentation Dataset.

Figure 3 shows the results of applying the pre-trained BSDS to the input RTP magnetic grid from the Peace River Arch area. By using this approach, we were able to detect structural edges or boundaries that are most likely related to geological block boundaries with contrasting magnetic susceptibility values within the Precambrian basement rocks of the study area.

Encouraged by the results of the BSDS application to the RTP magnetic image and in order to detect all kinds of edges, especially those related to faults and fractures and not just boundaries, we have designed a simple yet efficient edge and line (ridge) detection scheme with the CNN being its principal part as illustrated in Figure 4. This CNN based scheme is composed of an input layer, an output layer, and three hidden layers in-between. The hidden layers contain three sets



of edge and line detector kernels (filters). There are a number of edge and line detection kernels available in the literature and among them we selected the Sobel (edge) kernel as well as two types of derivative Gaussian (edge and line) kernels, for our CNN scheme (Figure 4). These kernels are designed to detect edges and lines along the horizontal, vertical and diagonal directions, as they slide horizontally and vertically in sequence over the input image matrix. At each sliding step, or stride, each kernel convolves with different regions of the input image matrix, and if there is a match (correlation) between the kernel transfer function and the region characteristics of the input image, then the edge or line will be detected.

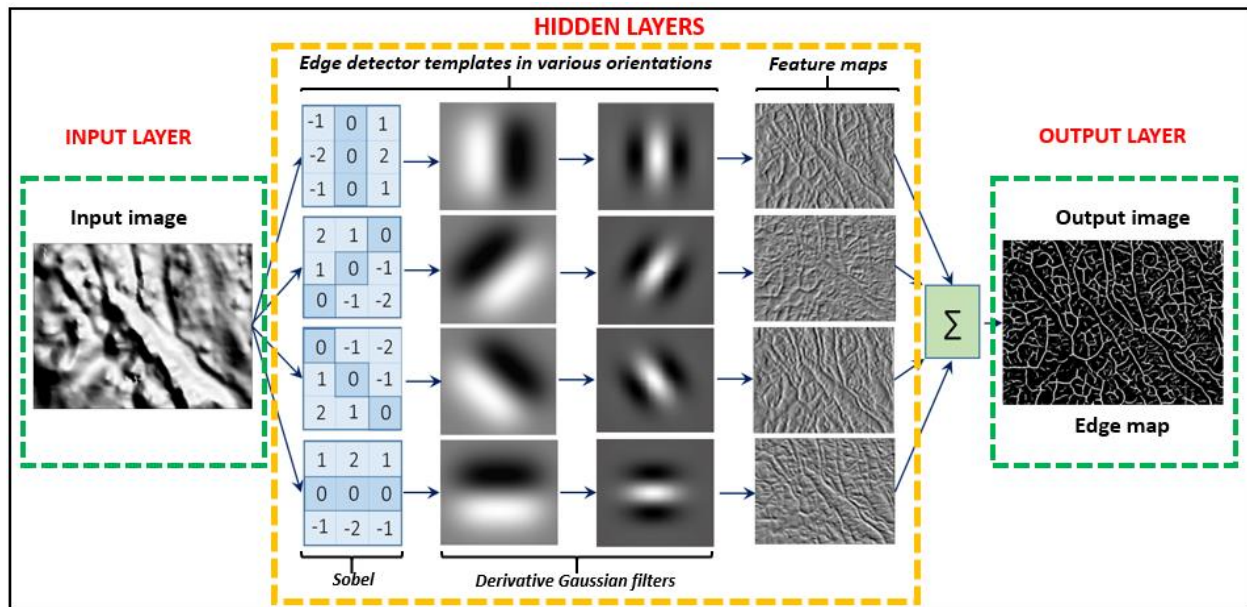


Figure 4. Schematic diagram of the proposed edge detectors using simple CNN setting.

Results

Final results of applying the deep learning CNN with three layers of edge and line detecting kernels to the RTP magnetic grid of the Peace River Arch are displayed in Figure 5. Figure 5a represents the integrated image obtained by summing-up all feature maps produced by the CNN based operations (Fig. 4). Figure 5a reveals a pronounced set of linear and curvilinear geological structures in the NW-SE direction and a weaker set of structures in the NE-SW direction. To highlight these geological structures further, we applied a skeletonization filter to the image in Figure 5a. Skeletonization is a process of converting the image into a binary form where we assign a value of one (black pixel) to the signal of interest (here the location of the geological structure) and a value of zero (white pixel) to the background based on a selected threshold value. Skeletonization resulted in additional visual enhancement of the NE-SW trending structures. Both displays demonstrate complexity of the PRA structure with continuous structural alignments of various orientations and lateral extent. Majority of these structures are most likely represent intra-sedimentary faults and fractures with roots in the Precambrian basement as well as boundaries of basement blocks with different magnetic susceptibilities.

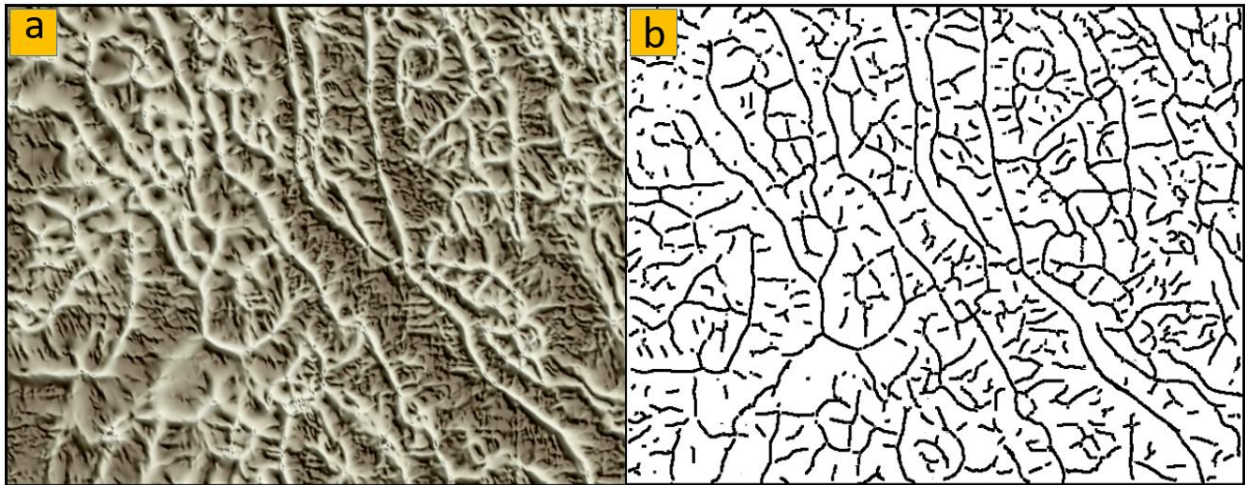


Figure 5. The results of applying CNN to the RTP magnetic image of the Peace River Arch structure.

Conclusions

The results obtained from this study demonstrate a successful application of the deep learning convolutional neural network (CNN) technique for automatic detection and mapping of faults, fractures and other geological structures from magnetic data. The CNN technique was applied to a publicly available aeromagnetic image over part of the petroliferous Peace River Arch (PRA) structure. The technique was able to reveal two sets of linear and curvilinear geological structures; a strong set in the NW-SE direction and a weaker set in the NE-SW direction. These geological structures are most likely represent intra-sedimentary faults and fractures that are originating in the Precambrian basement, plus boundaries of basement blocks with different magnetic susceptibility vales. In comparison with traditional faults and fractures detection techniques, the deep learning CNN is much faster and more accurate especially for analyzing big magnetic images. Even though, the technique was applied to magnetic data, we believe that it can be used to detect faults and fractures in other geophysical data such as gravity, electromagnetic and seismic.

References

Arbelaez, P., Maire, M., Fowlkes, C., and J. Malik, 2011, Contour detection and hierarchical image segmentation; *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33 (5), 898–916.

Krizhevsky, A., Sutskever, I, and G. E. Hinton, 2012, ImageNet classification with deep convolutional neural networks; In *Advances in Neural Information Processing Systems*, NeurIPS, 2012.

O'Connell, S.C., 1994, Geological history of the Peace River Arch; in *Geological Atlas of the Western Canada Sedimentary Basin*; G.D. Mossop and I. Shetsen (comp.), Canadian Society of Petroleum Geologists and Alberta Research Council, Special Report 4, 431–438.

Samuel, Arthur L., 1959, Some studies in machine learning using the game of checkers". *IBM Journal of Research and Development*, 44, 206–226.