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

Hassan H. Hassan and Serguei Goussev*
Multiphysics Imaging Technology Inc.

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 the sedimentary basins. These data, especially those acquired from the airborne platforms, could be considered as ‘big’ data because they are huge in volume and accumulating rapidly at fast rates. Thus, it is challenge to process and interpret magnetic data for faults and fractures using the traditional techniques. Traditional interpretation of magnetic images is rather limited due to its subjectivity as well as for being slow, time consuming, and tedious. In response to these challenges, a new method based on the deep learning is proposed in this study for the automatic detection of faults and fractures in the aeromagnetic data. Deep learning is a powerful artificial intelligence subset of machine learning in which a model learns directly from data, and it has potential to revolutionize the way we process and interpret our data. The deep learning technique owes its success to the use of powerful convolutional neural network (CNN) algorithms to perform a variety of image analysis tasks. This technique has already demonstrated its effectiveness in many image processing and interpretation applications, such as clustering, classification, pattern recognition, and object detection, and it is so fast and precise that in many cases surpasses the human capabilities. Unlike conventional neural network, which has one or two hidden layers, the deep learning CNN could have several hidden layers and each layer learns to detect different features of image, and it learns more as it advances deeper in the network. For example, the first layer is able to recognize object boundaries or edges, and the last layer can recognize the full object. This study shows results of the automatic detection and mapping of faults and fractures by applying deep learning technique to the publicly available aeromagnetic image over part of the Peace River Arch (PRA) structure in the Western Canada Sedimentary Basin (WCSB). Methodology applied to the magnetic image involves two deep learning approaches. In the first approach, we used a supervised pre-trained Berkeley Segmentation Dataset (BSDS) learning algorithm, and in the second approach we used unsupervised CNN learning algorithms with three layers of edge and line detectors. Edge detectors identify and locate abrupt discontinuities in the image pixels by sharp changes in color or intensity gradients, so that significant changes in the gradient magnitudes are identified as edges. Line detectors highlight the coherent pixel alignments of similar characteristics. Obtained results demonstrate high effectiveness of the deep learning technique in the automatic detection and mapping of faults, fractures, lithological boundaries, and other structural discontinuities with the use of the aeromagnetic data. We believe that its effectiveness will be even higher in application to magnetic data with the higher lateral and vertical resolutions.

Introduction

In recent years, deep learning convolutional neural networks (CNN) have achieved remarkable results in a wide range of applications, such as image clustering, classification, pattern recognition, and object detection. These achievements have inspired us to test CNN for the detection of faults and fractures in the magnetic images. Faults, fractures, and other structural discontinuities are shown on magnetic images as sharp changes, or high gradients, in the pixel color or intensity that can be detected by gradient-based edge filters. This approach, however, could produce inaccurate or poor results, because image color and intensity vary according to the image scale and orientation. In this study, we tested a new emerging technology based on the deep learning convolutional neural network (CNN) to detect faults and fractures in the magnetic images. Deep learning is a subset of machine learning. Machine learning uses statistical techniques to construct a model from data, whereas deep learning is capable to learn and identify characteristic features of the internal structure of images directly from the image data. For the large-volume data, machine learning techniques are less efficient than the deep learning techniques. This new techniques have already proved to be more accurate and much faster than the traditional approach in many applications, including the computer vision, medicine and remote sensing. These works also demonstrated that CNN is very effective in analyzing large-volume data and automatic detection and mapping of the identified objects.

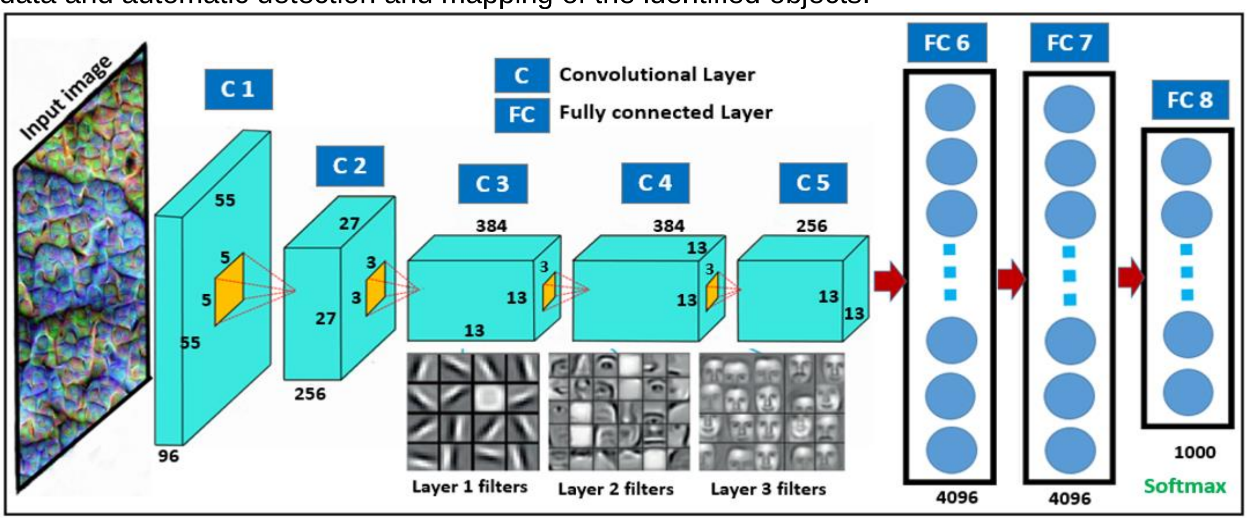

Figure 1. Alexnet architecture (modified after Krizhevsky *et. al*., 2012).

Surge of interest in the deep learning started in 2012 following the release of AlexNet (Krizhevsky *et. al*., 2012) at the **I**mage**N**et **L**arge **S**cale **V**isual **R**ecognition **C**hallenge 2012 (ILSVRC2012) competition. At this annual competition, research scientists compete to correctly identify and classify images. AlexNet outperformed all competitors and won the image classification challenge by a large margin. AlexNet is the deep learning CNN which is trained on more than a million images from the ImageNet datasets. As shown on Figure 1, 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), and it can classify images into 1000 object categories. Each convolutional layer learns to produce a more detailed image representation than the previous one. For example, the first layer is able to identify the major boundaries or edges, and the last layer represents the most detailed structure of the analyzed image (Fig. 1). Filters, or kernels, are applied to each training image 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, and in all these networks CNN remains the center around which deep learning is built.

Reduced-to-pole (RTP) magnetic grid for testing the CNN was downloaded from Canada Natural Resources Geoscience Data Repository website. Grid covers part of the Peace River Arch (Fig. 2) in the Western Canada Sedimentary Basin (WCSB). 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). Overlying Middle Devonian to Upper Cretaceous sedimentary rocks have been a focus of the extensive oil and gas exploration since 1949. Many of the discovered oil and gas traps are fault controlled. The Precambrian core of the Peace River Arch consists mainly of granites that have been subjected to several tectonic episodes over the past 400 million years. Each tectonic episode created its own set of faults and fractures that eventually became components of structural traps for oil and gas accumulation. Main structural elements of the study area along with faults mapped by the vintage seismic data are plotted in Figure 2 over the input magnetic grid.

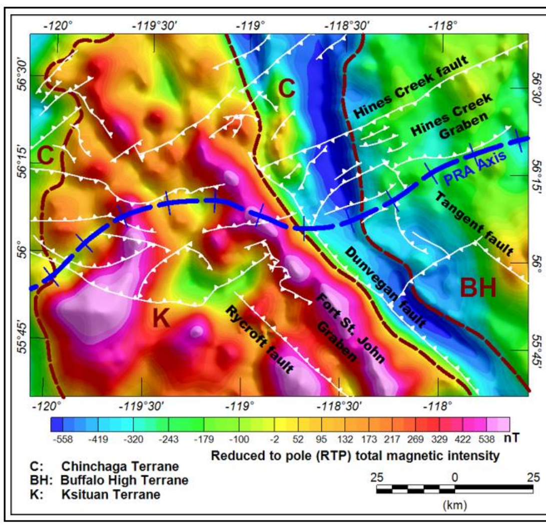

Figure 2. Input magnetic grid overlay part of The Peace River Arch structure.

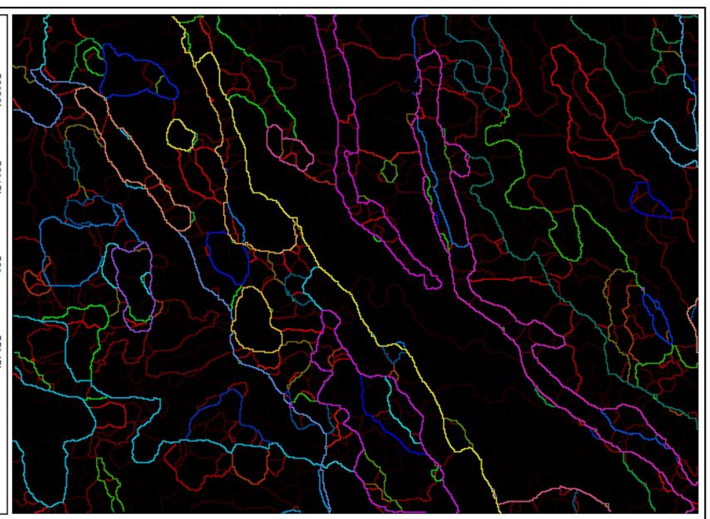

Figure 3. Edges detected using pre-trained Berkley Segmentation Dataset.

Methodology

Initially, our goal was to test a pre-trained deep learning CNN dataset such as AlexNet (Fig. 1), for detection of faults and fractures on the magnetic images. However, we were unable to achieve this goal, because networks were not trained for detection of edges in the large-size images. To make these networks more suitable for edge detection, they need some tuning, especially with regard to the size of the input image. For example, size of the input image in AlexNet is set at 227 by 227 pixels which is too small for our test. Instead, we decided to use the Berkeley Segmentation Dataset (BSDS) which is adaptable to large images and used extensively for detecting the boundaries and edges. This dataset has been trained on a smaller set of images:

200 for training and 100 for testing (Arbelaez *et al*., 2011). Results of applying the trained BSDS to the reduced-to-pole (RTP) magnetic grid in the Peace River Arch area are shown in Figure 3. Using this approach, we were able to detect structural edges that are most likely related to the geological block boundaries within the Precambrian basement rocks.

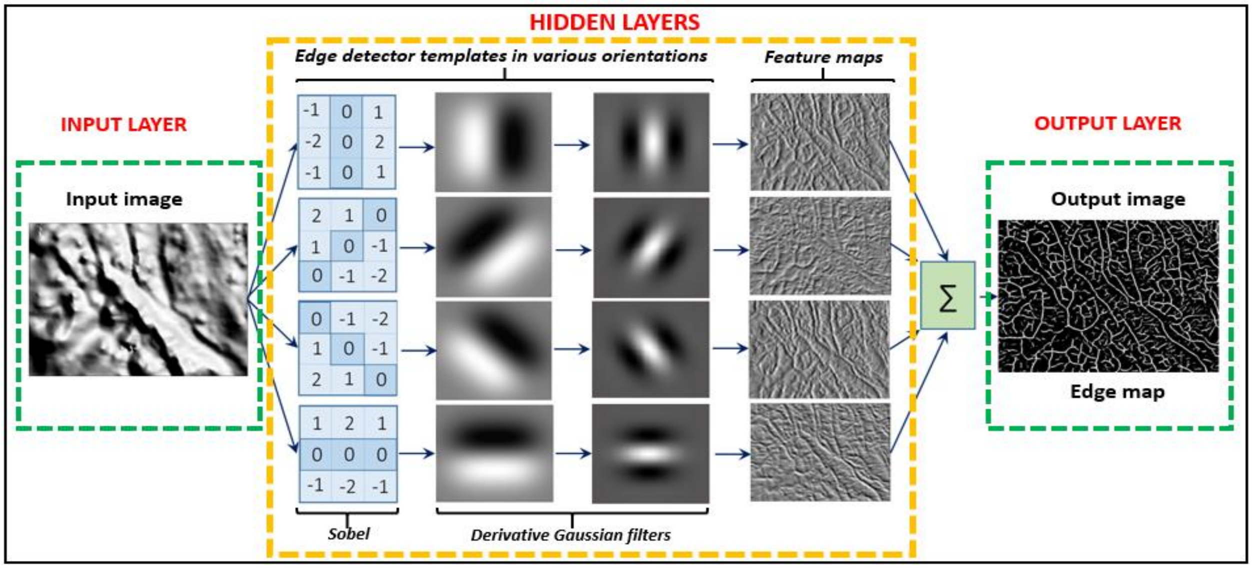

Figure 4. Schematic diagram of the proposed edge detectors using simple CNN setting.

Encouraged by results of the BSDS application and in order to detect all kinds of structural discontinuities, not just boundary edges, we designed a simple yet efficient edge and line detection scheme with CNN being adopted as its principal part (Fig. 4). This CNN scheme is composed of the input layer, output layer, and three hidden layers in-between. Hidden layers contain three sets of the edge and line detection filters, or kernels, such as Sobel and two types of Gaussian derivative filters. These kernels are designed to detect edges and lines in the horizontal, vertical and diagonal directions, as they slide horizontally and vertically over the input image. At each sliding step, or stride, filter convolves with different regions of the input image, and if there is a match between the kernel transfer function and region characteristics, then the edge or line will be detected.

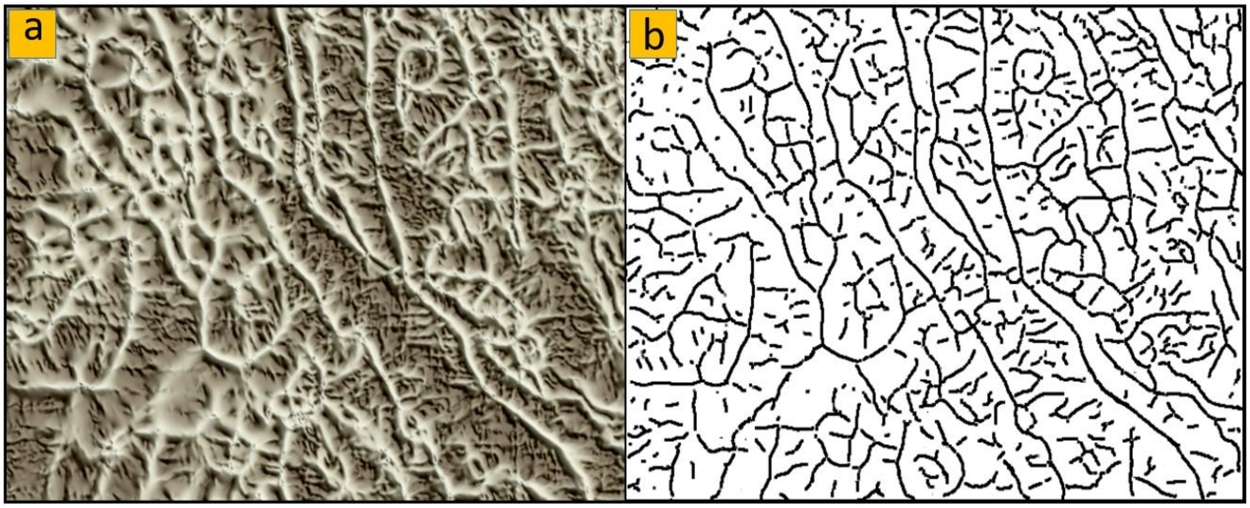

Figure 5. The results of applying CNN to the RTP magnetic image of the Peace River Arch structure.

Results

Final results of applying the CNN with three layers of edge and line detecting filters to the RTP magnetic grid of the Peace River Arch are displayed on Figure 5. Figure 5a represents the integrated image obtained by summing-up all feature maps produced by CNN-based operations (Fig. 4). It reveals pronounced geological structures in the NW-SE direction and a weaker structures in the NE-SW direction. To highlight these geological structures further, we applied a skeletonization filter to the image on Figure 5a. 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 lithological boundaries between the igneous and metamorphic rocks at the basement top.

Conclusions

Obtained results demonstrate successful application of the automated technique based on the deep learning convolutional neural network (CNN) for detection and mapping of faults, fractures, lithological boundaries, and other structural discontinuities in the public-domain aeromagnetic data. In comparison with traditional techniques, this new approach is much faster and more efficient. We believe that its effectiveness will be even higher in application to the data with a higher lateral and vertical resolution, including the high-resolution aeromagnetic data acquired over areas of the shale hydrocarbon exploration, where detection and mapping of the azimuthal orientation of faults and intensity of natural fracturing within unconventional reservoirs are among the primary goals.

References

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

Krizhevsky, A., Sutskever, I, and G. E. Hinton, 2012, Imagenet classification with deep convolutional neural networks; In NIPS, 2012.

Arbelaez, P., Maire, M., Fowlkes, C., and J. Malik, 2011, Contour detection and hierarchical image segmentation; IEEE Trans. Pattern Anal. Mach. Intell., 33 (5), 898–916.