Texture Analysis of High Resolution Aeromagnetic Data to identify Geological Features in the Horn River Basin, NE British Columbia

Hassan H. Hassan and Serguei Goussev

Fugro Gravity and Magnetic Services, Inc.

recovery energy environment economy

2011 CSPG CSEG CWLS Convention

FUGRO

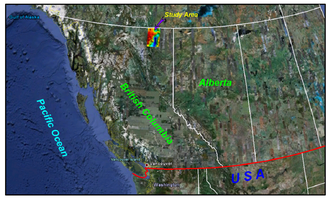

Figure 1. Location of the study area.

Summary

This study describes a pattern recognition technique to extract the anomalous texture from High-Resolution AeroMagnetic (HRAM) images. Images of HRAM data often exhibit regions of variable magnetic intensities that form certain patterns or anomalous textures. These textures are attributed to changes in the physical properties of subsurface rocks. Crystalline basements, as an example, contain rocks of different lithological composition and different geological structures that may be shown as different textures on magnetic images.

In order to extract textures from the aeromagnetic images, we applied Gray-Level Co-occurrence Matrices (GLCM) to the HRAM total magnetic intensity image over the shale gas play of the Horn River basin in NE British Columbia. The GLCM are composed of sets of spatial statistical parameters that convert magnetic images into texture images. The resultant texture images show the pixel-based spatial distribution of magnetic anomalies, associated with elements of subsurface structure, with much higher lateral resolution than the original magnetic images. Five GLCM texture features (angular second moment, contrast, correlation, entropy and homogeneity) were computed in this study. We combined these five GLCM texture images into a single image using a principle component analysis. The texture images produced in this study allowed us to identify different elements of geological structures in the Horn River basin including geological terranes, lithological contacts, fractures and faults. The aim of the study is therefore to show the properties of statistical analysis of the HRAM images that can be used for oil-and-gas exploration applications.

Introduction

Texture is one of the most important characteristics of an image as it contains valuable information about the subsurface structure of the area. Therefore, the texture analysis can be used to distinguish different spatial characteristics or patterns that are present in the image. Geological features such as lithological contacts, depositional edges, fractures and faults can be identified on enhanced filtered grids (for example, horizontal gradient magnitude) of the total magnetic intensity grid. However, these geological features are often difficult to recognize on original magnetic images. But they can be much more reliably identified on the magnetic texture images. Textures displayed on magnetic texture images reflect changes in physical properties of rock units including changes in geological structures and rock types. Haralick et al. (1973) proposed a series of simple yet powerful statistical features to compute various parameters of an image texture. These statistical features are commonly referred to them as Gray-Level Co-occurrence Matrices (GLCM) and used extensively by scientists since 1973 for textural analysis, image segmentation and image classification. These features and their functions are described in Table 1. We applied them to the total magnetic intensity image of the HRAM data to produce HRAM texture images.

The HRAM dataset used in this work is derived from a survey over the Horn River basin of NE British Columbia (Fig. 1) and it is owned by Fugro Airborne Surveys. The survey was flown with a flight line spacing of 400m by 1200m oriented NE/SW and EW with a draped ground clearance of 100m. Fugro Gravity and Magnetic Services performed cultural editing on these data to remove artifacts related to wells and pipelines in the survey area.

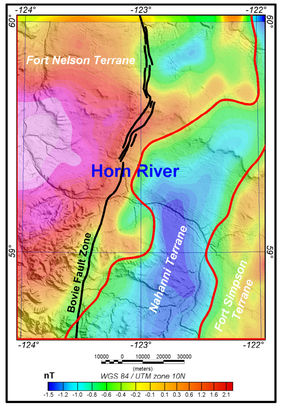

Figure 2. Major structural elements plotted on top of Total magnetic intensity of Horn River Basin HRAM data draped on NE-shaded relief topography.

The Horn River Basin is located at the border of the Foothills thrust belt within the Western Canada Sedimentary Basin (WCSB) and it intersects three main Precambrian litho-tectonic magnetic basement terranes (Fig. 2); Nahanni at the center, Fort Simpson Magmatic Arc to the east, and Fort Nelson Magmatic Arc to the west. The Precambrian basement terranes in the WCSB have been interpreted from the amplitude, texture and trends of the regional aeromagnetic data in conjunction with gravity data and isotopic age dating of Precambrian drill cores (Pilkington et al., 2000). The Fort Simpson and Fort Nelson Magmatic Arc Terranes have a distinctive NS trending magnetic high. The Fort Simpson and Fort Nelson Terranes are characterized by the presence of ferrimagnetic minerals, most likely magnetite, which has a sufficiently high susceptibility to produce the high amplitude anomalies that are characteristic of this terrane. Such large magnetization is usually indicative of calc-alkaline igneous rocks associated with magmatic-arc environments. The Nahanni terrane, which is associated with a magnetic low, is interpreted as thinned Fort Simpson basement (Cook et al., 1995).

The Precambrian basement is covered by sedimentary rocks of the Horn River Basin. The Horn River Basin contains a sequence of stratigraphic horizons and plays that are considered to have a high potential for shale gas exploration. The main formations of interest for shale gas exploration in the Horn River Basin include the Devonian Muskwa shale and Evie shale (Levson et al., 2009).

Methodology

In 1973, Haralick et al. introduced the gray-level co-occurrence matrix (GLCM) to extract texture features from images. They proposed two steps for extracting texture features from images, (1) creating the gray-level co-occurrence matrix and (2) computing texture features based on the created gray-level co-occurrence matrix.

GLCM is a tabulation of the frequencies or how often a combination of pixel intensity values in an image occurs. An example on how GLCM is created is described below:

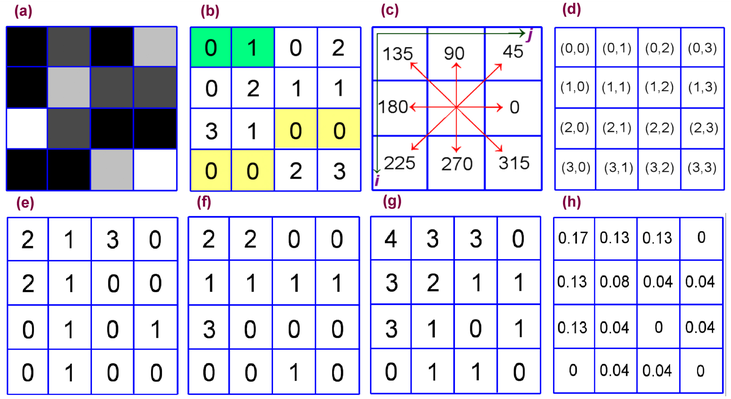

Figure 3. Steps of creating GLCM; (a) 4x4 gray-scale image; (b) Quantized matrix of the image sample; (c) directions of GLCM computation; (d) coordinated of image pixels; (e)created GLCM; (f) transpose matrix of GLCM; (g) symmetrical GLCM; (h) normalized GLCM.

1. Convert the image to gray-scale image. For example, we consider for this purpose a 4x4 image with four levels of gray as shown in Figure 3a.
2. Quantize the gray-scale image into a numerical matrix of pixels intensity (0 through 3) as indicated in Figure 3b.
3. Select the direction in which the GLCM is to be created. In our example we created the GLCM in the horizontal direction (0°). In addition to the horizontal direction (0º), GLCM can also be created for seven other directions (Fig. 3c).
4. Create the GLCM. The GLCM is a tabulation of how often different combinations of gray levels co-occur in an image. Define each element i,j of the numerical matrix (Figure 3d) as the number of times two samples of intensities i and j occur in specified spatial relationship (where i and j are intensities between 0 and 3). The yellow boxes in Figure 3b represent pixel-intensity 0 with a pixel intensity 0 as its neighbor and hence there are two occurrences of such pixels. Therefore, the GLCM matrix formed (Fig. 3e) with value 2 in row 0 and column 0. In the same way, GLCM matrix row 0 column 1 is given a value of 1, because there is one occurrence in which pixel intensity 0 has pixel intensity 1 as its neighbor (see the green box in Figure 3b). As a result, the matrix in Figure 3b can be transformed into GLCM as displayed in Figure 3e.
5. Make the GLCM symmetric. This can be accomplished by transposing the GLCM matrix of Figure 3e and add the transposed matrix (Fig. 3f) to the GLCM itself to create a symmetric matrix (Fig. 3g) in which the relationship i to j is indistinguishable for the relationship j to i for any two intensities i and j.
6. Normalize the GLCM. This is accomplished by dividing each element of Figure 3g by the sum of all elements (i.e., 24). The elements of the normalized GLCM (Fig. 3h) may now be considered probabilities of finding the relationship i,j in the GLCM matrix.

Using the procedures described above, we applied the formulas listed in Table 1 on the total magnetic intensity image of Horn River basin (Fig. 2) to measure textures.

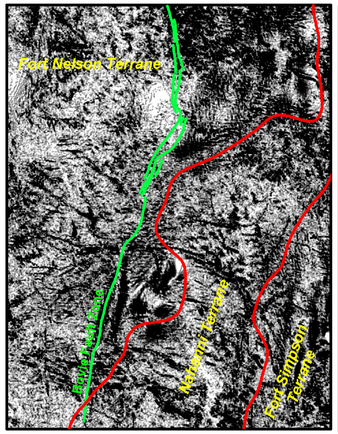

Figure 4. GLCM entropy texture features.

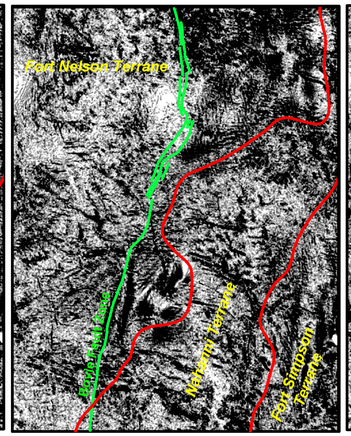

Figure 5. GLCM homogeneity texture features.

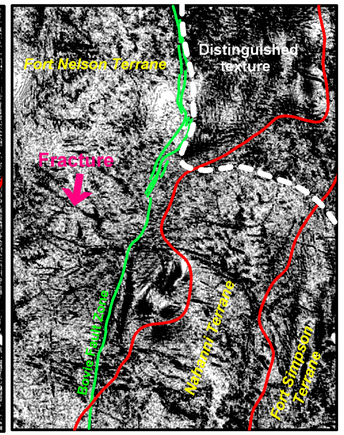

Figure 6. First principle component of five GLCM texture features.

In this study we selected five of Haralick et al. GLCM features for texture analysis. These five features (angular second moment, contrast, correlation, entropy and homogeneity) are shown with their functions in Table 1. These GLCM features find the conditional joint probabilities, Pi,j within the elements of the matrix or the image. The entry i and j are coordinates of the co-occurrence matrix Pi,j and N is the dimension of the co-occurrence matrix. These texture features are calculated in similar manner as filtering by computing texture values on a moving window with a specific size (in our case, 5x5 grid cell window size) and assigning a value to each of the image pixels corresponding to window centers. Visual inspection of the five texture images revealed that they are similar with only minor differences among themselves. In order to combine all the five images into a single image showing all the common features among them, we applied a principle component analysis to the images. We retained only the first principle component since it accounts for ~ 85% of total variations.

Table 1. GLCM statistical texture features and their main functions.

GLCM texture features	Function
$Angular\ second\ moment = (Energy)^2 = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P_{i,j}^2$	Measures the image homogeneity. Angular second moment is high when pixels are very similar. A small angular second moment indicates a spread of values in the co-occurrence matrix, thus a heterogeneous, or coarse image texture.
$Contrast = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-j)^2 P_{i,j}$	Contrast measures the amount of local variations present in the image. Contrast is zero when the neighbouring pixels have constant values.
$Correlation = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}} P_{i,j}$ σ² = variance	Correlation measures the joint probability occurrence of the specified pixel pairs.
$Entropy = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P_{i,j}\,(log P_{i,j})$	Entropy measures disorder or complexity of an image. It is maximal when all elements are equal. The high entropy image has a great contrast from one pixel to its neighbour. Complex textures tend to have high entropy.
$Homogeneity = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{P_{i,j}}{1+(i-j)^2}$	Homogeneity relates to contrast of the texture. It has maximum value when all elements in the image are same.

Results

Five GLCM texture features including angular second moment, contrast, correlation, entropy and homogeneity were applied to the total magnetic intensity image displayed in Figure 2. Out of these five texture features, we show the results of the entropy and the homogeneity (Fig. 4 and 5, respectively) which are to some extent show similar geological features. We also show the results of the first principle component (Fig. 6) which was calculated from the five GLCM texture features. Figures 4, 5 and 6 reveal several interesting geological features such as lithological contacts, fractures and faults that we were unable to see on the magnetic image. These geological features appear to be more obvious and better expressed on the texture images than on the magnetic image. It is also of interest to note variations in the texture within the study area. For example, the texture in the NE corner of the area is different from the one in other parts of the image. The geological ensemble in the NE corner of the area is apparently different from the rest of the area. It is also evident that this area is separated from the rest of the area by either geological contact or a fault since it borders the prominent Bovie Fault to the west and the Precambrian terrane to the south and east.

Conclusions

Five of Haralick's GLCM texture features were applied to the total magnetic intensity image of the Horn River sedimentary basin. The resulted texture images were combined into a single texture image using a principle component analysis. The texture images produced in this study appear to be effective in visualization of various geological features in the HRAM survey area. The visual inspection of results reveals well defined geological structures and patterns than we do not see conclusively on original magnetic images.