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CNNEDGEPOT: CNN based edge detection of 2D near surface potential field data

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ABSTRACT

All anomalies are important in the interpretation of gravity and magnetic data because they indicate some important structural features. One of the advantages of using gravity or magnetic data for searching contacts is to be detected buried structures whose signs could not be seen on the surface. In this paper, a general view of the cellular neural network (CNN) method with a large scale nonlinear circuit is presented focusing on its image processing applications. The proposed CNN model is used consecutively in order to extract body and body edges. The algorithm is a stochastic image processing method based on close neighborhood relationship of the cells and optimization of A, B and I matrices entitled as cloning template operators. Setting up a CNN (continues time cellular neural network (CTCNN) or discrete time cellular neural network (DTCNN)) for a particular task needs a proper selection of cloning templates which determine the dynamics of the method. The proposed algorithm is used for image enhancement and edge detection.

The proposed method is applied on synthetic and field data generated for edge detection of near-surface geological bodies that mask each other in various depths and dimensions. The program named as CNNEDGEPOT is a set of functions written in MATLAB software. The GUI helps the user to easily change all the required CNN model parameters. A visual evaluation of the outputs due to DTCNN and CTCNN are carried out and the results are compared with each other. These examples demonstrate that in detecting the geological features the CNN model can be used for visual interpretation of near surface gravity or magnetic anomaly maps.

1. Introduction

Image enhancement techniques are widely applied to geophysical images and make it easier to visually interpret them or to understand the geology. Most common enhancement techniques include contrast enhancement, edge detection, and filter types. Edge detection algorithms are suitable for the analysis of potential field data. These are used in the visual interpretation of both gravity and magnetic maps in order to detect main geological structures. The image edges are often visually identified by experienced interpreters or can be obtained in the form of automatic or criteria-based edge extraction techniques. Approaches based on derivative calculations are the most classical methods used in geophysics. First horizontal and vertical derivatives, analytical signals, and grid filters are employed to enhance gravity and magnetic anomalies due to near-surface geological features. Edge detection in gravity and magnetic maps is used to identify areas of high priority for further detailed exploration. The filters containing vertical and horizontal derivatives are generally used in order to enhance the anomalies (Cooper, 2005; Cooper and Cowan, 2007). Buckingham et al. (2003a, b) have developed a model for content base magnetic image retrieval (CBMIR) using intensity, texture and shape descriptors. Region and boundary based shape information is extracted using various edge detection algorithms, and texture content is derived using statistical and wavelet transform based methods. Based on modeling, theoretical arguments and field data, Pilkington and Keating (2009) used data enhancements in terms of their effectiveness for mapping the edges of magnetic sources or, equivalently, geologic contacts. Yu et al. (2011) used the support vector machine (SVM) technique to an automated lithological classification. Works on edge detection are adopted by various authors (Blakely and Simpson, 1986; McGrath, 1991; Mallat and Zhong, 1992; Miller and Singh, 1994; Moreau et al., 1997; Boschetti et al., 2001; Trompat et al., 2003; Cooper and Cowan, 2006). Several authors have developed several methods based on the use of horizontal or vertical derivatives of potential field anomalies (Rao et al., 1981; Grauch and Cordell, 1987; Reid et al., 1990; Roest et al., 1992; Marcotte et al., 1992; Zeng et al., 1994; Hsu et al., 1996, Fedi and Florio, 2001; Aydogan, 2011).

Although there have been notable improvements in the procedures of quantitative modeling and inverse solution recently, qualitative geological interpretation of gravity and magnetic data

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can also be performed manually or through image enhancement algorithms. Images derived from gravity and magnetic data using automatic image enhancement methods contribute to the mapping of tectonic elements. These maps show homogeneous zones with density/susceptibility which are distinguished by discontinuity changes.

In this study, a CNN model (DTCNN and CTCNN) used in image processing is used for the source boundary and edge detection from potential field data. It can be evaluated by various interesting applications in geophysics such as edge detection (Aydogan, 2007), data enhancement and separation of potential field anomaly maps (Aydogan et al., 2005). The most popular application for CNN has been in image processing, essentially because of their analog feature and sparse connections, which are conductive to real time processing. The dynamics of the CNN are described by the system of non-linear ordinary differential equations and by an associated computation energy function which is minimized during the computation process. The CNN is a fundamental and powerful toolkit for visual application in image processing tasks. The CNN structure designed as standard two-dimensional grid is only connected to nearby neighborhood. The CNN algorithm is often used for automatic edge detection in model-based digital image processing. In model-based methods, pixels of an image do not mean anything on their own, but become meaningful only when they are considered as a whole together with the neighborhood pixels named as neurons.

Since CNN is created by space invariant connection geometry, it is widely used in image processing (Guzelis, 1992; Guzelis and Karamahmut, 1994; Arik and Tavsanoglu, 1998; Dogaru, 2008). In this study, proposed CNN algorithm is used consecutively. Firstly, according to nonlinear approach, it is used for roughly source boundaries. Secondly, it is used to extract body edges.

2. Cellular neural network methodology

Cellular neural network (CNN) model was introduced by Chua and Yang (1988a, b). This model is an image processing algorithm with a large scale nonlinear circuit. Setting up the proposed algorithm for a particular task needs a proper selection of cloning template parameters (A, B and I) which determine the dynamic of the cellular neural network. After the introduction of the Chua and Yang network, a variety of CNN models are proposed. These models differ in cell complexity, cell parameterization, cell dynamics and network topology. A cell is the basic unit of a CNN model. Local connectivity is the most important characteristic of a CNN model. Each pixel in the image corresponds to a cell in the CNN model. This cell in the CNN model has an input, an internal state and an output. Any cell is connected only to its neighborhood cells. The standard CNN model consists of an $M \times N$ rectangular array of cells $C(i,j)$ with Cartesian coordinates (i,j), $i=1, \ldots, M$, $j=1, \ldots, N$. Each cell named as neuron $C(i,j)$ is bounded to a sphere of influence $N^r(i,j)$ of positive integer radius r. The cell located in the position (i,j) of a two-dimensional $M \times N$ array is denoted by C_{ij}, and its r-neighborhood $N^r(i,j)$ is defined below (Chua and Yang, 1988a,b; Chua and Roska, 2002).

$$N^r(i,j) = C_{kl} | \max(|k-i|, |l-j|) \le r, \quad (1 \le k \le M; \ 1 \le l \le N). \tag{1}$$

In this place, subscripts (i,j) defines cell location and (k,l) defines neighborhoods. If all neighborhood cells $C(k,l)\varepsilon S_r(i,j)$ exist, a $C(i,j)$ cell is called regular cell in terms of $N^r(i,j)$. Otherwise, $C(i,j)$ is called boundary cell (Fig. 1a). The outermost cells are called edge cells. In the event of $r>1$, all boundary cells are not edge cells. In the image processing, because CNN cells are locally coupled to their neighbors, different topologies (Fig. 1a–c) which is square, triangle or hexagonal grid have been developed (Roska et al., 1988). The structure of CNN, depicted in Fig. 2a, defines as a 2D array of $M \times N$ identical cell arranged in rectangular grid. The state equation for a cell $C(i,j)$ is depicted as follows:

$$\frac{\partial x_{ij}(t)}{\partial t} = -x_{ij}(t) + \sum_{kl \in N^r} A_{ij,kl} y_{kl}(t) + \sum_{kl \in N^r} B_{ij,kl} u_{kl}(t) + I_{ij} \tag{2}$$

where x_{ij}, u_{ij}, y_{ij} and I_{ij} are the state, input, output and bias of a cell $C(i,j)$, respectively. The state and output vary with time. The input is static (time independent). Matrices $A_{ij,kl}$, the feedback coefficients, and $B_{ij,kl}$, the control coefficients, are connected from cell $C(k,l)$ to $C(i,j)$. The control template represents the coupling coefficients of the cells and this completely defines the behavior of the CNN model with a given input and initial condition. The output (Fig. 2b) equation is described by the following piecewise linear equation:

$$y_{ij}(t) = f(x_{ij}(t)) = .5(|x_{ij}(t)+1| - |x_{ij}(t)-1|). \tag{3}$$

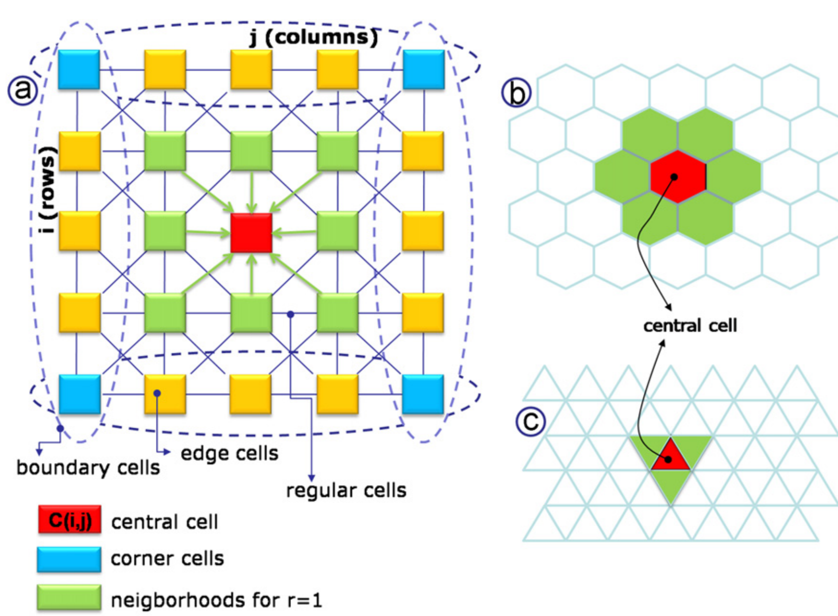

Fig. 1. 2D planar cell neighborhoods, (a) square topology of 2D planar CNN model for $r=1$ neighborhood, (b) triangle neighborhood and (c) hexagonal neighborhood.