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NEURAL NETWORK ALGORITHM APPLIED TO DETECTION OF EDGES OF OCEAN IMAGE

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ABSTRACT

In this project, a boundary detection algorithm between edge and boundary in ocean images is presented. In ocean land images, different land types can have the same intensity signature but the floe size and shape can be different. To measure the flow size and shape, proper boundary detection is crucial. Due to the inherent speckle noise with ocean satellite images, boundary detection in ocean images can be challenging. The implemented technique eliminates the unwanted edges from the overestimated boundary to obtain the desired boundaries by measuring the strength of each edge and the boundaries to which it belongs. Artificial Neural Network has been applied to train the system based on the input images. After training the system any test image can be processed and feed to the ANN. A back propagation algorithm then classifies the edges.

KEYWORDS: Neural Network, Ocean Image, Image Analysis

INTRODUCTION

Boundary detection is one of the bottlenecks for many image analysis and computer vision applications such as medical and satellite images. Due to the inherent speckle noise in SAR (synthetic aperture radar) images, boundary detection is very challenging. Due to the lack of acceptable ice type separation algorithm in SAR sea ice images, ice boundaries are visually estimated on SAR sea ice images at Canadian ice services (CIS). The boundary of an object in an image is perceptually very significant and conveys considerable image information. In addition, in some applications [6] the image structures are characterized by shape and size measures.

A pre-processing stage that does not preserve the boundary can make the computed measures useless. One of the problems in sea ice SAR images is that the floe boundary may not be clear. One floe can touch an adjacent floe in such a manner that even a human observer will find it difficult to estimate the ice boundary. Generally, there is no unique solution for SAR sea ice boundary detection. This algorithm will try to determine boundaries in SAR sea ice images which the ice analyst will find useful.

FLOW CHART

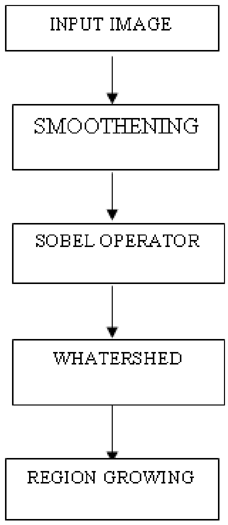

Figure 1: Flow Chart for Image Processing

A description of each block for figure 1 is given below.

Smoothing

One of the most common algorithms is the "moving average", often used to try to capture important trends in repeated statistical surveys. In image processing and computer vision, smoothing ideas are used in scale space representations. The simplest smoothing algorithm is the "rectangular" or "unweighted sliding-average smooth". This method replaces each point in the signal with the average of "m" adjacent points, where "m" is a positive integer called the "smooth width". Usually m is an odd number. The triangular smooth is like the rectangular smooth except that it implements a weighted smoothing function.

Sobel Operation

A simple 3x3 box operator is used to reduce the inherent noise in SAR images. Then the Sobel operator is used to obtain the gradients in the image. In the Sobel operation, x and y directional gradients are found using the directional masks and the final gradient is calculated by taking the square root of the sum of these directional gradients. Usually thresholding these gradients will detect the edges in the image. Because false edges appear and some real edges are missing, the gradients found in this stage will not be used for boundary detection. Instead they are used as input to watershed algorithm to obtain initial boundaries.

Water Shading

The watershed algorithm was introduced for the purpose of image segmentation by Lantuejoul and Beucher. Later, Vincent and Soille devised fast implementation methods for both sequential and parallel computation. This watershed algorithm becomes the basis for many boundary detection techniques. The idea of a watershed is drawn by considering an image as a topographical surface. The image intensity (the gray level) is considered as an altitude. A high value corresponds to a peak and a low value corresponds to a valley. If a drop of water were to fall on any point, it would find its way until it reached a local minimum. For image segmentation, the watershed algorithm is applied on the gradient image produced by Sobel operation in the previous step. In the gradient image, the homogeneous region becomes the inner region of a crater and the region boundary becomes the crater's borders.

Meyer's Flooding Algorithm

One of the most common watershed algorithms was introduced by F. Meyer in the early 90's.The algorithm works on a gray scale image. During the successive flooding of the grey value relief, watersheds with adjacent catchment basins are constructed. This flooding process is performed on the gradient image, i.e. the basins should emerge along the edges. Normally this will lead to an over-segmentation of the image, especially for noisy image material, e.g. medical CT data. Either the image must be pre-processed or the regions must be merged on the basis of a similarity criterion afterwards.

- A set of markers, pixels where the flooding shall start, are chosen. Each is given a different label.
- The neighbouring pixels of each marked area are inserted into a priority queue with a priority level corresponding to the gray level of the pixel.
- The pixel with the highest priority level is extracted from the priority queue. If the neighbours of the extracted pixel that have already been labelled all have the same label, then the pixel is labelled with their label.
- All non-marked neighbours that are not yet in the priority queue are put into the priority queue.
- Redo step 3 until the priority queue is empty.

The non-labelled pixels are the watershed lines. After Water shading we pass the water shading information to artificial neural network which operates on back propagation method

Neural Network

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurones. This is true of ANNs as well Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. Other advantages include:

- **Adaptive Learning:** An ability to learn how to do tasks based on the data given for training or initial experience.
- **Self-Organisation:** An ANN can create its own organisation or representation of the information it receives during learning time.
- **Real Time Operation:** ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
- **Fault Tolerance via Redundant Information Coding:** Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage

Back Propagation Technique

The back propagation learning algorithm can be divided into two phases: propagation and weight update.

Phase 1: Propagation

Each propagation involves the following steps: Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations. Backward propagation of the propagation's output activations through the neural network using the training pattern target in order to generate the deltas of all output and hidden neurons.

Phase 2: Weight Update

For each weight-synapse follow the following steps:

- Multiply its output delta and input activation to get the gradient of the weight.
- Bring the weight in the opposite direction of the gradient by subtracting a ratio of it from the weight.
- This ratio influences the speed and quality of learning; it is called the learning rate. The sign of the gradient of a weight indicates where the error is increasing; this is why the weight must be updated in the opposite direction.

Repeat phase 1 and 2 until the performance of the network is satisfactory.

RESULTS

Figure 2: Original Ocean Image

Ocean image (resolution of 300m) which is used for training purpose is as shown in figure 2. Results of feature extraction are shown in below figures for different images.

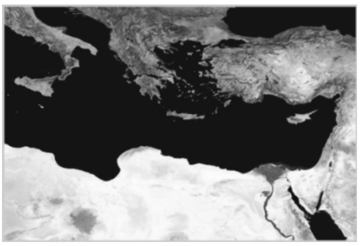

Figure 3: Gray Converted Image

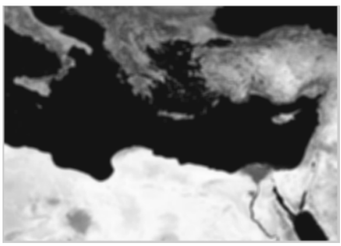

Figure 4: Smoothened Image

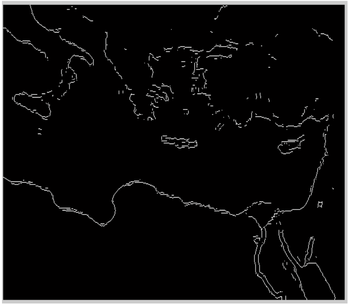

Figure 5: Sobeloperated Image

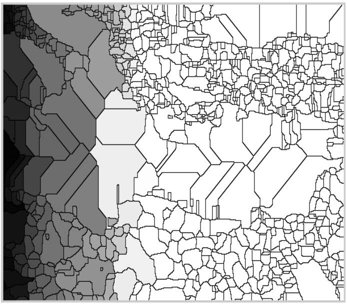

Figure 6: Watershed

Figure 7: Gradient Magnitude Operation

Figure 8: Final Feature

Figure 9: Original Ocean Image

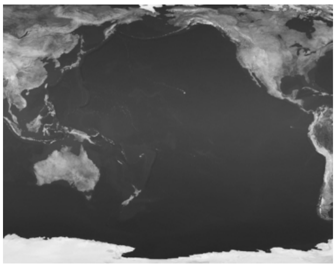

Figure 10: Gray Converted Image

Figure 11: Smoothened Image

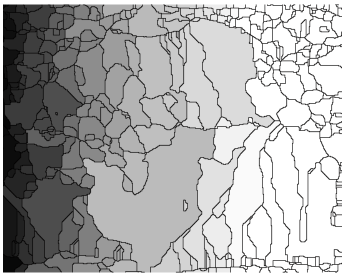

Figure 12: Watershed

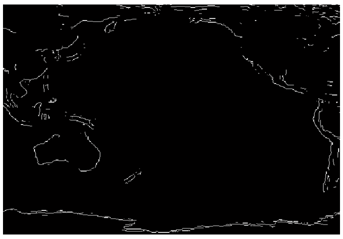

Figure 13: Sobeloperated Image

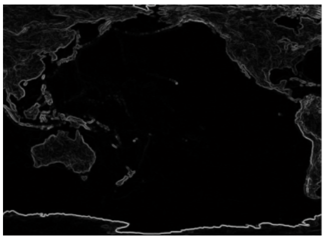

Figure 14: Gradient Magnitude Operation

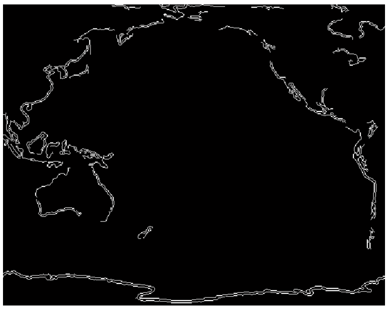

Figure 15: Final Feature

All the features are taken as training input data and the final feature is taken as target data. The test image is shown in the below figures 16 to 21

Figure 16: Test Ocean Image

Figure 17: Gray Converted Image

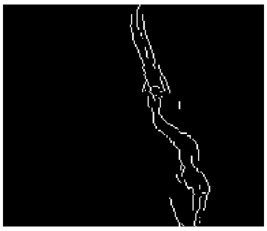

Figure 18: Smoothened Image

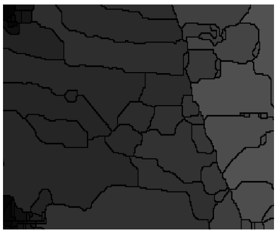

Figure 19: Watershed

Figure 20: Gradient Magnitude Operation

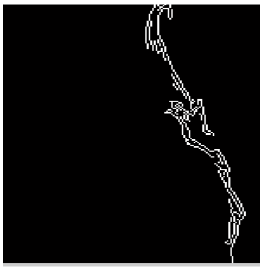

Figure 21: Final Feature

CONCLUSIONS

The method presented here estimates the feature extraction technique of a satellite image. However there are further constraints when estimating the presence of features in an image. Neural networks also contribute to other areas of research such as neurology and psychology. They are regularly used to model parts of living organisms and to investigate the internal mechanisms of the brain. In this project, a system is proposed for image recognition from satellite images based on neural networks algorithms. In this system initial image processing stage is implemented at first and image segmentation procedure is done. Then suggested features are calculated for each region. And a three layer perceptron neural network is trained for detection of Texture in satellite images. After these processes the system is evaluated using nctool. The plots value of these calculated parameters shows the percentage of Texture content in desirable level of a satellite image.

REFERENCES

1. Digital Image Processing Using Matlab by Rafael C. Gonzalez & Richard E. Woods, 2nd edition, Pearson Publication.
2. A. Salberg, & Oslash, Rudjord and A. Solberg "Model based oil spill detection using polarimetric SAR", *Proc. Int. Geosci. Remote Sens. Symp.*, 2012
3. Virendra P. Vishwakarma, M. N. Gupta, “A New Learning Algorithm for Single Hidden Layer Feed forward Neural Networks”, International Journal of Computer Applications (0975 – 8887), Volume 28– No.6, pp. 26-33, August 2011.
4. Adobe: Digital Negative (DNG) “The public, archival format for digital camera raw data”
5. Campbell, J. B. 2002, “Introduction to Remote Sensing”, New York London: The Guilford Press.
6. Ferraro G, B. Bulgarelli, S. Meyer-Roux, O. Muellenhoff, D. Tarchi, K. Topouzelis, 2008. The use of satellite imagery from archives to monitor oil spills in the Mediterranean Sea. In: Remote Sensing of the European Seas. V. Barale and M. Gade, editors. Springer, Heidelberg, pp. 371-382.