Cooperative neural network and low-level feature extraction scheme

Maher I. Rajab

***Abstract*—** One of the advantages of using prototype edge patterns in NN training set is that it may also be suitable to analyze the behavior of the NN investigated because of the generalization and the flexibility to alter the training set structure (size, orientation, and also the amount of random noise added). The strategy of minimizing the complexity and ambiguity in the training set is a significant factor in the success of neural network recognition. A neural network NN training set is designed and tested on a variety of real images and with different training set sizes. Experiments are carried out with a neural network edge detector NNED applied to general real images after being trained with simple and small data sets containing prototype edge patterns. Image fusion has been applied to segment a clinical skin lesion image by combining features from multiple features of NN outputs. The NNED and image fusion scheme may improve visual image interpretation for the identification and classification of benign or malignant lesions.

***Keywords*—** Neural networks analysis, image fusion, domain base function, edge detection, pattern recognition.

I. Introduction

Neural networks analysis method is applied to verify the ability of NN edge detection responses (zero, 1st, and 2nd order edge detection responses) [1]; the analysis method uses the domain base function which corresponds to the template of weights in the case of neural networks. The NN analysis method is used here to verify the success of a neural network scheme for feature detection. Neural network NN training set is designed and tested on a variety of real images and with different training set sizes. The neural network edge detector NNED has been trained with simple and small data sets containing prototype edge patterns. The most successful training sets are chosen as the basis in the analysis and design of a scheme to extract low-level features such as color, texture, and shape features from clinical skin lesions images. Feature maps are produced by the image convolution of NN output with each of the NN weights templates. Image fusion process is suggested to combine different NN feature maps. The fused image can have complementary spatial and spectral resolution characteristics. Xia The proposed scheme may improve the effectiveness of a computer-aided system for the analysis and classification of benign or malignant lesions.

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II. Background

Analogous to neurons in the brain the network in a sense learns from examples or by experience just as people do. Neural networks use a set of nodes (processing elements) which are sometimes described as connectionist systems, because of the connections between individual processing nodes. Sometimes the NNs is called as adaptive system or machine learning algorithm, because changing of its connection (training NNs) weights would make the system acquire new knowledge [2]; each connection between the neurons is stored as a weight-value or strength for the specific connection. Therefore, for the network to learn the solution to a given problem, the values of these connections can change so that the neural network performs more effectively. NNs are also called parallel-distributed processing systems, which give emphasis to the way in which the many nodes or neurons in a neural network operate in parallel [3]. The Multi Layer Perceptron (MLP) is one of the most common neural network architectures that has been used successfully in various applications. The Back propagation algorithm is normally used to train these networks. The MLP is a development of a Single Layer Perceptron (SLP) from the simple Delta rule. The rule is based on the idea of continuously modifying the strength of the input connections to reduce the difference (the delta) between the desired target value (output) and the current actual output of a neuron.

A machine vision system often deals with the processing of digital images which consist of a matrix of pixels representing intensities of various positions [4]. The main goal of this processing is to provide image improvement for human understanding [4-5]. This task is achieved by a number of steps. The initial step is the segmentation of the image into meaningful objects [4]. Edge extraction is usually the starting step in segmentation because it effectively detects the limits of the objects. These limits are commonly called “edges”. Moreover, edge extraction is used mostly in image recognition, classification or interpretation procedures because it provides a compressed amount of information for processing [6]. The success of an image recognition procedure is related to the quality of the edges marked [7].

Srinivasan [8], Leow [9], and Wong [10] each proposed a neural network model for edge detection and, in contrast to Ramalho [4], neural network arbitration was not considered. Ramalho [7] compared the capability of a neural network for edge detection with different conventional edge detection methods. Moreover, the study also established a strategy to arbitrate between any two edges maps (for some selected cases such as Roberts versus Canny [11] filters) using the neural network. The arbitration system is taught from data sets that are extracted from three edge maps. These maps include the two arbitrated edge maps and the reference edge map that could be generated from a synthetic image [4]. Inspired by the parallel nature of the neural network arbitration system, the number of algorithms that are used in the arbitration process was kept to two; note that an increase in the number of methods to be arbitrated would also increase the duration of network learning phase. In spite of the fact that the reference edge map does not mimic all the edges present in the natural scenes, the use of this image along with two more distinct edge maps from two different conventional edge approaches (for example Roberts versus Canny) have established a basic arbitration strategy using neural networks [7]. The research study in [12] concluded that some improvement could be achieved by such strategy because the neural network (described as an edge arbitrator) can inherit some of the edge features (e.g. sharpness, contrast, and thickness of an edge) from the arbitrated edge maps, which will finally assist the arbitration process.

A.Prototype Edge Patterns in NN Edge Detection

The previous section reviews the neural networks edge detection researches. However, there is a great necessity to analyze neural network models so as to achieve close insight into their internal functionality. Neural networks have been successfully applied to pattern recognition tasks and edge detection. This is because of their ability to handle incomplete or corrupted sets of data [13]. Research in neural networks edge detection has revealed the effectiveness of this technique when applied to real and/or synthetic images. To this purpose, new and general training sets, consisting of a limited number of prototype edge patterns, were proposed in [12] to analyze the problem of neural network edge detection. The high degree of generality of the proposed neural network edge detection method will probably make it more flexible to investigate for further neural network edge detection solutions, which will also meet the needs of certain applications. The error back-propagation algorithm [14] is used for training MLP feedforward neural networks to minimize the training error. The network topology is constrained to be feedforward: i.e. loop-free. After a neuron performs its function it passes its output to all of the neurons in the layer below it, providing a feedforward path to the output. NNs experiments use the MLPs which consists of one input layer, one output layer, and the possibility of one or more hidden layer(s). The training procedure is followed until a compromise solution is achieved and the NN is capable of detecting object boundaries.

B.Boundary Segmentation Network

However, to recognize objects in an image we also need to perform boundary segmentation [9]. Several neural networks methods proposed in the literature, not only perform edge detection but also boundary segmentation, i.e., to identify the edges that outline the object's boundaries. An improved version of the Boundary Contour System (BCS) [15], called the Boundary Segmentation Network (BSN) is able to extract thinner edges (in contrast with BCS) and is better at rejecting noisy background details, when segmenting the object's overall boundaries. Both of the two networks consist of five layers of units. In the BSN, the last sharpening layer performs the task of thinning edges, which is absent in the original work of BCS. Large networks like these can be particularly worthwhile if speed and cost are not important factors. Careful design of large architecture and specification of the tasks required by each layer are considered in these topologies. This could avoid the major drawbacks of large networks that they significantly learn more patterns; not only do they learn the main characteristics of the learning set but also the particularities of that set [7]. As a consequence of these large networks, they become an associative memory with little generalization capabilities.

III.NEURAL FUSION SCHEME

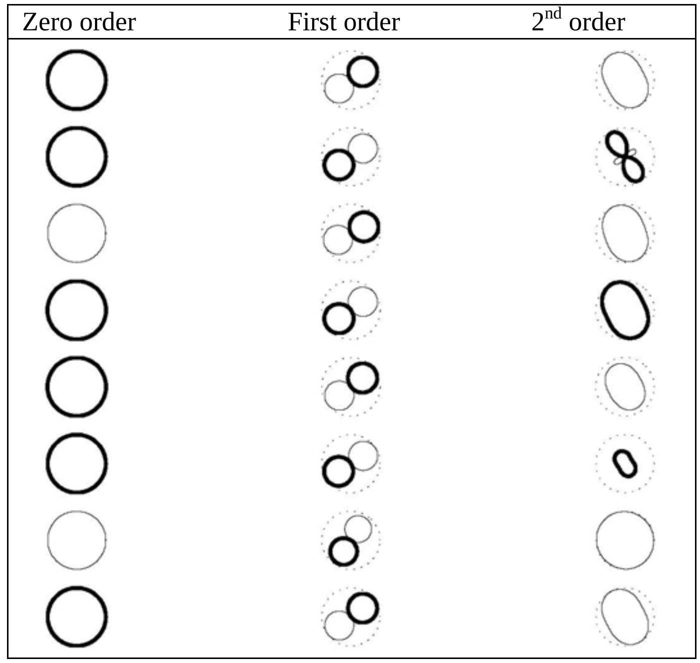
Youshen et al. [16] proposes a cooperative neural fusion (CNF) algorithm for image fusion. Compared with existing signal-level image fusion algorithms, the proposed CNF algorithm can greatly reduce the loss of contrast information under blind Gaussian noise environments. The performance analysis shows that the proposed two neural fusion algorithms can obtain a better image estimate than several well known image restoration and image fusion methods. In this work the NNED classification between edges and noise patterns is a critical issue especially for the case of very noisy images. In this case, the inputs to the NNED are the original noisy patterns, and if we also considering that there are no preprocessing steps that are used such as noise filtering operations that occur in non-neural network algorithms, then using the NNED will be advantageous to reduce the amount of image processing required and to minimize the execution time. It is interesting to mention here that the previous work in neural network edge detection have limited their analysis and application to certain classes of images whereas in our method the generated set of vectors simply corresponds to standard situations that are unequivocally understood as edges or non-edges and permit a controlled distribution of the edges enclosed. In this case we use a noise free training set of a limited number of prototype edge patterns with 3x3 pixels. It is important to mention here that further experiments could be possible with larger window sizes such as 5x5 or 7x7…etc. We choose the smallest window size of 3x3 because it is sufficient to define all edge patterns encountered in this work. Various experiments have been performed using the neural network model with multi-layer perceptron architecture. The neural network is trained with the error back-propagation algorithm [17], using different sizes of training sets. When constructing and experimenting with various training sets the total number of prototype edge patterns and their redundancy were considered.

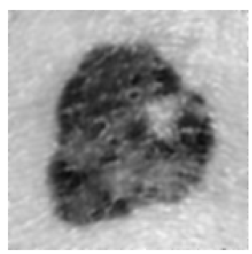
Computer aided diagnosis systems have been successfully applied for early detection of melanoma. For example, a recently developed PC-based pilot system by Binder et al. [18] promises to automatically segment the digitized ELM images, measuring 107 morphological parameters. A neural network classifier trained with these features is able to distinguish between benign and malignant melanoma. The work presented here was based on a neural network model of the three layer multi-layer perceptron architecture. An example application of neural network edge detection (NNED) to real and synthetic noisy images is investigated to analyze the internal functionality and also verify the ability of NN edge detection. A neural network of 9-10-7 multi-layer perceptron MLP is used where there are nine inputs in the input layer, ten hidden nodes (units), and seven nodes in its output layer. Successful training was achieved when the neural network's mean square error converges to the value of 0.009 with learning rate of 0.001 and momentum rate of 0.5. Similar training sets, consisting of a limited number of prototype edge patterns are used to train NNs to establish a base for a simple neural network edge detection scheme. Neural network edge detector NNED has been tested to find sharp edge patterns in noisy synthetic lesion images.

The training procedure is followed until a compromise solution is achieved and the neural network is capable of detecting object boundaries. Previous works analyses some NNED neural networks analysis method is also applied to verify the ability of NN edge detection responses (zero, 1st, and 2nd order edge detection responses) [1]; the analysis method uses the domain base function which corresponds to the template of weights in the case of neural networks. Moreover, image fusion process has been applied as another analysis method to add up the NN edge maps. These edge maps are produced by an image convolution of NN output with each of the NN weights templates. Van der Zwaag method has been applied to analyze the gradients: low pass, gradient, and second-order gradient for 8 hidden nodes of a 9x8x1 neural network edge pattern detector, as shown in Table 1.

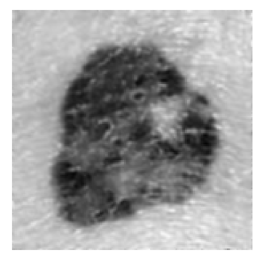
Low-pass or averaging behaviour makes the network less sensitive to noise and improves the edge detection ability. Fig.1 shows seven NNED outputs (left column of Fig.1) which are resulted by convolving the template of weights at hidden layer for each output node with the original real image. Low-level feature extraction has been applied. An example of sharp edges and internal dark segments and regions are extracted by finding maximum thresholds for each NNED output as shown in the right column of Fig. 1. Fig. 2 shows a fusion between five thresholded NNED outputs of Fig. 1 (Outputs 3,4,5,6, and 7) are combined form different features of a skin lesion image and compared with the output edges of the Sobel edge detector. The number of edges produced by the NNED tends to be less than the gradients detected by Sobel filter, this is possibly due to the lack of more probable sharp edge patterns in the original trained NNED.

Table 1 low pass, gradient, and second-order gradient analysis results for all 8 hidden nodes of a 9x8x1 neural network edge pattern detector. (MATLAB results).

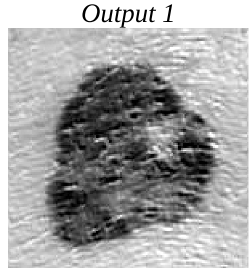




Output 1

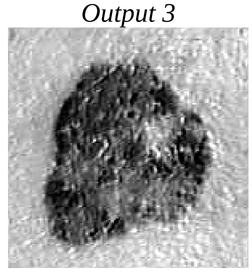


Output 2



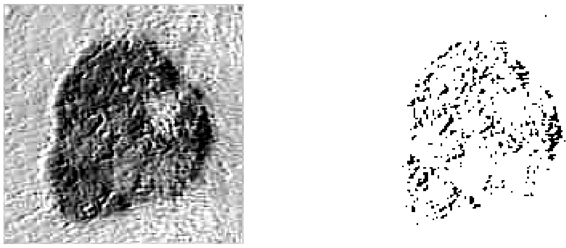
Output 3

Threshold of Output 3

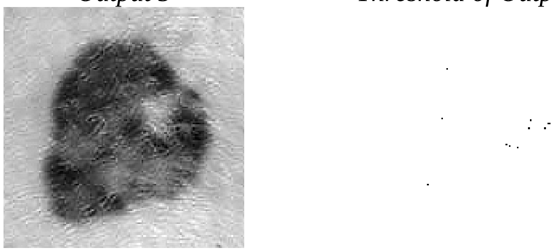


Output 4

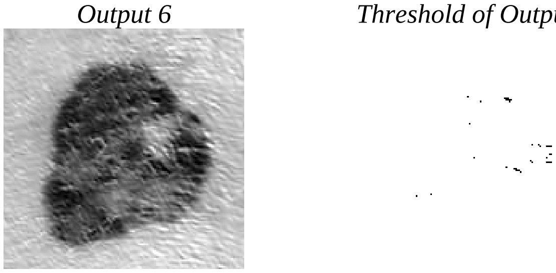
Threshold of Output 4



Output 5 *Threshold of Output 5*



Output 6 *Threshold of Output 6*



Output 7 *Threshold of Output 7*

Fig. 1 Left column represents the NNED outputs; outputs number 1 and 2 show smooth images of melanoma. NN outputs number 3 to 7 are convolved with the original melanoma image and then thresholded to verify sharp edges.

(a) (b) (c)

Fig. 2 (a)-(b) Sobel edge detector and edge strength at a maximum threshold respectively. (c) Image fusion of NNED outputs 3,4,5,6 and 7 that are shown in Fig. 1.

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