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The Improved Potential of Neural Networks for ImageProcessing in Medical Domains

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Abstract
The principal method of obtaining physical information about the biological human body is called medical imaging. It is accomplished by creation of specialized images of human body or its parts for clinical purposes. Over the past twenty to thirty years clinical applications are habitually utilizing medical imaging in different forms and helping in better disease diagnostic and treatment. In last decade or so the usage of Neural Networks in applications of Medical Imaging opened new doors for researchers, stirring them to excel in this domain. This paper is the summarized overview of research and development held in recent past highlighting the role of Neural Networks in advancement of Medical Imaging.
Keywords:*Neural Network, Image Processing, Medical Image Processing, Edge Detection, Feed-forward network, RBF, Hopfield Network*

I. INTRODUCTION

Advances in clinical medical imaging have brought about the routine production of vast numbers of medical images that need to be analyzed. As a result an enormous amount of computer vision research effort has been targeted at achieving automated medical image analysis. This has proved to be an elusive goal in many cases. The complexity of the problems encountered has prompted considerable interest in the use of neural networks for such applications. However, many reports of such work have been unsatisfactory in that often only qualitative results are reported, or only few patient cases are used. This paper presents a study of the use of neural networks for medical image analysis which aims to quantitatively investigate and demonstrate the potential of neural networks in such an application. Since neural networks excel at statistical pattern recognition tasks a broadly bottom-up approach to the problem was adopted. Neural networks were utilized for`intelligent' tasks which were supported by more conventional image processing operations in order to achieve the objectives set.

II. NEURAL NETWORK

Artificial Neural Networks (ANNs) are non linear data driven self adaptive approach as opposed to the traditional model based methods. They are powerful tools for modeling, especially when the underlying data relationship is unknown. Artificial Neural Networks (ANN) have been developed as generalizations of mathematical models of biological nervous systems. A first wave of interest in neural networks (also known as connectionist models or parallel distributed processing) emerged after the introduction of simplified neurons by McCulloch and Pitts (1943). The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. A typical artificial neuron and the modeling of a multilayered neural network .

Referring to above figure, the signal flow from inputs $X_1, \ldots, X_n$ is considered to be unidirectional, which are indicated by arrows, as is a neuron's output signal flow (O). The neuron output signal O is given by the following relationship:

The variable net is defined as a scalar product of the weight and
input vectors,

T is the transpose of a matrix, and, in the simplest case, the output value O is computed as

Where θ is called the threshold level.

Neural Networks (NNs) have been used for a wide variety of applications where statistical methods are traditionally employed. They have been used in classification problems, such as identifying under water sonar currents, recognizing speech and predicting the secondary structure of global proteins. In time series applications, NNs have been used in predicting stock market performance. Neural Network (NN) architectures have been recognized for a number of years as a powerful technology for solving real- world image processing problems. Image Processing is an area of investigation that uses several techniques and algorithms in order to interpret and understand the information contained in a digital image.

Techniques from statistical pattern recognition have, since the revival of neural networks, obtained a widespread use in digital image processing. Initially, pattern recognition problems were often solved by linear and quadratic discriminants or the (non- parametric) k-nearest neighbor classifier and the Parzen density estimator. In the mid-eighties, the PDPgroup together with others, introduced the back-propagation learning algorithm for neural networks. This algorithm for the 1rst time made it feasible to train a non-linear neural network equipped with layers of the so-called hidden nodes. Since then, neural networks with one or more hidden layers can, in theory, be trained to perform virtually any regression or discrimination task.

III. CLASSES OF NEURAL NETWORKS

A. Feed-forward Network

In a feed forward network, information flows in one direction along connecting pathways, from the input layer via the hidden layers to the final output layer. There is no feedback i.e. The output of any layer does not affect that same or preceding layer. Feed-forward networks commonly use the Back Propagation (BP) supervised learning algorithm to dynamically alter the weight and bias values for each neuron in the network. A Multilayer Perceptron (MLP) is a special type of feed-forward network employing three or more layers, with nonlinear transfer functions in the hidden layer neurons. MLPs are able to associate training patterns with outputs for nonlinearly separable data

IV. NEURAL NETWORK AND MEDICAL IMAGING TOOLBOXE

B. Radial Basis Function Networks

The basic architecture for a RBF is a 3-layer network. The input layer is simply a fan-out layer and does no processing. The second or hidden layer performs a non-linear mapping from the input space into a (usually) higher dimensional space in which the patterns become linearly separable. The final layer performs a simple weighted sum with a linear output. If the RBF network is used for function approximation (matching a real number) then this output is fine. If pattern classification is required, then a hard- limiter or sigmoid function could be placed on the output neurons to give 0/1 output values. The Gaussian function is applied to the net input of each neuron to produce a radial function of the distance between each pattern vector and each hidden unit weight vector. RBF networks have been successfully applied to a number of visual processing and analysis problems, including analysis of3D structures, as well as time-series data. They have the potentialto be useful tools for medical image analysis.

C. Hopfield Network

Hopfield network is a specific type of feedback network designed to act as a form of associative memory, in a similar way to certain parts of the human brain. Hopfield networks are constructed from artificial neurons.These artificial neurons have N inputs.With each input i there is a weight wi associated. They also have an output. All neurons are both input and output, and all are connected to every other neuron in both directions. After receiving the input simultaneously by all the neurons, they output to each other continuously until a stable state is reached.

A. Matlab

Neural Network Toolbox for MATLAB provides functions and applications for modeling complex nonlinear systems that are not easily modeled with a closed-form equation. It provides graphical user interfaces for designing, training, visualizing and simulating neural networks. Medical Imaging Interaction Toolkit (MITK) is implemented in C++ is a free and open source software system that allows users to build applications. http://www.mathworks.com/products/neuralnethttp://amide.sourceforge.net

B. Medical Imaging Interaction Toolkit

MITK [16] is a toolkit being developed with an algorithm library for research and software development. Initially planned as an in-house solution for reliable software development in the medical imaging domain. First, it started primarily as a toolkit, focusing on support for interactive multi-view applications by combining and extending Insight Toolkit (ITK) and Visualization Toolkit (VTK). Although VTK and ITK are the most famous and popular in medical image processing, there are several bottlenecks that limit their applications.The initial scope of the toolkit expanded over the years, some of the original ideas were adapted and a lot of work went into the architecture to maintain a toolkit and development environment for a diverse range of applications. Concepts of the MITK presently includes simple preparation of consistent and multiple views onto the same data, semantic organization of the available data in a common data repository, creation and alteration of data by means of generic interaction patterns, uniform geometric descriptions for the location of objects in space and the areas to be depicted and Customizable properties of data nodes for the modification of visualizations and for semantic purposes. MITK is implemented in C++ and released under open-source license by which users are allowed to build applications using MITK without imposing any restrictions or obligations on them. MTIK is not based on VTK and ITK, but is a novel consistent toolkit that provides the function of reconstruction, segmentation,registration, visualization, etc. Some excellent features ofVTK and ITK are used for reference. All other dependencies to third party libraries are optional to ensure a small footprint if required. ITK provides leading-edge registration and segmentation algorithms and forms the algorithmic basis. VTK has powerful visualization capabilities, but only low-level support for interaction (like picking methods, rotation, movement and scaling of objects). MITK employs the data flow model to design the computational framework. A medical data is abstracted to a Data class, while an medical image processing algorithm is abstracted to a Filter class which receives an input data and generates an output data. In medical domain processing of color images like pathological or histological data is supported, although the focus is on radiological images like computed tomography, magnetic resonance imaging and ultrasound. The creation of augmented reality applications is supported through methods for video background rendering and real-time processing, e.g. camera distortion correction.

Fig. 3: Medical Imaging Interaction Toolkit

V. NEURAL NETWORKS IN MEDICAL IMAGE PROCESSING

A. Preprocessing

Image preprocessing using neural networks generally falls into one of the following two categories: image reconstruction and image restoration. The Hopfield neural network is the most widely used neural networks for image reconstruction. Of our reviewed papers related to these areas, Hopfield neural network based methods pose more than fifty percent. Major advantage of using Hopfield neural network in medical image reconstruction is that the problem of medical image reconstruction can be considered as an optimization problem. Reconstruction of an image in electrical impedance tomography requires the solution of a nonlinear inverse on noisy data. This problem is typically ill-conditioned and requires either simplifying assumptions or regularization based on a priori knowledge. The feed forward neural network and the self-organizing Kohonen Neural Network , which pose 5 of 11 papers among our reviewed papers, seem to have more advantages for medical image reconstruction compared with other available techniques, they can calculate a linear approximation of the inverse problem directly from finite element simulations of the forward problem. Many applications of neural networks in medical image pre-processing are found in medical image restoration, 11 papers from our reviewed literatures focused their interests here. In which, one paper on Hopfield neural network, 6 papers on the feed forward neural network, and 3 papers on fuzzy neural network and for cellular neural network, respectively. In the most basic medical image restoration approach, noise is removed from an image by filtering. Suzuki developed neural network based filters (NFs) for this problem. Suzuki [5] also suggested a new Neural Edge Enhancer (NEE) based on a modified multilayer neural network, for enhancing the desired edges clearly from noisy images. The Neural Edge Enhancer is a supervised edge enhancer. Throughtraining with a set of input noisy images and teaching edges, the Neural Edge Enhancer acquires the function of a desired edge enhancer. Compared with conventional edge enhancers, the Neural Edge Enhancer mechanism was robust against noise, was able to enhance continuous edges from noisy images, and was superior to the conventional edge enhancers in similarity to the desired edges.

B. Image Segmentation

The feed forward neural network is the mostly used neural network in the field of medical image segmentation. Among our reviewed papers, 5 papers had implemented the feed forward network for medical image segmentation. Compared with the traditional Maximum Likelihood Classifier (MLC) based image segmentation method, it has been observed that the feed forward neural networks based segmented images appear less noisy, and the feed forward neural networks classifier is also less sensitive to the selection of the training sets than the MLC. Most feed forward neural network based methods have a very slow convergence rate and require a priori learning parameters. These drawbacks limited the application of feed forward neural networks in medical image segmentation field. Hopfield neural networks were introduced as a tool for finding satisfactory solutions to complex optimization problems.Whichmakesthemaninterestingalternativetotraditional optimization algorithms for medical image reconstruction which can be formulated as optimization problem. Four of our reviewed papers used Hopfield neural network to segment some organs from a medical image.

C. Edge Detection

Chang [9] designed a two-layer Hopfield neural network called the competitive Hopfield edge-finding neural network to detect the edges of CT and MRI images. The competitive Hopfield edge- finding neural network extends the one-layer 2D Hopfield network at the original image plane to a two-layer 3D Hopfield network with edge detection to be implemented on its third dimension. With the extended 3D architecture, the network is capable of incorporating a pixel's contextual information into a pixel-labellingprocedure.As a result, the effect of tiny details or noises will be effectively removed by the competitive Hopfield edge-finding neural network and the drawback of disconnected fractions can be overcome. In addition, they discovered that high-level contextual information cannot be incorporated into the segmentation procedure in techniques using traditional Hopfield neural networks and thus proposed contextual constraint-based Hopfield neural cube for image segmentation. Contextual constraint-based Hopfield neural cube uses a three dimensional architecture with pixel classification implemented on its third dimension. With the three-dimensional architecture, the network is capable of taking into account each pixel's feature and its surrounding contextual information, achieving up to 95.86% segmentation accuracy on real MRI images. Recently, still for the edge detection, Chang presented a special design Hopfield neural network called the Contextual Hopfield Neural Network. The Contextual Hopfield Neural Network maps the 2D Hopfield network at the original image plane. With the direct mapping, the network is capable of incorporating pixels'contextual information into an edge-detecting procedure. As a result, the Contextual Hopfield Neural Network can effectively remove the influence of tiny details and noise. In Suzuki, a Neural Edge Detector [4] is proposed to extract contours from left ventriculograms. A modified multilayer neural network is employed and trained using a modified back propagation algorithm through supervisedlearning from a set of images with manually extracted edges by a cardiologist. It is found that the NED is able to extract the contours in agreement the ground truth, where an average contour error of6.2% and an average difference between the ejection fractions at4.1% are reported. However, how to deal with edges under severe noise and low contrast using techniques like active contour model needed to be further investigated.

VI. CONCLUSION

As described in the previous sections, neural networks have been classified into three major categories. They seem quite different from each other and cover many aspects of medical image processing. Here all the neural networks successfully applied to medical imaging are highlighted and compared based on their application patterns, structures, operations, training design, etc. Since there is no theory nor compelling evidence to indicate a single "best" neural network approach for medical image processing and pattern recognition, the information such as "type of network", "type of input", "number of inputs", "neurons in hidden" and "neurons in output" is listed to help with searching and designing similar neural networks for the future applications. Although these applications may come from different areas such as CAD and segmentation, and inputs for neural networks are various, the essential purpose of applying these neural networks lies in their classifications, providing inspiring summary for existing modes of neural network applications and thus leading to further developments. In summary, the applications of NNs in medical image processing have to be analysed individually although many successful models have been reported in the literature. NNs has been applied to medical images to deal with the issues that cannot be addressed by traditional image-processing algorithms or by other classification techniques. By introducing neural networks, algorithms developed for medical image processing and analysis often become more intelligent than conventional techniques.While this paper provided a focused survey on a range of neural networks and their applications to medical imaging, the main purpose here is to inspire further research and development on new applications and new concepts in exploiting neural networks.

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