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Application of Neural Networks in Medical Image Processing

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***Abstract*—This paper reviews the application of artificial neural networks in medical image preprocessing, in medical image object detection and recognition. Main advantages and drawbacks of artificial neural networks were discussed. By this survey, the paper try to answer what the major strengths and weakness of applying neural networks for medical image processing would be.**

***Index Terms*—Neural Network; Medical Image preprocessing; Object Detection;Computer Aided Diagnosis**

I. Introduction

In the past years, artificial neural networks (ANNs) have seen an an increasingly interests in medical image processing[1]-[2]. According to our searching results with Google Scholar, more than 33000 items were found on the topic of medical image processing with ANNs during the past 16 years. The intention of this article is to cover those approaches introduced and to make a map for ANN techniques used for medical image processing. Instead of trying to cover all the issues and research aspects of ANNs in medical image processing, we focus our discussion on three major topics: medical image preprocessing, medical image segmentation, and medical image object detection and recognition. We do not contemplate to go into details of particular algorithms or describe results of comparative experiments, rather we want to summarize main approaches and point out interesting parts of the neural networks for medical image processing, further more by this survey, we try to answer what the major strengths and weaknesses of applying ANNs for medical image processing would be.

II. Applications of Neural Networks in Medical Image Processing

A. Preprocessing

Image preprocessing with neural networks generally falls into one of the following two categories: image reconstruction and image restoration. The Hopfield neural network is one of the most used neural works for image reconstruction [3]-[7]. Of our reviewed literatures related to this areas, Hopfield neural network based methods pose 55 percent. The major advantage of using Hopfield neural network for medical image reconstruction is that the problem of medical image reconstruction can be taken as an optimization problem, which is easily solved by letting the network converge to a stable state while minimizing the energy function.

Reconstruction of images 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 [8]-[9] and the self-organizing Kohonen neural network [10]-[11] , which pose 2 of 9 papers among our reviewed literatures, respectively, seem to have more advantage for such medical image reconstruction compared with other techniques, they can calculate a linear approximation of the inverse problem directly from finite element simulations of the forward problem.

The majority of applications of neural networks in medical image preprocessing are found in medical image restoration, 13 of 24 papers among our reviewed literatures focused their interests here [12]-[21]. Among which, one paper for Hopfield neural network, seven papers for the feed forward neural network, and two papers for 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 et al. developed neural network based filters (NFs) for this problem [12]-[14]. Suzuki et al. also proposed a new neural edge enhancer (NEE) based on a modified multilayer neural network, for enhancing the desired edges clearly from noisy images [15]. The NEE is a supervised edge enhancer: Through training with a set of input noisy images and teaching edges, the NEE acquires the function of a desired edge enhancer. Compared with conventional edge enhancers, the NEE 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 most used neural network for medical image segmentation. Among our reviewed papers, 6 of 17 papers employed the feed forward network for medical image segmentation [22]-[27]. 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

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the selection of the training sets than the MLC. However, 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.

Hopfield neural networks were introduced as a tool for finding satisfactory solutions to complex optimization problems. This makes them an interesting alternative to traditional optimization algorithms for medical image reconstruction which can be formulated as optimization problem. Among our reviewed literatures, 4 of 17 paper used Hopfield neural network to segment some organs from a medical image [28]-[31].

C. *Object detection and recognition*

For using neural networks for medical image detection and recognition, the back propagation neural network poses most places, 11 of 23 papers among our reviewed literatures employed it [37]-[47]. Compared with conventional image recognition methods, no matter used for the interpretation of mammograms [37], or used for cold lesion detection in SPECT image [38], or used for diagnosing classes of liver diseases based on ultrasonographic [39], or used for separation of melanoma from three benign categories of tumors [41], or distinguish interstitial lung diseases [42], or used for reduction of false positives in computerized detection of lung nodules in LDCT [43]-[46]and chest radiography [47], all these feed forward neural network based methods show their preference in recognition accuracy and computing time compared with conventional methods.

Other neural networks, i.e. Hopfield neural network [48], ART neural network [49], radial basis function neural network [50], Probabilistic Neural Network [51], convolution neural network [53]-[56], and fuzzy neural network [52] [57], have also found their position in medical image detection and recognition, which poses 1 of 23, 1 of 23, 1 of 23, 1 of 23, 2 of 23 and 2 of 23 papers, respectively.

Different from what mentioned above, in [58] and [59], artificial neural network ensembles are employed for cancer detection. The ensemble is built on two-level ensemble architecture. The first-level ensemble is used to judge whether a cell is normal with high confidence where each individual network has only two outputs respectively *normal cell* or *cancer cell*. The predictions of those individual networks are combined by some a method. The second-level ensemble is used to deal with the cells that are judged as cancer cells by the first-level ensemble, where each individual network has several outputs respectively, each of which represents a different type of lung cancer cells. The predictions of those individual networks are combined by a prevailing method, i.e. *plurality voting*. Experiments show that the neural network ensemble can achieve not only a high rate of overall identification but also a low rate of false negative identification, i.e. a low rate of judging cancer cells to be normal ones, which is important in saving lives due to reducing missing diagnoses of cancer patients.

III. Discussion

From the reviewed literatures, we find that no matter what neural network model employed for medical image processing, compared with conventional image processing methods, the time for applying a trained neural network to solve a medical image processing problem was negligibly small, though the training of a neural network is a time cost work and also medical image processing tasks often require quite complex computation [12]-[15]. We think that this may be the major contribution of using neural network for solving medical image processing tasks.

Despite their success story in medical image processing, artificial neural networks have several major disadvantages compared to other techniques.

The first one is that a neural network is hard to express human expert's knowledge and experience, and the construction of its topological structure lacks of theoretical methods [60]. Moreover the physical meaning of its joint weight is not clear. All these can make the image processing method by neural networks unstable. A solution to these problems may be to combines fuzzy technique with neural networks together by using neural networks to process fuzzy information. It provides neural networks the ability to express qualitative knowledge, and network topological structure and joint weight have clear physical meaning. Also, it can make the initialization of network easier, avoid the local optimization of network training, and ensure the stability of networks [61].

The second problem relates to the amount of input data. For achieving a high and reliable performance for non-training cases, a large number of training cases are commonly required [62] [63]. If an ANN is trained with only a small number of cases, the generalization ability (performance for non-training cases) will be lower (e.g., the ANN may fit only the training cases). Because medical images are progressing rapidly as technology advances, the timely development of CAD schemes is important. However, it is very difficult to collect a large number of abnormal cases for training, particularly for a CAD scheme with a new modality, such as lung cancer screening with multi-detector-row CT. This significantly degraded the results obtained.

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