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Using a Two-Layer Competitive Hopfield Neural Network for Medical Image Edge Detection

Chuan Yu Chang and Pau-Choo Chung

Department of Electrical Engineering
National Cheng Kung University, Tainan, Taiwan, R.O.C.
Email:pcchung@eembox.ncku.edu.tw

ABSTRACT

In medical applications, detection and outlining of boundaries of organs and tumors in CT and MRI images are prerequisite. In this paper, a specifically designed two-layer Hopfield neural network called competitive Hopfield edge finding neural network(CHEFNN) is presented for finding the edges of CT and MRI images. Different from the conventional 2-D Hopfield neural networks, CHEFNN extends the one layer two-dimensional Hopfield network at the original image plane into a two-layer three-dimensional Hopfield network with edge detection to be implemented on its third dimension. With the extended 3D architecture, the network is capable of taking each pixel's contextual information into pixels' labeling procedure. As CHEFNN takes pixel's contextual information into its consideration, the effect of tiny details or noises will be effectively removed. As a result, the drawback of disconnected fractions can be avoided. Furthermore, due to the incorporation of competitive learning rule to update the neuron states to avoid the trouble of having to satisfy strong constraints, facilitate the network to converge fast. Our experimental results show that the CHEFNN can obtain more appropriate, more continued edge points than Marr-Hildreth's and Laplacian-based methods.

1. INTRODUCTION

Computed tomography (CT) and magnetic resonance imaging (MRI) are nonintrusive techniques that are rapidly gaining popularity as the diagnostic tools. In applying CT and MRI as diagnosis assistance, detection and outlining of boundaries of organs and tumors are prerequisite, which is one of the most important steps in a medical image understanding system. The goal of edge detection is to obtain a complete and meaningful description from an image by characterizing intensity changes. Edge points can be defined as pixels at which an abrupt discontinuity in gray level, color, and texture exists. However, due to the medical image acquisition properties, noise or artifacts arising in the course of image acquisition will increase the difficulty in edge detection. Thus, the first step of the traditional edge detection algorithm is employ a noise-suppression process to original image (i.e. low-pass filter). This process also causes the loss of sharpness in the edges of objects. At present, detection and outlining of boundaries of organs and tumors are usually performed manually, a task which is both costly and tedious.

Different approaches have been used to solve the edge detection problem based on the detection of zero crossing. However, most of these methods require a predetermined threshold to determine whether the zero-crossing points of an image are edge points or not. The threshold value is usually obtained through trial and errors resulting the poor efficiency. On the other hand, Marr and Hildreth also proposed to obtain edge maps of different scales and augured that the different scales of edges will provide important information. They suggested that the original image be band-limited at several different cutoff frequencies and that an edge detection algorithm be applied to each of the band-limited image [2]. This kind of multiresolution edge detection method has a trade-off between localization and detection of edges. The fine resolution gives too much redundant details, whereas the coarse resolution lacks the accuracy of detecting edges.

On the other hand, neural networks with their features of fault tolerance and potential for parallel implementation, has been widely applied in edge detection these years. Yan. *et. al.* [3] based on an active contour model, proposed a modified Hopfield network to detection the brain tumor boundaries in medical images. Lu *et. al.* [4] used BP network to extract the boundary and then boundary enhancement by a modified Hopfield neural network. However, these 2-D Hopfield Neural Networks perform the edge detection by considering only the binary-segmented image but not the original image, resulting that the quality of edge detection results heavily depends on the pre-segmented results. In addition, the conventional 2-D Hopfield Neural Networks lack the capability of taking the pixel's contextual information into its evolution consideration, resulting the detection results consisting of fragmentation and disconnected points.

Thus, despite that tremendous amount of researches have been done on finding image edges, finding the true physical boundary edges in a medical image remains a challenging problem.

In this paper, we propose an edge detection approach based on a two-layer Competitive Hopfield Edge Finding Neural Network (CHEFNN) for detecting edges of CT and MR images. Different from other neural networks [3,4], CHEFNN extends the one layer two-dimensional Hopfield network at the original image plane into a two layers three-dimensional Hopfield network with edge detection to be implemented on its third dimension. With the extended 3D architecture, the network is capable of taking each pixel's contextual information into pixels' labeling procedure. As CHEFNN takes pixel's contextual information into its consideration, the effect of tiny details or noises will be effectively removed. As a result, the drawback of disconnected fractions can be avoided.

All the Hopfield based optimization methods require an energy function that satisfies the basic assumption to be set and evolved through the neural network in search of its local or global minimum. The constraints usually play a very important role in the solution of optimized problems. There are two types of constraints: weak constraints and hard constraints. Weak constraints are used to facilitate the network to obtain a more desirable result. It is unnecessary to satisfy all weak constraints so long as a proportional balance can be maintained among them in the entire operation. On the contrary, hard constraints are required ones that enable the network to reach a feasible resolution. Therefore, they must be fully satisfied. In the treatment of optimized problems with the Hopfield Neural Network in the past, some hard constraints had to be added to the energy function for the network to reach a reasonable solution. However, it is proved to be very difficult to determine the weighting factors between hard constraints and problem-defined energy function. Improper parameters would lead to unfeasible solutions. Later on, Chung et al. [1] proposed the concept of competitive learning to exclude the hard constraints in the Hopfield network and eliminate the trouble in the determination of weighting factors. The competitive learning rule proposed by Chung is also adopted in CHEFNN. Meanwhile, two weak constraints are also used in CHEFNN to serve the purpose to adjust the edge detection. One of the two gives the restrict that the gray levels assigned to the same class have the minimum Euclidean distance measure. The other meant to use the contextual information so as to obtain completely connected edge points. Given the two weak constraints, CHEFNN takes into consideration both the local gray level variance and contextual information of pixels, making it possible to create desirable edge effects from noisy images.

Experimental results show that the CHEFNN can obtain more precise and continued edge points than Marr_Hildreth and Laplacian-based methods[3]. In addition the adoption of the competitive learning rule in CHEFNN relieves us from the burden of determining the proper values for the weighting factors and facilitates the network to converge fast.

The remaining of this paper is described as follows. In Section II, the architecture of the CHEFNN is described. The computer simulation of the CHEFNN is presented in Section III. The experimental studies for the comparison of the proposed method with two existing methods are also shown in Section IV. Finally, conclusions are given in Section V.

2. TWO-LAYERS COMPETITIVE HOPFIELD NEURAL NETWORK

As mentioned previously, edge detection should be considered as a pixel labeling process in which the pixels are classified to be edge points based on their spatial contextual information. In this paper, we proposed a three dimensional neural network architecture called Competitive Hopfield Edge Finding Neural Network(CHEFNN), which considers both the local gray level variance and the neighbors contextual information to avoid the result of fraction and disconnected points in edge extraction results. Because of the conventional 2-D Hopfield architecture, the network is unable to take the pixel's contextual information into network, resulting the detection results consist of fragmentation and disconnected points.

In order to allow the network take the pixel's contextual information into network and identify whether each pixel is an edge point or not directly in an $N x N$ image, the CHEFNN consists of $N x N x 2$ neurons which can be conceived as a three-dimensional neural cube. In the CHEFNN, the input is the original two-dimensional image and the output is the classified edge-based feature map, where each pixel of the image has two neurons arranged into a vertical direction associated with it, where each neuron represents one possible label (edge point or not). Therefore, the output of the neurons with the same vertical level is an edge-based feature map. The architecture of the CHEFNN is shown in Fig. 1.

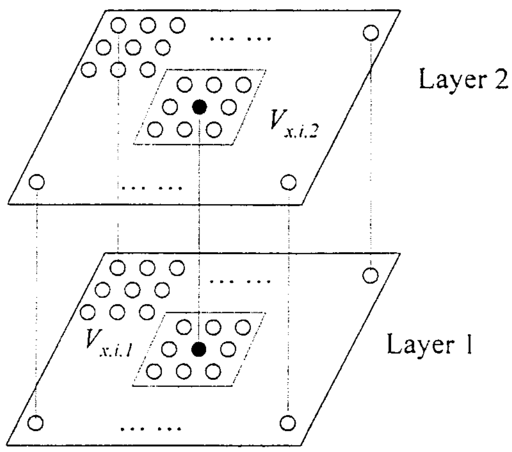

Fig.1 The architecture of the CHEFNN

The CHEFNN is a two-layer neural network, extended from the one-layer two-dimensional Hopfield neural networks, each neuron without self-feedback interconnection. Let $V_{x,i,k}$ denote the binary state of the $(x,i)th$ neuron in layer k (1 for firing and 0 for resting) and $W_{x,i,k;y,j,z}$ denote the interconnection weight between the neuron (x,i) in layer k and the neuron (y,j) in layer z. A neuron (x,i,k) in this network receives weighted inputs $W_{x,i,k;y,j,z}\, V_{y,j,z}$ from each neuron (y,j,z) and a bias input $I_{x,i,k}$ from outside. The total input to neuron (x,i,k) is computed as

$$Net_{x,i,k} = \sum_{z=1}^{2}\sum_{y=1}^{N}\sum_{j=1}^{N} W_{x,i,k;y,j,z} V_{y,j,z} + I_{x,i,k}\,, \tag{1}$$

and the activation function in the network is defined as

$$V_{x,i,k}^{n+1} = \begin{cases} 1 & (Net_{x,i,k} - \theta) > 0 \\ V_{x,i,k}^{n} & (Net_{x,i,k} - \theta) = 0\,, \\ -1 & (Net_{x,i,k} - \theta) < 0 \end{cases} \tag{2}$$

where θ is a threshold value.

Based on the update equation, we can define the Lyapunov energy function of the two layers Hopfield neural network as

$$E = -\frac{1}{2}\sum_{k=1}^{2}\sum_{z=1}^{2}\sum_{x=1}^{N}\sum_{y=1}^{N}\sum_{i=1}^{N}\sum_{j=1}^{N} V_{x,i,k} W_{x,i,k;y,j,z} V_{y,j,z} - \sum_{k=1}^{2}\sum_{x=1}^{N}\sum_{i=1}^{N} I_{x,i,k} V_{x,i,k} \tag{3}$$

The network achieves a stable state when the energy of the Lyapunov function is minimized. The layers of the CHEFNN represent the possible label of each pixel. For example, a neuron $V_{x,i,k}$ in a firing state indicates that the pixel locate at (x,i) in the image is identified as an edge point or a non-edge point.

In order to ensure the CHEFNN has the capability of taking contextual information for edge detection. The energy function of CHEFNN must satisfy the following conditions:

1. The gray levels within an area belonging to the same class have the minima Euclidean distance measure. In other words, the difference between the gray level pairs $g_{x,i}$ and $g_{y,j}$ is minimum where $g_{x,i}$ and $g_{y,j}$ are located within an area and which belong to the same class. This condition is given as

$$\sum_{z=1}^{2}\sum_{x=1}^{N}\sum_{\substack{y=1\\(y,j)\neq(x,i)}}^{N}\sum_{i=1}^{N}\sum_{j=1}^{N} d_{x,i;y,j}\Phi_{x,i}^{p,q}(y,j) V_{x,i,z} V_{y,j,z}\,, \tag{4}$$

where $d_{x,i;y,j}$ is defined as

$$d_{x,i;y,j} = \left(\frac{g_{x,i} - g_{y,j}}{Max(G)}\right)^2 \tag{5}$$

, and $\Phi_{x,i}^{p,q}(y,j)$ is used for specifying whether pixel (y,j) is located within a $p*q$ window area with pixel (x,i) being the window center. The function $\Phi_{x,i}^{p,q}(y,j)$ is defined as

$$\Phi_{x,i}^{p,q}(y,j) = \sum_{l=-q}^{q} \delta_{j,i+l} \sum_{m=-p}^{p} \delta_{y,x+m}\,, \tag{6}$$

where $\delta_{i,j}$ is the Kronecker delta function defined as

$$\delta_{i,j} = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases}. \tag{7}$$

With this definition, $\Phi_{x,i}^{p,q}(y,j)$ will give a value 1 if (y,j) is located inside the window area, and 0 otherwise. And the $V_{x,i,z}\, V_{y,j,z}$ in Eq.(4) is used to restrict that the local gray level differences are computed only for the same class pixels.

2. Considering the contextual information of any pixel (x,i), if the labeling result of the pixel (x,i) is the same as its neighborhood's, then energy function is decreased. Otherwise, energy function is increased. The similarity of each pixel's labeling result with its neighborhoods' is computed as

$$\sum_{k=1}^{2}\sum_{z=1}^{2}\sum_{x=1}^{N}\sum_{\substack{y=1\\(y,j)\neq(x,i)}}^{N}\sum_{i=1}^{N}\sum_{j=1}^{N} V_{x,i,k} V_{y,j,z}\Phi_{x,i}^{p,q}(y,j)(1-\delta_{1,z})\,, \tag{8}$$

In addition to the constraints mentioned above, in order to obtain a complete correct segmentation results, the CHEFNN needs to satisfy the following two hard conditions:

1. Each pixel is assigned as one and only one label(edge or not).

$$\sum_{z=1}^{2} V_{x,i,z} = 1 \tag{9}$$

2. All the pixels need to be classified

$$\sum_{z=1}^{2}\sum_{x=1}^{N}\sum_{i=1}^{N} V_{x,i,z} = N^2\,. \tag{10}$$

Therefore, based on the above four conditions, by considering the contextual information of an image, the objective function of the network for our edge detection, is obtained as:

$$\begin{aligned} E = &\frac{A}{2}\sum_{z=1}^{2}\sum_{x=1}^{N}\sum_{\substack{y=1\\(y,j)\neq(x,i)}}^{N}\sum_{i=1}^{N}\sum_{j=1}^{N} d_{x,i;y,j}\Phi_{x,i}^{p,q}(y,j) V_{x,i,z} V_{y,j,z} \\ &+\frac{B}{2}\sum_{k=1}^{2}\sum_{z=1}^{2}\sum_{x=1}^{N}\sum_{\substack{y=1\\(y,j)\neq(x,i)}}^{N}\sum_{i=1}^{N}\sum_{j=1}^{N} V_{x,i,k} V_{y,j,z}\Phi_{x,i}^{p,q}(y,j)(1-\delta_{1,z}) \\ &+\frac{C}{2}\sum_{x=1}^{N}\sum_{i=1}^{N}\sum_{z=1}^{2}\sum_{k=1}^{2} V_{x,i,k} V_{x,i,z} + \frac{D}{2}\left(\sum_{z=1}^{2}\sum_{x=1}^{N}\sum_{i=1}^{N} V_{x,i,z} - N^2\right)^2 \end{aligned} \tag{11}$$

It is noted that the first two terms are weak constraints. They are used to improve the edge results (For example, to obtain a more complete and more connected edge detection results.); the network should find a balance between these weak constraints. Therefore, these constraints are not necessarily to be completely obeyed. On the other hand, the last two terms are hard constraints; they are the basic assumption of the edge detection problem and cannot be violated. Thus, the network must completely satisfy these two hard constraints. Otherwise, the obtained results would not be correct.

To avoid the difficulty of searching for the proper values for the hard constraints, the competitive winner-take-all rule proposed by Chung *et al.* [1] is imposed in the CHEFNN for the updating of the neurons. Based on the winner-take-all rule, for each pixel, one and only one of the neurons $V_{x,i,z}$ which receives the maximum input would be regarded as the winner neuron and, therefore its output would be set to one, and the other neuron $V_{x,i,z}, \forall z \neq k$ associated with the same pixel is set to zero. Thus, the output function for $V_{x,i,k}$ is given as

$$V_{x,i,k} = \begin{cases} 1 & if \quad V_{x,i,k} = \max\{V_{x,i,1}, V_{x,i,2}\} \\ 0 & otherwise \end{cases} \tag{12}$$

The winner-take-all rule guarantees that no two neurons $V_{x,i,1}$ and $V_{xi,2}$ fires simultaneously. The winner-take-all rule also ensures that all the pixels are classified. Due to these two properties, the last two terms (hard constraints) in Eq. (11) is embed into the network. Therefore, the hard constraints are completely removed. According above discussion, the objection function of the CHEFNN may be modified as:

$$E = \sum_{k=1}^{2}\sum_{z=1}^{2}\sum_{x=1}^{N}\sum_{\substack{y=1 \\ (y,j)\neq(x,i)}}^{N}\sum_{i=1}^{N}\sum_{j=1}^{N}\left[\frac{A}{2}d_{x,i;y,j}\delta_{k,z} + \frac{B}{2}\Phi_{x,i}^{p,q}(y,j)(1-\delta_{k,z})\right]V_{x,i,k}V_{y,j,z} \tag{13}$$

Comparing the objection function of the CHEFNN in Eq.(13) and the Lyapunov function Eq.(3) of the three-dimensional Hopfield network, the synaptic interconnection strengths and the bias input of the network are obtained as

$$W_{x,i,k;y,j,z} = -\frac{A}{2}d_{x,i;y,j}\Phi_{x,i}^{p,q}(y,j)\delta_{k,z} - \frac{B}{2}\Phi_{x,i}^{p,q}(y,j)(1-\delta_{k,z}) \tag{14}$$

and

$$I_{x,i,z} = 0, \tag{15}$$

respectively. Applying Equations (14) and (15) to Eq.(1), the total input to neuron (x,i,k) is

$$Net_{x,i,k} = -\frac{1}{2}\sum_{z=1}^{2}\sum_{\substack{y=1 \\ (y,j)\neq(x,i)}}^{N}\sum_{j=1}^{N}\left(Ad_{x,i;y,j}\delta_{k,z} + B(1-\delta_{k,z})\right)\Phi_{x,i}^{p,q}(y,j)V_{y,j,z} \tag{16}$$

From Eq.(16), we can see that due to the use of competitive winner-take-all rule, the CHEFNN is not fully interconnected. Each neuron receives inputs only from the outputs of the neurons having the same height and the outputs of the neighborhood with the different height. This property significantly reduces the complexity of the network, and thus, increases the network evolution speed.

3. THE CONTEXTUAL-CONSTRAINT BASED NEURAL CUBE ALGORITHM

The algorithm of the three-dimensional CHEFNN is summarized as follows:

Input: The original image X, the neighborhood parameters p and q and the factors A and B.

Output: The stabilized neuron states of different heights representing the different segmented feature map of the original images.

Algorithm:

Step 1) Arbitrarily assigns the initial neuron states to be 2 classes.

Step 2) Use Eq.(16) to calculate the total input of each neuron (x,i,k).

Step 3) Apply the winner-take-all rule given in Eq.(12) to obtain the new output states for each neuron.

Step 4) Repeat Step 2 and Step 3 for all classes and count the number of neurons which state is changed during the updating. If there are any changed neurons, then go to Step 2. Otherwise, go to Step 5.

Step 5) Output the final states of neurons that indicate the segmented results.

4. EXPERIMENTAL RESULTS

To validate its effectiveness, this CHEFNN technique has been tested on the CT and MR images shown in Fig. 2(a), 3(a), and 4(a) respectively, of image size of 256×256 pixels, each pixel of 256 grey level. All the cases used for the evaluation of the CHEFNN are collected from the National Cheng Kung University Hospital. The MR images are taken from the Siemens Magnetom 63SPA, T2 weighted spin-echo sequences. The CT images are acquired by a GE 9800 CT scanner..

Experiment 1

The edge detection results of the skull-based phantom CT (Fig. 2(a)) are shown in consist of skull and stuffing. The irregular gray mesh exposed in the bottom of the image is a towel that is used to fix the phantom in the image acquisition process. Fig 2(b) shows the edge detection result of Laplacian-based method and Fig. 2(c) shows the results obtained by Marr-Hildreth's method, respectively. We can obviously see the double edges and the redundant edges in the results of their methods. The result of CHEFNN is shown in Fig. 2 (d). We have found in Fig. 2(d)that the skull, stuffing and background are clearly outlined and the noise at the outer of the head is removed when the contextual information is taken into consideration.

Experiment 2

Fig 3(a) is a CT head image in which there exist a number of tiny tissues. Shown in Fig. 3(b) is the edge detection images by means of the Laplacian-based method, respectively. Obviously, the Laplacian-based method can not effectively outlined the skull from the image. Thus, the edge detection results are quite mess. Fig. 3(c) is the edge detection results of and Marr-Hildreth's method.

From the results, we can see that the double edges, many fragments and little holes in the image. Fig. 3(d) shows the edge detection results using CHEFNN. From Fig. 3(d), we can clearly see that more continued edge are obtained when contextual information is considered in the edge detection process. Thus, the proposed CHEFNN can obtain clear and complete edge detection images.

Experiment 3

Fig. 4(a) is a MR knee joint based transverse image. The results obtained by using the Laplacian-based with threshold=5, N=7, δ=1 and the Marr-Hildreth's method (N=7, δ=1) are illustrated in Figs. 4(b) and 4(c), respectively. From Figs. 4(b) and 4(c) we can see the fragmental edges, the redundant edges and redundant edges in Laplacian-based and Marr-Hildreth's method. The result obtained by CHEFNN is shown in Fig. 4(d) from which we can see that the boundaries of the knee joint, articular and patella were complete detected.

5. CONCLUSIONS

In this paper, a modified Hopfield neural network architecture, called the Competitive Hopfield Implementing Edge Finding (CHEFNN) neural network, is presented for the detection of organ edges. The CHEFNN extends the one layer two-dimensional Hopfield network at the original image plane into a two layers three-dimensional Hopfield network with edge detection to be implemented on its third dimension. With the extended 3D architecture, the network is capable of taking each pixel's contextual information into pixels' labeling procedure. As CHEFNN takes pixel's contextual information into its consideration, the effect of tiny details or noises will be effectively removed. As a result, the drawback of disconnected fractions can be avoided. The experimental results show that the CHEFNN can obtain more appropriate, more continued, and more intact edges in comparison with the Laplacian-based [6] and Marr-Hildreth's [5] methods. Besides, CHEFNN follows the competitive learning rule to update the neuron states to avoid the trouble of having to satisfy strong constraints, facilitating the network to converge fast.

The network, CHEFNN, is a self-organized structure that is highly interconnected and can be implemented in a parallel manner. It can also be easily designed with hardware devices to achieve high-speed implementation.

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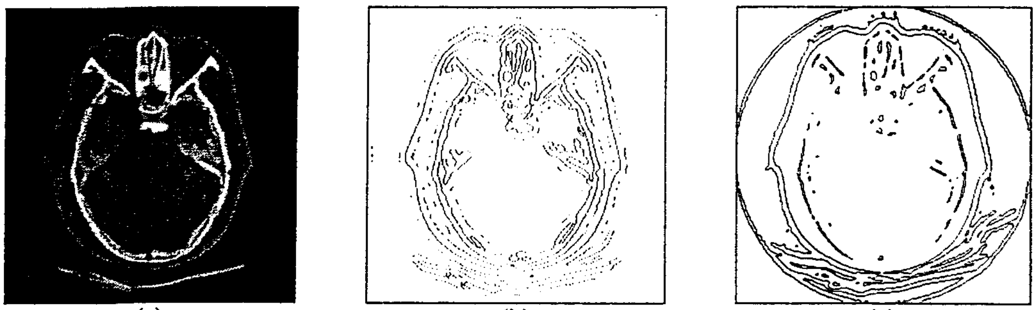
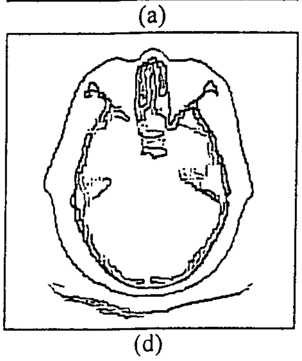
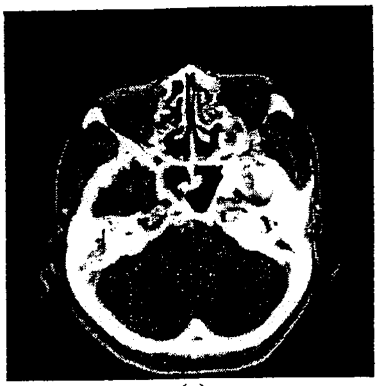


(a) (b) (c)



(d)

Fig. 2. (a) The original phantom CT (b) result by the Laplacian-based method with threshold=5. N=7, δ=1, (c) result by Marr-Hildreth's method (N=7. δ=1). (d) result by CHEFNN (p=q=2, A=0.01, B=0.028).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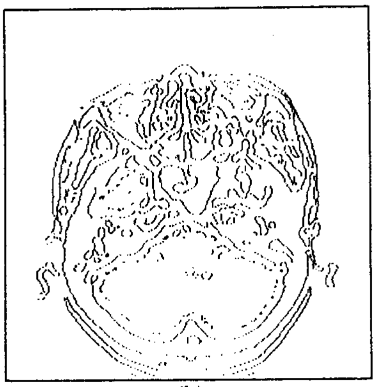
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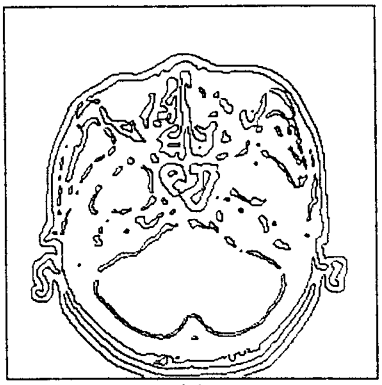
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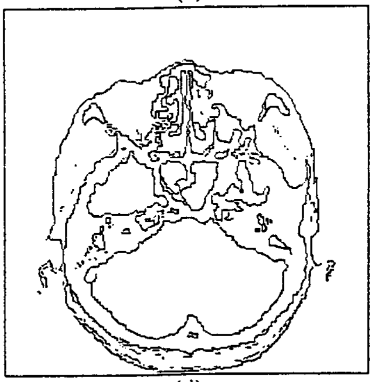
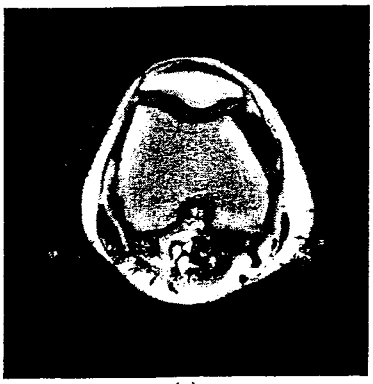

(d)

Fig. 3. (a) The original CT image. (b) The result by the Laplacian-based method with threshold=5. N=7, δ=1, (c) The result by Marr-Hildreth's method (N=9, δ=1). (d) The Result of CHEFNN.(p=q=1, A=0.01, B=0.032)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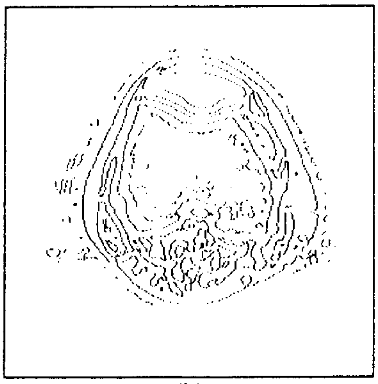
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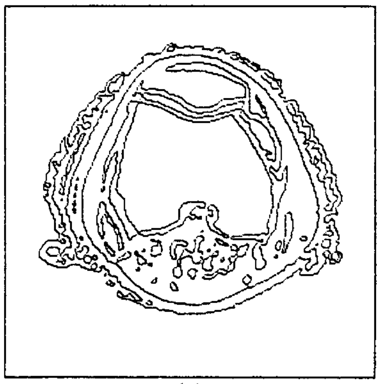
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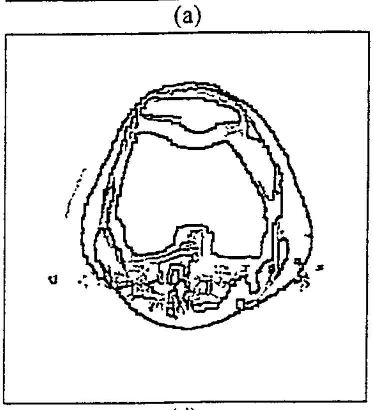
(d)

Fig. 4. (a) The original MR knee joint based transverse image (b) result by the Laplacian-based method with threshold=5. N=7, d=1, (c) result by Marr-Hildreth's method (N=9, d=1). (d) result by CHEFNN (p=q=2, A=0.01, B=0.03).