Contextual Hopfield Neural Networks for Medical Image Edge Detection

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Abstract

Outlining of boundaries of organs and tumors in CT and MRI images are prerequisite in medical applications. In this paper, a single layer Hopfield neural network called Contextual Hopfield Neural Network (CHNN) is presented for finding the edges of CT and MRI images. Different from the conventional 2-D Hopfield neural networks, the CHNN maps the two-dimensional Hopfield network at the original image plane. With the direct mapping, the network is capable of incorporating pixels’ contextual information into a pixels’ labeling procedure. As a result, the effect of tiny details or noises will be effectively removed by the CHNN and the drawback of disconnected fractions can be overcome. Furthermore, the problem of satisfying strong constraints can be alleviated and results in a fast converge. Our experimental results show that the CHNN can obtain more appropriate, more continued, and more perceptual edge points than Laplacian-based, Marr-Hildreth’s, Canny’s, wavelet-based, and CHEFNN methods in noisy images.

1. Introduction

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 computer aided surgery. 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, or texture exists. Different approaches have been used to solve edge detection problems based on zero-crossing detection. However, most of these methods require a predetermined threshold for determining whether or not a zero-crossing point is an edge point[1]. The threshold value is usually obtained through trial and error that causes poor efficiency. On the other hand, Marr and Hildreth also proposed to obtain edge maps of different scales and augured that 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 edge details. A fine resolution gives too much redundant detail, whereas a coarse resolution lacks accuracy of edge detection.

The Hopfield neural networks, using unsupervised learning, adeptly precludes the necessity of pre-training the networks [3-4]. However, 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. In a recent work [5], a two-layer Hopfield based neural network called Competitive Hopfield Edge Finding Neural Network (CHEFNN) by including pixel’s surrounding contextual information into image edge detection technique was proposed. It takes into account each pixel’s feature and the pixel’s surrounding contextual information for image segmentation. The proposed approach was demonstrated to be able to obtain more continued, and smoother segmentation results in comparison with other methods. However, the CHEFNN is make up of $2 \times N \times N$ neurons, where $N$ is the size of image. The massive numbers of neurons make the evolution of the CHEFNN is time consuming. Therefore, inspired by the concept of CHEFNN, we present a reduced two dimensional Hopfield-based neural network, called Contextual Hopfield Neural Network.
Network (CHNN) by including pixel’s surrounding contextual information into image edge detection. In order to allow the network to consider the pixel’s contextual information and identify whether or not each pixel is an edge point directly from an N×N image, the designed CHNN is make up of N×N neurons. In the CHNN, the input is the original two-dimensional image and after network evolution the output is an edge map. To validate its effectiveness, the CHNN has been tested on various kinds of medical images including Phantom-based, CT, and MRI. The simulation results show that CHNN can produce more continuous and precise edge detection in comparison with the Laplacian-based[1], Marr_Hildreth[2], wavelet-based[7], and Canny’s[8] methods. Furthermore, the reduced burden of determining the proper values for the weighting factors and facilitates fast converge of the network.

The remainder of this paper is organized as follows. In Section II, the architecture of the CHNN is described. Computer simulations of the CHNN are then presented in Section III. An experiment-base comparative study among the proposed method and four existing methods is conducted in Section IV. Finally, some conclusions are drawn in Section V.

2. The Contextual Hopfield Neural Network, CHNN

In general, edge detection can be considered as a pixel labeling process that assigns pixels to edge points in accordance with their spatial contextual information. Unfortunately, the conventional 2-D Hopfield architecture cannot include the pixel’s contextual information into the network. This results in fragmentation and disconnected points in edge detection. In this paper, we proposed a parameter-free Hopfield neural network architecture, called Contextual Hopfield Neural Network (CHNN), which considers both the local gray level variance and the neighbor-contextual information to avoid fraction and disconnected points in edge extraction.

In order to allow the network to consider the pixel’s contextual information and identify whether or not each pixel is an edge point directly from an N×N image, the designed CHNN is make up of N×N neurons as shown in Fig.1. In the CHNN, the input is the original two-dimensional image and the output is an edge-based feature map.

Let $V_{x,j}$ denote the binary state of the $(x,i)$th neuron ($V_{x,j} = 1$ for excitation and $V_{x,j} = 0$ for inhibition) and $W_{x,j,y,j}$ denote the interconnection weight between the neuron $(x,i)$ and the neuron $(y,j)$. A neuron $(x,i)$ in this network receives weighted inputs $W_{x,j,y,j}V_{y,j}$ from each neuron $(y,j)$ and a bias input $I_{x,j}$ from outside. The total input to neuron $(x,i)$ is computed as

$$Net_{x,j} = \sum_{y=1}^{N} \sum_{j=1}^{N} W_{x,j,y,j}V_{y,j} + I_{x,j}$$

(1)

and the activation function in the network is defined by

$$V_{x,j}^{n+1} = \begin{cases} 0 & Net_{x,j} > \theta \\ 1 & \eta Net_{x,j} e^{\eta Net_{x,j}} \\ 0 & otherwise \end{cases}$$

(2)

where $\theta$ is a threshold value, $\eta$ is the slope parameter of the sigmoid function. According to the update equations (1) and (2), we can define the Lyapunov energy function of the two dimensional Hopfield neural network as

$$E = -\frac{1}{2} \sum_{x=1}^{N} \sum_{y=1}^{N} \sum_{j=1}^{N} V_{x,j} W_{x,j,y,j} V_{y,j} - \sum_{x=1}^{N} \sum_{j=1}^{N} I_{x,j} V_{x,j}$$

(3)

The network achieves a stable state when the energy of the Lyapunov function is minimized. The output of the CHNN represents the state of each pixel which indicates if the pixel is an edge point. A neuron $V_{x,j}$ in a firing state indicates that the pixel locate at $(x,i)$ in the image is identified as a edge point.

In order to ensure that the CHNN has capability of dealing with contextual information in edge detection. The energy function of CHNN must satisfy the following condition:

The intensity values belonging to the non-edge point have the minimal Euclidean distance measure. That implied that the edge point have larger Euclidean distance. The total gray level differences are computed as

$$\sum_{x=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} d_{x,j,y,j} \Phi_{x,j}^{p,q}(y,j)V_{x,j}V_{y,j}$$

(4)

where $d_{x,j,y,j}$ is the normalized difference between and , defined by

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

(5)

where $g_{x,j}$ represent the gray levels of pixel $(x,i)$, and $\Phi_{x,j}^{p,q}(y,j)$ is a neighborhood function used to specify whether or not pixel $(y,j)$ is located within a $p^*q$ window area centered at pixel $(x,i)$. The function is defined as :
\[ \Phi_{x,y}(y, j) = \sum_{l=-q}^{q} \delta_{i,j+l} \sum_{m=-p}^{p} \delta_{y,x+m}, \]  
where \( \delta_{i,j} \) is the Kronecker delta function given by:

\[ \delta_{i,j} = \begin{cases} 
1 & i = j \\
0 & i \neq j 
\end{cases} \]  

With this definition \( \Phi_{x,y}(y, j) \) will give a value 1 if \((y, j)\) is located inside the window area, and 0 otherwise.

From the above constraint Eq. (7), the objective function of the network for edge detection with consideration of contextual information is obtained as:

\[ E = \frac{1}{2} \sum_{(y, j) \in (x, i)} \sum_{y} \sum_{j} \sum_{x} \sum_{i} \sum_{x'} \sum_{i'} \Phi_{x',y'}(y, j) V_{x',y'} \]  

Observing the Eq.(8), there is no user-defined parameter, thus, avoid the difficulty of searching for proper values for the hard constraints.

Comparing the objection function of the CHNN in Eq.(8) and the Lyapunov function Eq.(3) of the Hopfield network, the synaptic interconnection strengths and the bias input of the network are obtained as

\[ W_{x,y,j} = -\frac{1}{2} d_{x,y,j} \Phi_{x,y}(y, j) \]  
and

\[ I_{x,i} = 0, \]  
respectively. Applying Equations (9) and (10) to Eq.(1), the total input to neuron \((x, i)\) is

\[ Net_{x,i} = \frac{1}{2} \sum_{(y, j) \in (x, i)} \sum_{y} \sum_{j} \sum_{x} \sum_{i} \sum_{x'} \sum_{i'} \Phi_{x',y'}(y, j) V_{x',y'} \]  

From Eq.(11), the neurons receive inputs only from the neighboring neurons. This property significantly reduces the complexity of the network, and thus, increases the network evolution speed.

3. The CHNN algorithm:

The algorithm of the CHNN is summarized as follows:

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

Output: The stabilized neuron representing the classified edge map of the original images.

Algorithm:

Step 1) Assigning the initial neuron states as 1.
Step 2) Use Eq.(11) to calculate the total input of each neuron \((x, i)\).
Step 3) Apply the activation rule given in Eq.(2) to obtain the new output states for each neuron.
Step 4) Repeat Step 2 and Step 3 for all neurons and count the number of neurons whose state is changed during the updating. If there is a change, then go to Step 2. Otherwise, go to Step 5.
Step 5) Output the final states of neurons that indicate the edge detection results.

4. Experimental Results:

To show that the proposed CHNN have good capability of edge detection and noise immunity, the proposed CHNN is compare with Laplacian-based [1], Marr-Hildreth’s [2], wavelet-based [7], Canny’s [8], and CHEFNN[5] methods. In the evaluations, the most appropriate parameters (e.g. mask size \( N \), local variance \( \delta \), and threshold) for each method to gain the best edge detection results in the original computer generated phantom image are obtained by trial-and-error. All the cases used for evaluating the CHNN were collected from the National Cheng Kung University Hospital. The MRI images were taken from the Siemens’s Magnetom 63SPA, T2 weighted spin-echo sequences, while the CT image is acquired from a GE 9800 CT scanner. The image sizes of CT and MR images are 256×256 pixels, each pixel of 256 gray levels.

A. Phantom Study

Fig 2(a) is a computer-generated phantom image, which was made up of seven overlapping ellipses. Each ellipse represents one structural area of tissue. From the periphery to the center, they were background (BKG, gray level=30), skin or fat (S/F, gray level=120), gray matter (GM, gray level=165), white matter (WM, gray level=75), and cerebrospinal fluid (CSF, gray level=210), respectively. The gray levels for each tissue were set to a constant value, thus, the edge points can be easily obtained. In addition to show the proposed CHNN have good capability of noise immunity, the noise of uniform distribution with the gray levels ranging from –K to K was also added to this simulation phantom to generate several noisy test images. The noise ranges were set to be 18, 20, 23, 25, and 30, as shown in Figs. 2(b)-(f).

The results using these methods for the noiseless image are shown in Figs.3 (a)-(f). From Figs. 3(a, d, e, f), it can be seen that Laplacian-based, Canny’s, CHEFNN and CHNN methods extract the edges correctly for the noiseless image. On the other hand, the wavelet-based method though has the capability of
The thick edge map is more approximate to human vision. With the noise increasing the error rate of the proposed CHNN are increasing slowly. The experimental results show that the CHNN has nice noise immunity. In addition, the evolution time of the CHNN is much faster than CHEFNN. The average evolution time for CHNN is about 5 seconds and 26–38 seconds for CHEFNN. Table II shows the time taken for edge detection on an Intel Pentium IV 1.8GHz processor.

Figure 9(a) is a CT head image in which there exist a number of tiny tissues. Figure 9(b) is an MR knee joint-based transverse image. Fig. 10(a) and Fig. 10(d) is the edge detection image using the Laplacian-based method and wavelet-based method, respectively. Obviously, the Laplacian-based method and wavelet-based method can not effectively outline the skull in the image. Thus, the edge detection results are poor. Figure 10(b) is the edge detection results of Marr-Hildreth’s method. As we can see, there are double edges, many fragments and little holes in the image. The results using Canny’s edge detector is illustrated in Fig. 10(c), which shows many unwanted details. Figure 10(e) and Fig. 10(f) are the edge detection results using CHEFNN and CHNN, respectively. It clearly shows that more continued edges were found when contextual information was used in the edge detection process. Thus, the proposed CHNN obtained more clear and accurate edges in the image.

The edges of Fig. 9(b) obtained by using the Laplacian-based with threshold=5, N=7, δ=1 and the wavelet-based method are illustrated in Figs. 11(a) and 11(d), respectively. As we can see, there exist fragment and redundant edges in Laplacian-based and wavelet-based methods. Illustrated in Fig. 11(b) is the result of Marr-Hildreth’s method, from which we can see that edges extracted by Marr-Hildreth’s method are considerably continued; however, the method also resulted in double edges. Result using Canny’s edge detector is shown in Fig. 11(c). It is obvious from Fig. 11(e) that many unwanted details are also falsely detected by Canny’s method as edges. The results obtained by CHEFNN and CHNN are shown in Fig. 11(e) and Fig. 11(f), respectively, from which we can see that the boundaries of the knee joint, articular and patella were completely and precisely detected.

5. Conclusion

This paper extending my prior work, propose a Contextual-Hopfield Neural Network, (CHNN) for performing edge detection. The CHNN consist of N×N
neurons, the input is the original two-dimensional image and the output is an edge-based feature map. Since the ingenious design, the CHNN saved a half of neurons than CHEFNN (2×N×N) resulting the networks evolution fast. The CHNN is capable of taking into account each pixel’s feature and its surrounding contextual information. As a result, the effect of tiny details or noises will be effectively removed by the CHNN and the drawback of disconnected fractions can be overcome. Our experimental results show that the CHNN can obtain more appropriate, more continued edge points than Laplacian-based, Marr-Hildreth’s, Canny’s, and wavelet-based methods. In addition, the network’s evolution speed is fast than CHEFNN. Despite the error rate is larger than CHEFNN in noiseless and in small noise level image, the noise immunity is better than CHEFNN in large noise level. Also, the CHNN obtain thick edges; the edge detection results are more perceptual for human vision.

Acknowledgment
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Reference
Figure 4. The edge detection results of phantom image with added noise (K=18), (a) result by the Laplacian-based method, (b) result by the Marr-Hildreth’s method, (c) result by the wavelet-based method, (d) result by the Canny’s method, (e) result by the CHEFNN, and (f) result by the proposed CHNN.

Figure 5. The edge detection results of phantom image with added noise (K=20), (a) result by the Laplacian-based method, (b) result by the Marr-Hildreth’s method, (c) result by the wavelet-based method, (d) result by the Canny’s method, (e) result by the CHEFNN, and (f) result by the proposed CHNN.

Figure 6. The edge detection results of phantom image with added noise (K=23), (a) result by the Laplacian-based method, (b) result by the Marr-Hildreth’s method, (c) result by the wavelet-based method, (d) result by the Canny’s method, (e) result by the CHEFNN, and (f) result by the proposed CHNN.

Figure 7. The edge detection results of phantom image with added noise (K=25), (a) result by the Laplacian-based method, (b) result by the Marr-Hildreth’s method, (c) result by the wavelet-based method, (d) result by the Canny’s method, (e) result by the CHEFNN, and (f) result by the proposed CHNN.

Figure 8. The edge detection results of phantom image with added noise (K=30), (a) result by the Laplacian-based method, (b) result by the Marr-
Hildreth’s method, (c) result by the wavelet-based method, (d) result by the Canny’s method, (e) result by the CHEFNN, and (f) result by the proposed CHNN.

Figure 9. (a) The original MR knee joint based transverse image, (b) The original CT image

Figure 10. The edge detection results of Fig.9(a) (a) result by the Laplacian-based method with threshold=5. N=7, δ=1, (b) result by Marr-Hildreth’s method (N=9, δ=1). (c) result by Canny’s method. (d) result by wavelet-based method. (e) result by CHEFNN (p=q=1, A=0.01, B=0.03), and (f) result by the proposed CHNN.

Figure 11. The edge detection results of Fig.9(b) (a) result by the Laplacian-based method with threshold=5. N=7, δ=1, (b) result by Marr-Hildreth’s method (N=9, δ=1). (c) result by Canny’s method. (d) result by wavelet-based method. (e) result by CHEFNN (p=q=1, A=0.01, B=0.03), and (f) result by the proposed CHNN.

Table I. The detection error rates for Laplacian-based, Marr-Hildreth, Canny, wavelet, and the proposed CHEFNN methods using the simulated phantom image with noise level K=0 to 30.

<table>
<thead>
<tr>
<th>Nois</th>
<th>Method</th>
<th>0</th>
<th>18</th>
<th>20</th>
<th>23</th>
<th>25</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Laplacian</td>
<td>1.3%</td>
<td>51.9%</td>
<td>70.6%</td>
<td>89.2%</td>
<td>131.4%</td>
<td>328.1%</td>
</tr>
<tr>
<td>18</td>
<td>Marr-Hildreth</td>
<td>4.1%</td>
<td>43%</td>
<td>44%</td>
<td>45.9%</td>
<td>53%</td>
<td>91.2%</td>
</tr>
<tr>
<td>20</td>
<td>Canny</td>
<td>1.3%</td>
<td>23.9%</td>
<td>39.2%</td>
<td>46.1%</td>
<td>101.5%</td>
<td>123.4%</td>
</tr>
<tr>
<td>23</td>
<td>Wavelet</td>
<td>28.1%</td>
<td>41%</td>
<td>41.3%</td>
<td>42%</td>
<td>47.6%</td>
<td>65.2%</td>
</tr>
<tr>
<td>25</td>
<td>CHEFNN</td>
<td>1.3%</td>
<td>3.1%</td>
<td>3.1%</td>
<td>4.9%</td>
<td>8.7%</td>
<td>16.1%</td>
</tr>
<tr>
<td>30</td>
<td>CHNN</td>
<td>3.19%</td>
<td>3.62%</td>
<td>3.66%</td>
<td>3.7%</td>
<td>3.89%</td>
<td>4.39%</td>
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Table II. The execution time for the CHEFNN, and the proposed CHNN methods using the simulated phantom image with noise level K=0 to 30.

<table>
<thead>
<tr>
<th>Nois</th>
<th>Method</th>
<th>0</th>
<th>18</th>
<th>20</th>
<th>23</th>
<th>25</th>
<th>30</th>
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</thead>
<tbody>
<tr>
<td>0</td>
<td>CHEFNN</td>
<td>26</td>
<td>26</td>
<td>26</td>
<td>26</td>
<td>31</td>
<td>38</td>
</tr>
<tr>
<td>18</td>
<td>CHNN</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>6</td>
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