Energy Based Medical Imaging Segmentation Methods by using Cellular Neural Networks

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Abstract: - The paper presents energy based medical imaging segmentation methods by using Cellular Neural Networks (CNN). By implementing the proposed algorithm on FPGA (Field Programmable Gate Array) with an emulated digital CNN-UM (CNN-Universal Machine), due to complete parallel processing, computing-time reduction is achieved and there is a possibility to meet the requirements for medical image segmentation.

Key-Words: - medical imaging; energy based segmentation; cellular neural networks.

1 Introduction

In many medical imaging applications image segmentation for defining anatomical structures and regions of interest can have a very important role. Information obtained in this way can be used both in the phase of establishing the diagnosis by locating pathology, and in planning and carrying out appropriate treatment, such as for example, biopsy, radiation therapy, and minimally invasive surgery.

To solve the problem of image segmentation various approaches have been developed. First, for grey scale images, one may classify the segmentation methods into edge-based methods and region-based techniques. Region-growing methods can be made less sensitive to noise than simple edge-based or morphological methods, but they may become extremely computationally complex for even simple rules. On the other hand, curve evolution, active surfaces, statistical approaches, and energy based methods have become popular approaches in this field. The majority of these methods prove remarkable performances when the processed image corresponds to the model of the algorithm but fails or gives significant artifacts otherwise [1].

Of particular importance is the evaluation of image segmentation methods in terms of their integration into semi-automatic or fully automatic medical diagnosis systems, which provides results in real time, which can be used in everyday medical practice. A relevant example for semiautomatic systems for aided diagnosis involving labeling occurs when the image is segmented into different regions and regions are subsequently labeled as healthy tissue or a tumor. For this purpose may be used, for example, Magnetic Resonance Imaging (MRI), Computer Tomography (CT) or Positron Emission Tomography (PET).

Unfortunately the performances of segmentation techniques are difficult to evaluate. Currently there isn't a specific general method of segmentation to produce acceptable results for all types of medical images. Each of these methods have their advantages and disadvantages, as some algorithms optimized for a particular hardware structure can no longer work as well on another structure. However, there is a major need for new mathematical techniques and possibilities of implementation that will lead to more efficient methods that can be integrated into the semiautomatic systems [2,3].

2 CNN Based Image Segmentation

The cellular neural network (CNN - Cellular Neural Network [4]) is an analog, nonlinear, dynamic, multi-dimensional circuit having locally recurrent topology.

A CNN is entirely characterized by a set of nonlinear differential equations associated with the cells in the circuit. The mathematical model for the state equation of the single cell C(i,j) is given by the following set of relations:

$$\begin{aligned}\dot{x} = \frac{dx_{ij}}{dt} &= -x_{ij} + \sum_{C_{kl}\in N_r} A_{ij,kl}y_{kl} + \sum_{C_{kl}\in N_r} B_{ij,kl}u_{kl} + z_{ij} + \\ &+ \sum_{C_{kl}\in N_r} C_{ij,kl}x_{kl} + \sum_{C_{kl}\in N_r} D_{ij,kl}(u_{kl}, x_{kl}, y_{kl})\end{aligned} \quad (1)$$

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where x_{ij} denotes the state of the cell C_{ij}; y_{kl}, u_{kl} denote the output and input respectively of cells C_{kl} located in the sphere of influence with radius r, N_r, from C_{ij} cell, $C_{kl} \in N_r$. The template (A(ij,kl) and, B(ij,kl) C(ij,kl) D(ij,kl) and z_{ij}) specifies the interaction between each cell and all its neighboring cells in terms of their input, state, and output variables. For example A(ij,kl) and, B(ij,kl) are the feedback and control templates respectively; z_{ij} is the bias term. The inter-cell interaction could be linear, nonlinear, or delay type.

Cellular Neural Networks (CNN) proved to be very useful regarding real-time image processing [4,5]. The reduction of computing time, due to parallel processing, can be obtained only if the algorithm can be implemented on a processor array [6,7,8,9]. In general, the CNN based implementation of medical imaging methods is not a purpose in itself. In this way computing time can be reduced because of full parallel processing. For noise extraction, image segmentation, contour determination, various mathematical models were examined and proposed on the possibility of implementation on hardware structures based on cellular neural networks. Unfortunately, comparison the efficiency of CNN implementations of these methods is practically impossible because some of the methods use a dedicated (designed) hardware structure optimized for the concrete application and are available in a limited way [9,10,11,12,13]. For comparison of methods, computing time results as an objective quantitative parameter, while the precision of the processing can be judged qualitatively only based on the opinion of radiologists.

For image segmentation the latest approach uses the active contours method, which is usually classified as either energy-based or level-set based, as well as their variants.

3 Energy Based CNN Segmentation Method

3.1 Energy based images processing

Over the last decade, energy based methods (variational methods) and partial differential equations [14,15] based techniques have been introduced for a variety of purposes including but not limited to image denoising, curve evolution, mathematical morphology, and image segmentation. Comparing with other approaches image processing based on variational computing or PDE have significant benefits both theoretically (precision, flexibility in modeling) and in terms of numerical implementation facility. The major limiting factor of the algorithms is the huge computing power requirements.

Consider a grey-scale image $\Phi(p,q)$, where Φ: $R^2 \to R$, and $\Omega=\{(p,q)$: $p\in[1,M]$, $q\in[1,N]$, M and N $\in R^+\}$, by using a variational formulation, an image processing problem can be obtained as the minimization of a cost function:

$$\arg\{\mathrm{Min}_{\Phi} E(\Phi)\} \qquad (2)$$

where E is a given energy function, and F the first order derivative of E. Through minimizing E, Φ results from condition: $F(\Phi)=0$, which is a steady state solution of the

$$\frac{\partial \Phi}{\partial t} = F(\Phi) \qquad (3)$$

Regardless of the chosen formulation for modeling image processing, some solutions allow us to make combinations of them, resulting in another complex processes. If, e.g., two distinct processing are described by energy functions E1 and E2, another complex image processing can be formulated minimizing the energy:

$$\alpha E_1 + \beta E_2 \qquad (4)$$

Weighting the terms E_1 and E_2, with scalar parameters α and β (α and $\beta \in R^+$), lets us balance the complex processing between the limits described by the initial results. It is desirable that the image processing method should be based on a smaller number of imposed parameters at the beginning of the algorithm and the elements deduced from the processed image content should be dominant.

3.2 Energy based image segmentation

Representing the starting point for many image segmentation methods based on variational calculations, a special importance in this field is the energy function introduced by Mumford and Shah [15,16]: (5)

$$E_{MS}(\Phi,\Gamma) = \alpha \iint_{R\setminus\Gamma} |\nabla\Phi|^2 \, dxdy + \beta \iint_R (\Phi - \Phi_0)^2 dxdy + |\mathbf{\Gamma}|$$

where R is a connected, bounded, open subset of $\mathbf{R}^2$, Φ_0 is the original image (the feature intensity), Γ is a curve segmenting R, Φ is the smoothed image $\subset \mathbf{R}^2 \setminus \Gamma$, $|\Gamma|$ is the length of Γ and α and β are the weights, scalar parameters, (α and $\beta \in R^+$). Minimizing this classical functional requires estimating two processes, the continuous segmented field, Φ, and a binary edge process, Γ.

Actually it can be shown that the deterministic edge detection based, region based, active contour based and stochastic methods are subsets of the more general problem of variational functional minimization [15].

Since it is difficult to apply gradient descent with respect to Γ, Ambrosio and Tortorelli [17] replace Γ by a continuous variable K and obtain:

$$E_{AT}(\Phi, \mathrm{K}) = \iint_R \Big\{ \alpha(1-\mathrm{K})^2 |\nabla\Phi|^2 + \beta(\Phi - \Phi_0)^2 + \\ + \frac{\rho}{2}|\nabla \mathrm{K}|^2 + \frac{\mathrm{K}^2}{2\rho} \Big\} dxdy \qquad (6)$$

Solving for the minimum of equation (6) simultaneously produces a segmented image estimate $\tilde{\Phi}$ and edge process estimate $\tilde{\mathrm{K}}$. Minimizing the segmentation energy functional in equation (6) has been used by a number of researchers for image segmentation even if the results obtained have proved to be more modest in relation to subsequent methods based on other mathematical models.

It is very important to note that the minimization of (6) is equivalent to the joint minimization of the following pair of subfunctionals, which is the main advantage of this method.

Keeping K fixed, the first equation minimizes:

$$E_{\mathrm{K}}(\Phi) = \iint_R \Big\{ \alpha(1-\mathrm{K})^2 |\nabla\Phi|^2 + \beta(\Phi - \Phi_0)^2 \Big\} dxdy \qquad (7)$$

Keeping Φ fixed, the second equation minimizes:

$$E_{\Phi}(\mathrm{K}) = \iint_R \left\{ |\nabla \mathrm{K}|^2 + \frac{1+\Psi}{2\rho^2}\left(\mathrm{K} - \frac{\Psi}{1+\Psi}\right)^2 \right\} dxdy \qquad (8)$$

where $\Psi(\Phi) = 2\alpha\rho|\nabla\Phi|^2$ and ρ is another weight, scalar parameter ($\rho \in \mathrm{R}^+$).

The corresponding gradient descent equations are [17]:

$$\frac{\partial \Phi}{\partial t} = -2\nabla \mathrm{K} \cdot \nabla\Phi + (1-\mathrm{K})\nabla^2\Phi - \frac{\beta}{\alpha(1-\mathrm{K})}(\Phi - \mathrm{K}) \qquad (9)$$

$$\frac{\partial \mathrm{K}}{\partial t} = \nabla^2 \mathrm{K} - \frac{\mathrm{K}}{\rho^2} + \frac{2\alpha}{\rho}(1-\mathrm{K})|\nabla\Phi|^2 \qquad (10)$$

$$\frac{\partial \Phi}{\partial n}\Big|\partial R = 0; \quad \frac{\partial \mathrm{K}}{\partial n}\Big|\partial R = 0; \qquad (11)$$

where ∂R denotes the boundary of R and n denotes the direction normal to ∂R.

In order to implement the image segmentation on CNN structures, representation (7-8) emphasize the following:

- Solving for the minimum of equations simultaneously produces a segmented image estimate $\tilde{\Phi}$ and edge process estimate $\tilde{\mathrm{K}}$.
- In the case of CNN processing a multi-layered structure is necessary. The two main layers are necessary to obtain $\tilde{\Phi}$ and $\tilde{\mathrm{K}}$. The other layers are needed to calculate some components of the main layers.
- Each energy function contains weighted smoothing terms ($|\nabla\Phi|^2$ from (7) or $|\nabla \mathrm{K}|^2$ from (8)) and weighted fidelity terms, or terms for edge conservation, ($(\Phi - \Phi_0)^2$ from (7) respectively edge calculation $\left(\mathrm{K} - \frac{\Psi}{1+\Psi}\right)^2$ from (8)).
- Solving this system of partial differential equations includes an number of operations that can be effectively solved by parallel processing structures, including CNN methods.
- Inclusion in these equations of a significant number of scalar parameters dependent on image content that need to be specified a priory, makes the task of optimizing the solutions obtained very difficult.
- Even in the case of strict implementation of this model by numerical methods, resultant accuracy is modest. This is mainly a consequence of smoothing imperfections with a function of the form $|\nabla(\cdot)|^2$.
- In addition, by implementing the image processing CNN on 8-bit digital structures, solving these equations introduces approximations and additional errors.

Based on the above, as compromise solution, currently is justified the evaluation of some algorithms that eliminate the interaction between the two main layers, so basically the two partial differential equation can be solved successively.

3.3 Energy based CNN segmentation

Even if variational computing (energy based) methods are used, the determination of templates ensuring the desired processing of the grey-scale image remains a difficult problem. For energy based template design, using the standard CNN types for gray-scale image processing, all design constrains mentioned in [19] are respected.

For variational computing based CNN image segmentation, in the following it will be examined the behavior of energy functions to determine the two images, the filtered image Φ and the edged image K. The estimate segmented image, $\tilde{\Phi}$, will result from the fusion of these two images.

To determine the noise filtered Φ image, the following energy functions will be used:

- using the energy function proposed by Rudin, Osher and Fatemi [18]:

$$E_{RUOSFA} = \iint_R \Big\{ \alpha|\nabla\Phi_0| + \beta(\Phi - \Phi_0)^2 \Big\} dxdy \qquad (12)$$

the following CNN template results: (13)

A =

0	a	0
a	1	a
0	a	0

D =

0	0	0
0	d	0
0	0	0

osrufa.tem

where $a = \alpha \cdot \mathrm{sgn}\left(x_{ij} - x_{kl}\right)\ \alpha \in [0, 1]$

$d = 2\beta\left(x_{ij} - u_{kl}\right);\ 2\beta \in [0, 1]$, with (B=0, z=0).

- using the energy function proposed by Chan and Esedoglu [19]:

$$E_{CHES} = \iint_R \left\{\alpha\left|\nabla\Phi_0\right| + \beta\left|\Phi - \Phi_0\right|\right\} dxdy \qquad (14)$$

the following CNN template results: (15)

A =

0	a	0
a	1	a
0	a	0

D =

0	0	0
0	d	0
0	0	0

ches.tem

where $a = \alpha \cdot \mathrm{sgn}\left(x_{ij} - x_{kl}\right)\ \alpha \in [0, 1]$

$d = \beta \mathrm{sgn}\left(x_{ij} - u_{kl}\right);\ \beta \in [0, 1]$, with (B=0, z=0).

This function of energy (*CHES*), is proposed to improve edge conservation behavior of CNN image filtering [20]. As it can be observed, actually these energy functions represent a simplified variant of energy function (7).

To determine image edges would justify an energy function dependent on $\left|\nabla\Phi\right|^2$:

$$E(\mathrm{K}) = \iint_R \rho\left|\nabla\Phi\right|^2 dxdy \qquad (16)$$

It results the nonlinear control template:

B =

0	b	0
b	0	b
0	b	0

grad.tem

(17)

where: $b = \rho\left(u_{ij} - u_{kl}\right);\ \rho \in [0, 1]$, with (A=0, z=0).

We examined the behavior of the template regarding the production of false contours and we compared the results with those obtained through template avergrad.tem [21]. It was noted that the latter has higher efficiency, because it includes a average process. Therefore, in the segmentation methods analyzed in this paper avegrad.tem template was used for edge detection.

B =

b	b	b
b	0	b
b	b	b

avegrad.tem

(18)

where $b = \rho\left(u_{ij} - u_{kl}\right);\ \rho \in [0, 1]$, with (A=0, z=0).

4 Testing Energy Based CNN Segmentation Methods

In this section the simulated experimental results obtained by using the "CadetWin" (CNN Application Development Environment and Toolkit under Windows [20]) and the Matlab Tools and Development Environment are presented.

To test how the proposed algorithms work to obtain CNN segmentation, synthetic images without noise were used and also images which were artificially added Gaussian white noise, with zero mean and different variance, Fig.1. The obtained results are shown in Fig.2.

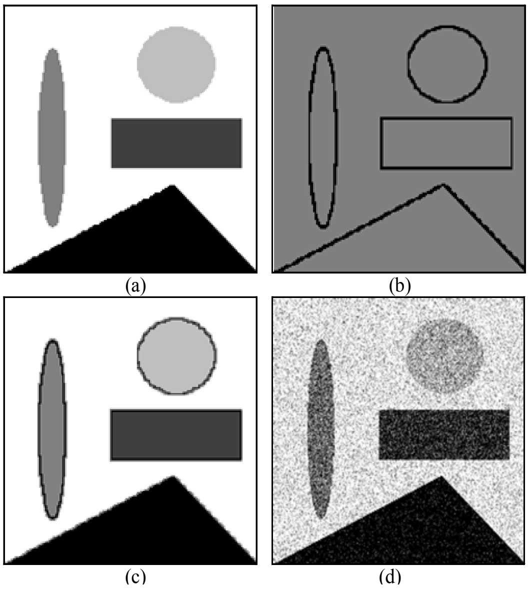

Fig.1. Energy based CNN segmentation: a) ideal image without noise; b) output image after edge detection; c) result of segmentation of the noiseless image; d) input image with Gaussian white noise, zero mean and 0.04 variance.

In Fig. 3 an example of real CT images obtained after segmenting is presented. Radiologist experts were involved in visual evaluation of results.

5 Conclusion

In this paper, the authors propose methods for images segmentation, in particular segmentation of CT images using CNNs.

Evaluation of traditional methods of segmentation in medical imaging applications reveal some of their advantages and disadvantages, but also many difficulties regarding their way of implementation on different hardware structures. Segmentation methods have to ensure reproducibility, programmability, robustness, sensitivity and high selectivity, but at the same time high immunity to noise and reduced processing time.

A special importance is the evaluation of the methods in regard to their integration into semiautomatic or automatic medical diagnosis systems, which provide results in real time. To provide the conditions required in medical imaging the proposed CNN method for image segmentation have nonlinear templates, therefore an emulated digital CNN-UM implemented on an FPGA is necessary [6], which enables integration of the method into an assisted diagnostic system.

Due to the diversity and difficulty of currently existing problems, both theoretically and concerning the mode of implementation, segmentation remains a topical issue in general and particularly in image processing for medical imaging.

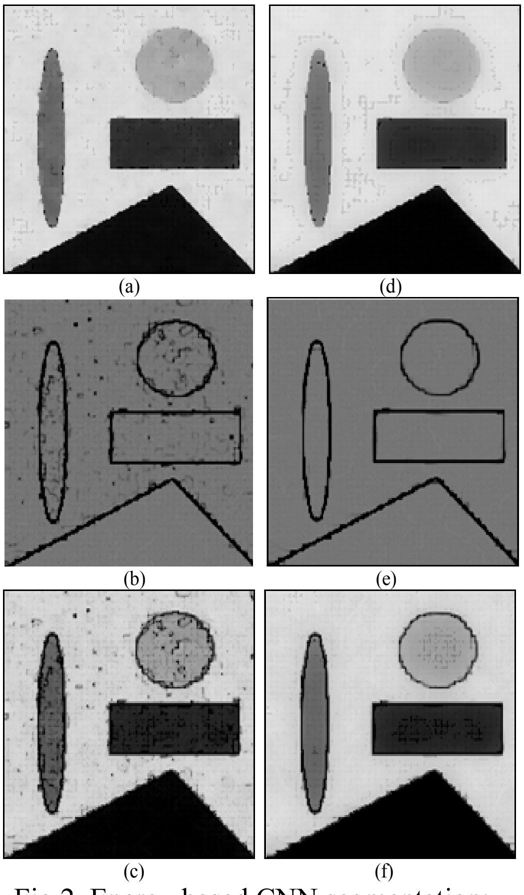

Fig.2. Energy based CNN segmentation: a) filtered output image, Φ, by using osrufa.tem; b) output image, K, after edge detection, by using avegrad.tem; c) result of image segmentation on the noisy image by using osrufa.tem; d) filtered output image, Φ, by using ches.tem.tem; e) output image, K, after edge detection by using avegrad.tem; f) result of image segmentation on the noisy image by using ches.tem.

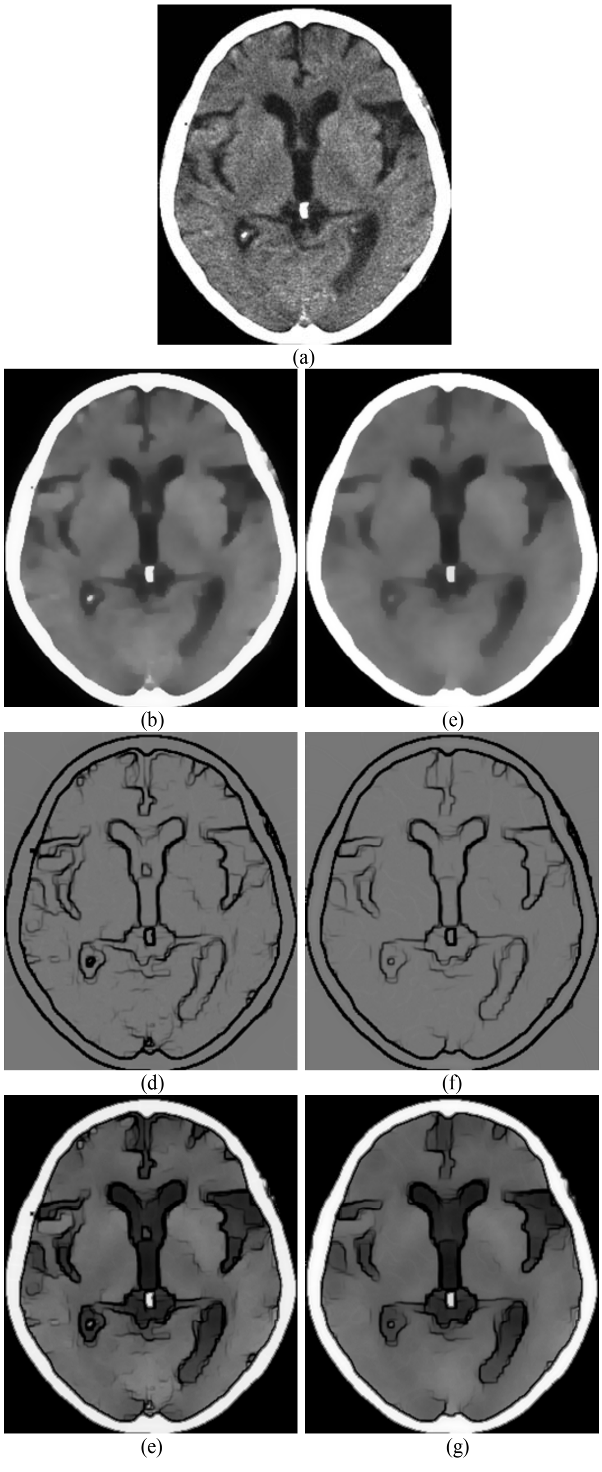

Fig.3. Energy based CNN segmentation of real CT image: a) input image with noise; b) filtered output image, Φ, by using osrufa.tem; c) output image, K, after edge detection, by using avegrad.tem; d) segmented output image using osrufa.tem; e) filtered output image, Φ, by using ches.tem.tem; f) output image, K, after edge detection by using avegrad.tem; g) segmented output image using ches.tem.

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