ISTANBUL UNIVERSITY –
JOURNAL OF ELECTRICAL & ELECTRONICS ENGINEERING

YEAR : 2004 (1227-1231)
VOLUME : 4
NUMBER : 2

BIOMEDICAL IMAGE PROCESSING USING COMBINED MRF-CNN METHOD

Niyazi KILIC[1] **Osman Nuri UCAN[2]**

[1,2] Istanbul University, Engineering Faculty,
Electrical & Electronics Engineering Department
Avcilar 34850, Istanbul, TURKEY

[1]E-mail: niyazik @istanbul.edu.tr [2]E-mail: uosman@istanbul.edu.tr

ABSTRACT

In this paper, to improve image performance of biomedical data, Markov Random Field (MRF) and Cellular Neural Network (CNN) structures are combined and a new approach, Markov Random Field-Cellular Neural Networks (MRF-CNN) is introduced. MRF-CNN structure can be applied to biomedical data for various image processing problems such as noise filtering, edge detecting, blank filing etc., with noise variance up to 9 dB and better results are obtained according to MRF and CNN schemes. In training of MRF-CNN, Recursive Perceptron Learning Algorithms (RPLA) is studied.

Keywords: *Image segmentation, Markov random field, Gibbs random field, Cellular Neural Networks*

1. INTRODUCTION

Markov Random Field (MRF) models have been successfully applied to many fundamental issues of image analysis and computer vision such as image restoration, edge detection, image segmentation, computed tomography, surface reconstruction, and motion analysis or scene interpretation. The mathematical framework of MRF is a statistical models and Bayesian estimation theory is used to extract the relevant information from the observed images. By defining comprehensive global statistical models, MRF theory leads to significant improvement over local methods. Recently the MRF has been successfully in corporate into various image algorithms by converting the image processing into Bayesian estimation with some appropriate constraints [1].

Cellular Neural Network (CNN) is a large-scale non-linear analog circuits which processes signals in real time. CNN is an analog parallel computing paradigm defined in space and characterized by locality of connections between processing elements (cells or neurons) [2]. Like cellular automata, it is made of massive aggregate of regularly spaced circuits clones, called cells, which communicate with each other directly only through its nearest neighbors. The

Received Date : 22.08.2002
Accepted Date: 15.06.2004

adjacent cells can interact directly with each other. Cells not directly connected together may affect each other indirectly because of the propagation effects of the continous-time dynamics of cellular neural networks [3].

In this paper, to enhance 2-Dimensional images, we have combined MRF and CNN schemes and introduced Markov Random Field-Cellular Neural Network (MRF-CNN). We have compared MRF-CNN performance of image enhancement with MRF and CNN. We have found satisfactory results.

In Section II we have presented MRF-CNN model. In Section III, we have discussed enhancement performance of our scheme with MRF and CNN.

2. MRF-CNN MODEL

2.1. MARKOV RANDOM FIELD MODEL

We are able to formulate the image segmentation as a Bayesian estimation problem. It was shown in refs. [4-6] that image can be modeled as a Gibbs random field and image segmentation can be acomplished through a maximum a posteriori (MAP) probability estimation process. If we denote a given image by y and a segmentation of this this image by x, then a Bayesian formulation of the image segmentation can be obtained by relating the a posteriori probability densty function P(x/y) with the conditional probability density function P(y/x) a priori probability density function P(x). According to Bayesian theorem those probability density function are related as;

$$P(x/y)=P(y/x).P(x) \quad (1)$$

It is clear from the defination of the conditional probability density function that P(y/x) represent the image data given the orginal well-defined regions. This probability density function is closely related to an imaging process whose parameters can be estimated from the given image. The a priori probability density function P(x) is also related to the given image and represent the relationship between region as well as pixels within each region.

The conditnional density is modeled as a with gaussian process, with mean $\mu_s{}^i$ and variance σ^2. Each region i is characterized by a different $\mu_s{}^i$ which is a slowly varying function of s. This the intensity of each region is modeled as a signal $\mu_s{}^i$ plus white Gaussian noise whith varience σ^2.

The combined probability density has the form

$$P(x/y)=l_j=-\sum_{c\in C}V_c(x)-\left(\frac{1}{2\sigma^2}\sum_{m=1}^{M}\sum_{i=1}^{N_1}(y_s-q_m{}')^2\right) \quad (2)$$

We observe that the probability density fonction has two components . One contraints the region intensity to be close the data. The other imposes spatial continuity. If we assume the noise variance σ^2 are known, the we must estimate both the distribution of regions x and the quantisation level q_m'. This will be done using histogram technique.

2.2 ESTIMATING OF PAREMATER OF A GIBBS DISTRIBUTION

Our objective is to estimate the parameters of a Gibbs distribution a realization from this distribution. Using similar optimization approach of Derin and Elliot (1987) [5], we present the formulation in terms of a second order neighborhood system η^2, although its extension to any order is possible. Consider a site *(i,j)* and its neighborhood η_{ij} at residual map of *X*. Let $q_m{}'$ is the transient quantization level of biomedical image during optimization at (i,j) pixel and t' represent the vector of neighboring values of $q_m{}'$ at (i,j).

$$t'=\left[u_1,u_2,u_3,u_4,v_1,v_2,v_3v_4\right] \quad (3)$$

where the location of u_i's and $v_i{}'s$ with respect to $q_m{}'$.

We define indicator functions,

$$I(z_1,z_2,...,z_k)=\begin{cases}-1 & , \quad z_1\approx z_2\\ 1 & , \quad \text{otherwise}\end{cases} \quad (4)$$

is the approximation defined as,

$$z_k\approx z_{k+1}\equiv\left|z_k-z_{k+1}\right|\le\varepsilon \quad (5)$$

where ε is a small value given regarding to optimization tolerance.

Another indicator $J_m(q_m^{'})$ is defined as,

$$J_m(q_m^{'}) = \begin{cases} -1. & , \quad q_m^{'} \approx q_m \\ 1 & , \quad \text{otherwise} \end{cases} \quad (6)$$

Using these indicators we can express the potential function Eq. (4) of all cliques that contain (i, j), the site of $q_m^{'}$. That is

$$V(q_m^{'}, t', \theta) \equiv \sum_{c:q_m^{'} \in C} V_C(x) \quad (7)$$

where θ is the parameter vector. Thus both Eq. (3) and Eq. (4) are defined as a function of $q_m^{'}$, resulting common optimization which improves the MRF performance greatly. θ is defined as (Ucan et. al, 2000a) [7],

$$\theta = [\alpha_1, \alpha_2, .. \alpha_M, \beta_1, \beta_2, \beta_3, \beta_4, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \xi_1]^T \quad (8)$$

The clique potentials associated with η^2 are defined as,

$$V(q_m^{'}, t', \theta) \equiv \phi^T(q_m^{'}, t')\theta. \quad (9)$$

where,

$$\begin{aligned} &\phi(q_m^{'}, t') = [J_1(q_m^{'}), J_2(q_m^{'}), \ldots J_M(q_m^{'}), (I(q_m^{'}, u_1) + I(q_m^{'}, u_3)), \\ &(I(q_m^{'}, u_2) + I(q_m^{'}, u_4))(I(q_m^{'}, v_2) + I(q_m^{'}, v_4))(I(q_m^{'}, v_1) + I(q_m^{'}, v_3)), \\ &(I(q_m^{'}, u_2, v_2) + I(q_m^{'}, u_4, u_3) + I(q_m^{'}, u_1 v_4)), \\ &(I(q_m^{'}, u_4, v_3) + I(q_m^{'}, u_2, u_3) + I(q_m^{'}, u_1, v_1)), \\ &(I(q_m^{'}, u_2, v_1) + I(q_m^{'}, u_1, u_4) + I(q_m^{'}, u_3, v_3)), \\ &(I(q_m^{'}, u_1, u_2) + I(q_m^{'}, u_4, v_4) + I(q_m^{'}, u_3, v_2)), \\ &(I(q_m^{'}, u_1, v_1, u_2) + I(q_m^{'}, u_2, v_2, u_3) + I(q_m^{'}, u_3, v_3, u_4) + I(q_m^{'}, u_4, v_4, u_1))]^T \end{aligned} \quad (10)$$

Suppose $P(q_m^{'}, t')$ is the joint distribution of random variables on $3x3$ block centered at (i, j) and $P(t^{'})$ is the joint distributions on η_{ij} only. Then the conditional probability, using Bayes rule can be written as,

$$\frac{P(q_m^{'}, t')}{P(t')} = P(q_m^{'} | t') = \frac{e^{-V(q_m^{'}, t', \theta)}}{W(t', \theta)} \quad (11)$$

where

$$W(t', \theta) \equiv \sum_{s \in Q} e^{-V(q_m^{'}, t', \theta)} \quad (12)$$

Rearranging

$$\frac{e^{-V(q_m^{'}, t, \theta)}}{P(q_m^{'}, t')} = \frac{W(t', \theta)}{P(t')} \quad (13)$$

is obtained. Considering only left hand side of Eq. (16), for two distinct values of $q_m^{'} = j, q_m^{'} = k$ values we have,

$$e^{-V(j, t', \theta) + V(k, t', \theta)} = \frac{P(j, t')}{P(k, t')} \quad (14)$$

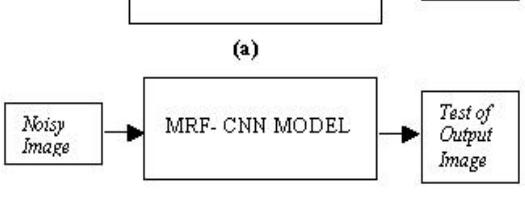
Taking the natural logarithm of (17) and replacing (12), we obtain,

$$(\phi(k, t') - \phi(j, t'))^T \theta = \ln\left(\frac{P(j, t')}{P(k, t')}\right) \quad (15)$$

2.3. COMBINED MRF-CNN STRUCTURE

This section we presents a novel combined structure. In this proposed model, by cascade connecting MRF and CNN, we developed new structure. The main target of this new model is to remove disadvantage of MRF and CNN. For example MRF model cannot make the process of fullfill blank very well and CNN model cannot filtering high noise from image. Howover, with this proposed structure, both it can filtering high noise from image and gets nearly orginal image.

Combined MRF-CNN structure can be shown fig.1,



(a)

(b)

Figure 1. MRF-CNN Scheme

The CNN is a dynamical system

In our model shown above, input of CNN (U_{kl}) is output of MRF (l_j).
Then,

$$U_{kl}=l_j=-\sum_{c\in C}V_c(x)-\left(\frac{1}{2\sigma^2}\sum_{m=1}^{M}\sum_{i=1}^{N_l}(y_s-q_m')^2\right), \quad (18)$$

And

$$X_{i,j}(n+1)=\sum_{(k,l)\in EN_r(i,j)}A_{i,j;k,l}.y_{k,l}(n)+\sum_{(k,l)\in EN_r(i,j)}B_{i,j;k,l}.l_i+I_{i,j} \quad (19)$$

is obtained.

In combined MRF-CNN model; the output of MRF which has obtained before, is used for the input of CNN. Weights (w) are calculated by training the input data using the RPLA algorithm. This weights are calculated, are used in test algorithm and results are obtained for the other data.

3. ENHANCEMENT PERFORMANCE of MRF-CNN MODEL

The proposed MRF-CNN model is applied to synthetic biomedical images which has gray-scale range is 0 to 255.

First image is enamel image which has a resolution of 279×392 pixels and it has been added white gauss noise (μ=0 (mean) , σ=9 (variance)). Parameter vector is calculated as θ=[0 0 0 0 0 0 0 0 0.1075 0.02855 0.06855 0.1284 0 0 0 0 0].

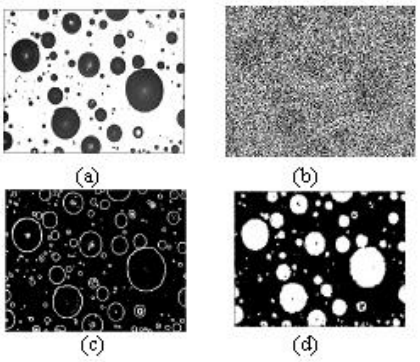


Figure 2. a) Orginal image, b) Noisy image (σ=9) , c) Segmented image with MRF
d) Segmented image with MRF-CNN

Second image is mre image which has a resolution of 128×128 pixels and it has been added white gauss noise (μ=0 (mean) , σ=4 (variance)). Parameter vectors is calculated as θ=[0 0 0 0 0 0 0 0 –0.0188 0.1354 0.0543 0.2139 0 0 0 0 0].

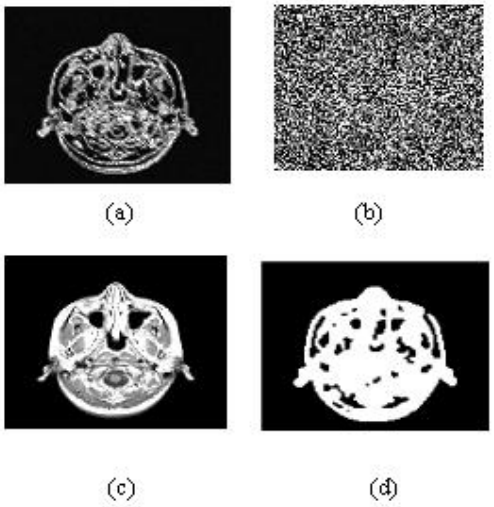


Figure 3. a) Orginal image, b) Noisy image (σ=4) , c) Segmented image with MRF
d) Segmented image with MRF-CNN

CONCLUSIONS

In this paper, we mentioned a new technique, combined MRF-CNN model. Its simulation results are shown figure 2 and figure 3. As seen figures, results of MRF-CNN model beter than only MRF results. With this proposed technique, both it can filtering high noise from image and gets nearly orginal image.

REFERENCES

[1] T. N. Pappas, “An Adaptive Clustring Algorithm for image segmentation” IEEE Trans. Sig. , vol.40, no.4, Apr.1992

[2] L.O. Chua, L.Yang, “Cellular Neural Networks Theory”, IEEE Transactions on Circuits and System, vol.35, no.10, pp.1257-1272, oct.1998

[3] C. W. Chen and L. Chen , “Cellular Neural Network architecture for Gibbs random field-

based image segmentation" Journal of Electronic Imaging , vol.7, no.1, pp.45-51, jan.1998.

[4] S. Geman and D. Geman, "Stochastic relaxation, gibbs Distrubution and the Bayesian Restoration of images" IEEE Trans. Pattern. Anal., vol.PAMI-6, no.6,pp.721-741, nov.1984

[5]] H. Derin and H. Elliot, " Modeling and segmentation of noisy of textured images using Gibbs random field" IEEE Trans. Patt. Anal. ,vol. PAMI-9, no.1, pp.39-55 , jan.1987.

[6] S. Lakshmannan and H. Derin, "Simultaneous parameter estimation and segmentation of Gibbs random fields using simulated annealing" IEEE Trans. Patt. Anal. , vol.11, no.8, pp. 799-813, Aug.1989.

[7] O.N. Uçan, B. Şen, A.M. Albora, A. Özmen, "A New Gravity Anomaly Separation Approach: Differential Markov Random Field (DMRF)", Electro-Geophysics, 2000

Niyazi KILIÇ was born in Bolu, Turkey in 1978. He recieved his B.S. degree in Electrical-Electronics in 1999, and M.S. degree in Biomedical Engineering in 2003 from the Electrical and Electronics Engineering Department of Istanbul University. Since 2000 he has been working as a research assistant in Istanbul University Engineering Faculty, Department of Electrical and Electronics Engineering where he continous to work on his Ph.D. dissertation. His current research interest is medical image processing.