FAST IMAGE SEGMENTATION USING C-MEANS BASED FUZZY HOPFIELD NEURAL NETWORK

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ABSTRACT

In this paper, we propose a fast C-means based training of Fuzzy Hopfield neural network and apply it to image segmentation. According to the other ways which usually take a long time, we define a fast method for image segmentation. We present a new objective function, and its minimization by Lyapunov energy function which is based on two dimensional fuzzy Hopfield neural network. This objective function is the same energy function Hopfield neural network which is improved, and includes average distance between image pixels and cluster centers. In this new method, numbers of iterations are less than the other methods it means the proposed method has a faster convergence rate in comparison with the other ways. Therefore, Fuzzy Hopfield neural network method provides image segmentation better than the other methods according to experimental results.

Index Terms— segmentation, fuzzy, neural network, Hopfield neural network

1. INTRODUCTION

Image segmentation, a process to divide a given image into meaningful regions with homogeneous properties, is an important step in image analysis and recognition .A large number of algorithms have been proposed in previous years. Those conventional image segmentation algorithms can be categorized generally into three classes:1) histogram-based schemes, where the pixels are segmented into classes based on overall gray levels; 2) clustering by which homogeneous properties around a given pixel are enlarged; and 3) edge-based schemes, which detect the pixels with abrupt changes in gray levels, and then connects selected pixels to form completely enclosed boundaries [1].

Clustering is useful in several exploratory pattern analysis, grouping, and machine-learning situations, decision-making, data mining, document retrieval, image segmentation, and pattern classification. In image segmentation techniques, image is segmented to different regions separated with contours.Region growing, k-means, and split and merge methods are used generally for image segmentation. Besides these crisp classical segmentation methods, the fuzzy logic methods were also seen very effective for segmentation [2,3,4]. In 1982, Hopfield proposed the so-called Hopfield network, which possesses auto-associative properties. It is a recurrent (fully interconnected) network in which all neurons are connected to each other , with the exception that no neuron has any connection to itself [5].The Hopfield neural network is a well-known technique used for solving optimization problems based on Lyapunov energy function. Amatur, Piriano and Takefuji used the two dimensional Hopfield neural network for segmentation of multi-spectral MR images [13].Robust segmentation of medical images using competitive Hopfield neural network as a clustering tool was proposed by Roozbahani, Ghassemian and Sharafat [15].Combination of Fuzzy and Hopfield is a good technique for some problems. For example, Lin, Cheng and Mao proposed the segmentation of single and multi-spectral medical images using a fuzzy Hopfield neural network [6, 8].Fuzzy Hopfield neural network with fixed weight for medical image segmentation was proposed by Chang and Ching [1].

In this paper, we propose a new method for image segmentation using a fuzzy Hopfield neural network. We prove that the proposed method has a faster convergent speed in comparison with the other ways. In other words, number of iteration of new method is less than other methods. So it takes a few time to reach the result. Then, FHNN method provides image segmentation better than other methods according to experimental results. This new idea includes new object function, and its minimization by Lyapunov energy function. In summary, after applying new method from the simulation and the experiment results, the proposed algorithm could perform satisfactority.

2. CLUSTERING ALGORITHMS

Clustering analysis is based on partitioning a collection of data points into a number of subgroups, where the objects inside a cluster (a subgroup) show a certain degree of closeness or similarity. It has been playing an important role in solving many problems in pattern recognition and image processing. Clustering methods can be considered as either hard (crisp) or fuzzy depending on whether a pattern data belongs exclusively to a single cluster or to several clusters

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with different degrees. In hard clustering, a membership value of zero or one is assigned to each pattern data (feature vector), whereas in fuzzy clustering, a value between zero and one is assigned to each pattern by a membership function. In general, fuzzy clustering methods can be considered to be superior to that of its hard counterparts since they can represent the relationship between the input pattern data and clusters more naturally [9].

Fuzzy partition

Fuzzy partition can be seen as a generalization of hard partition, it allows to attain real values in [0,1].A N × c matrix $U=[\mu_{ik}]$ represents the fuzzy partitions, its conditions are given by [10]:

$$\mu_{ij} \in [0,1], 1 \le i \le N, 1 \le k \le c,$$
$$\sum_{k=1}^{c} \mu_{ik} = 1, 1 \le i \le N, \qquad (1)$$
$$0 < \sum_{i=1}^{N} \mu_{ik} < N, 1 \le k \le c.$$

2.1. Fuzzy C-means algorithm

The Fuzzy C-means clustering algorithm is based on the minimization of an objective function called *C-means functional* .It is defined by Dunn as:

$$J(X,U,V) = \sum_{i=1}^{c}\sum_{k=1}^{N} (\mu_{ik})^m \left\| x_k - v_i \right\|_A^2 \qquad (2)$$

Where $V=[v_1, v_2, ..., v_c], v_i \in R^n$ is a vector of *cluster prototypes* (centers).For more information, refer to [10].

4. PROPOSED METHOD: FUZZY HOPFIELD NEURAL NETWORK

At this part, the new image segmentation method based on fuzzy Hopfield neural network is introduced. In this paper the fuzzy Hopfield neural network use the fuzzy c-means algorithm to eliminate the need for finding weighting factors in the energy function. The number of neurons is dependent on image size; the larger the image size, the more neurons that are required. These neurons are fully interconnected. The total input of neuron (i,k) denoted as $Net_{i,k}$ can be formulated as [8] .

$$Net_{i,k} = \sum_{q=1}^{N}\sum_{j=1}^{c} W_{i,k;j,q} V_{j,q} + I_{i,k} \qquad (3)$$

Where N is the number of data points, c is number of clusters, $V_{j,q}$ denotes the binary state of neuron (j,q), $W_{i,k;j,q}$ is interconnection weight between neuron (i,k) and neuron (j,q), $I_{i,k}$ is external bias vector for neuron (i,k). The Hopfield neural network consists of *N* x *c* neurons that can be conceived as a 2-D array for the image-segmentation problem. Lyapunov energy function of two dimensional Hopfield neural network is also given [8] as

$$E = -\frac{1}{2}\sum_{k=1}^{N}\sum_{q=1}^{N}\sum_{i=1}^{c}\sum_{j=1}^{c} V_{i,k} W_{i,k;j,q} V_{j,q} - \sum_{k=1}^{N}\sum_{i=1}^{c} I_{i,k} V_{i,k} \qquad (4)$$

The neural network reaches a stable state, when the Lyapunov energy function is minimized. The optimization problem can be mapped into a two dimensional fully interconnected Hopfield neural network with the fuzzy c-means algorithm. The total input for neuron (i,k) can be modified [8] as

$$Net_{i,k} = \left[x_k - \sum_{q=1}^{N} W_{i,k;i,q} \mu_{i,q}^m \right]^2 + I_{i,k} \qquad (5)$$

and Lyapunov energy can be changed [8] as

$$E = \frac{1}{2}\sum_{k=1}^{N}\sum_{i=1}^{c} \mu_{i,k}^m \left[x_k - \sum_{q=1}^{N} W_{i,k;i,q} \mu_{i,q}^m \right]^2 - \sum_{k=1}^{N}\sum_{i=1}^{c} I_{i,k} \mu_{i,k}^m \qquad (6)$$

m is the fuzzification parameter , $\sum_{q=1}^{N} W_{i,k;i,q} \mu_{i,q}^m$ is the total weighed input received from the neuron (i,q), x_k is x. pixel value of image , and membership value $\mu_{i,k}$ is the output state at neuron (i,k). A neuron (i,k) in a maximum membership state indicates that x_k pixel belongs to class i. Each column of this Hopfield neural network represents cluster centroids, and each row represents an image pixel in a proper class. In order to generate an adequate classification with the constraints, we define Lyapunov energy function as follows [8]:

$$E = \frac{A}{2}\sum_{k=1}^{N}\sum_{i=1}^{c} \mu_{i,k}^m \left[x_k - \sum_{q=1}^{N} \frac{1}{\sum_{h=1}^{N} \mu_{i,h}^m} x_q \mu_{i,q}^m \right]^2 + \frac{B}{2}\left[\left(\sum_{k=1}^{N}\sum_{i=1}^{c} \mu_{i,k} \right) - N \right]^2 \qquad (7)$$

E is the total intra-class scatter energy that accounts for the scattered energies distributed by all pixels in same class.

The first term in (7) is the within-class scatter energy, which is the Euclidean distance between samples to the cluster center over c clusters. The second term, guarantees those number of data point N in image can only be distributed among these c classes. More specifically, first term minimizes the intra-class Euclidean distance from a sample to the cluster center in any given cluster and the second term, imposes constraints on the objective function [8].

The quality of classification result is very sensitive to the weighting factors. Searching for optimal values for these weighting factors is expected to be time-consuming and laborious. To alleviate this problem, a Hopfield neural network with a fuzzy c-means clustering method, called FHNN, is proposed. Because each image pixel can only be occupied by one class, every row can have at most 1. In other words, the summation of states in the same row equals 1. This also ensures that only N data points will be classified into these c clusters [14]. That is, the network must match the following constraints

$$\sum_{i=1}^{c} \mu_{i,k} = 1 \qquad (8)$$

$$\sum_{k=1}^{N}\sum_{i=1}^{c} \mu_{i,k} = N$$

Therefore, the energy function can be further simplified as

$$E = \frac{1}{2}\sum_{k=1}^{N}\sum_{i=1}^{c}\mu_{i,k}^{m}\left[x_k - \sum_{q=1}^{N}\frac{1}{\sum_{h=1}^{N}\mu_{i,h}^{m}} x_q \mu_{i,q}^{m}\right]^2 \qquad (9)$$

The normalization operation guarantees that each image pixel will be absorbed on several classes with certain probability degrees so there will be N data points assigned among c clusters. The minimization of energy E is greatly simplified because it contains only one term and hence the requirement of having to determine the weighting factors A , and B vanishes.

Comparing Eq. (9) with the modified energy function Eq. (6) , the synaptic interconnection weights and the bias input can be obtained as

$$W_{i,k;i,q} = \frac{x_q}{\sum_{h=1}^{N}\mu_{i,h}^{m}} \qquad (10)$$

$$I_{i,k} = 0$$

By introducing equations (10) into (5), the input to neuron (i,k) can be expressed as

$$Net_{i,k} = \left[x_k - \sum_{q=1}^{N}\frac{1}{\sum_{h=1}^{N}\mu_{i,h}^{m}} x_q \mu_{i,q}^{m}\right]^2 = [x_k - v_i]^2 = D_{i,k}^2 \qquad (11)$$

The membership function for k-th pixel is given as

$$\mu_{i,k} = \left[\sum_{j=1}^{c}\left(\frac{Net_{i,k}}{Net_{j,k}}\right)^{2/m-1}\right]^{-1} \qquad (12)$$

This membership function is effective to minimize new objective function in iteration. New objective function consists of average distance between image pixels and cluster centroids for separate and compact clustering. New objective function is given as

$$J = \frac{1}{N}\sum_{k=1}^{N}\sum_{i=1}^{c}\mu_{i,k}^{m} D_{i,k}^{2} \qquad (13)$$

FHNN Algorithm

1) Given the data set X, choose the number of clusters $1 < c < N$, the weighting exponent $m > 1$(Membership functions for large value *m* are fuzzier than those for small value *m,* but the interconnection weights are updated slowly.**) , the termination tolerance $\varepsilon > 0$ (**is used as a criterion to determine the performance of the objective function. The larger the threshold value *ε,* the less the number of iterations will , however, be the optimal membership function can not be found.**) and the norm-inducing matrix A.**

2) Normalization, (gray levels of image)

3) Calculate of primary centroids v0.

4) Compute the distances

$$D_{ikA}^2 = (\mathbf{x}_k - \mathbf{v}_i)^T A(\mathbf{x}_k - \mathbf{v}_i), \quad 1 \le i \le c, \quad 1 \le k \le N.$$

5) Compute the initial membership value

$$U^{(0)} = \mu_{i,k}^{(0)} = \frac{1}{\sum_{j=1}^{c}\left(D_{ikA}/D_{jkA}\right)^{2/(m-1)}}$$

6) Compute new cluster centroid

$$v_i = \sum_{q=1}^{N}\frac{1}{\sum_{h=1}^{N}\mu_{i,h}^{m}} x_q \mu_{i,q}^{m}$$

7) Calculate the input to each neuron (i,k)

$$Net_{i,k} = \left[x_k - \sum_{q=1}^{N}\frac{1}{\sum_{h=1}^{N}\mu_{i,h}^{m}} x_q \mu_{i,q}^{m}\right]^2 \qquad (11)$$

8) Compute new membership value (Fuzzy c-means)

$$\mu_{i,k} = \left[\sum_{j=1}^{c}\left(\frac{Net_{i,k}}{Net_{j,k}}\right)^{2/m-1}\right]^{-1} \qquad (12)$$

9) Compute J^t (13)

$$J^t = \frac{1}{N}\sum_{k=1}^{N}\sum_{i=1}^{c}\mu_{i,k}^{m} D_{i,k}^{2}$$

10) If $|J^{t+1} - J^t| > \varepsilon$ go to step 6, otherwise stop.

5. EXPERIMENTAL RESULTS

To see the capability of the proposed FHNN algorithm ,for image segmentation, Three images with 256*256 pixels and 256 gray levels are tested with FHNN (Fuzzy hopfield neural network) ,FCM(Fuzzy c-means) [10] , Gk) Gustafson-Kessel) [11],GG (Gath-Geva) [12] and k means [10] techniques. We also, compare this new idea (for cameraman , lena and phantom images) with FHNN which is proposed by J.S.Lin [8].Parameters are fixed to the following values: m = 2, ε = 0.001, c Є [2 10]. For more information refer to Table 1.In this new method, number of iteration is less than other methods and it provides separate clustering by cluster validity measures. As , It is difficult to compare different image segmentation methods visually , Only Original and segmented images by FHNN method are presented according to different number of clusters (figures 1 , 2, 3).So, FHNN method provides a faster speed on image segmentation in comparison with other methods.

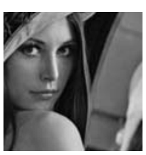
(a)

(b)

(c)

(d)

Figure 1 Cameraman image:a)original image ;b)segmented image c=3; c)segmented image c=5; d)segmented image c=7



(a)

(b)

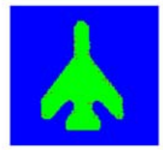
(c)

(d)

Figure 2 Lena image:a)original image ;b)segmented image c=3; c)segmented image c=5; d)segmented image c=7

(a)

(b)



(c)

(d)

Figure 3 Phantom image:a)original image; b)segmented image c=2; c)segmented image c=5; d)segmented image c=7

Table 1.Experimental result: number of iteration of algorithms

	Number of iteration					
C: number of cluster	**FHNN by own**	**FCM**	**Gk**	**GG**	**k-means**	**FHNN by [8]**
lena's picture						
C=2	10	21	21	No-converge	16	23
C=3	6	13	15	No-converge	7	14
C=4	5	36	36	No-converge	7	32
C=5	7	58	58	No-converge	8	47
c=6	5	103	105	No-converge	45	91
C=7	5	146	146	No-converge	15	121
C=8	5	251	250	No-converge	12	147
C=9	5	212	200	No-converge	21	175
C=10	6	224	221	No-converge	7	125
Cameraman's picture						
C=2	7	9	8	No-converge	4	11
C=3	9	20	20	No-converge	8	20
C=4	6	95	90	No-converge	8	62
C=5	6	104	104	No-converge	27	103
C=6	5	150	145	No-converge	10	138
C=7	6	78	78	No-converge	24	67
C=8	5	71	70	No-converge	19	50
C=9	5	220	230	No-converge	12	167
C=10	6	373	370	No-converge	24	315
Phantom's picture						
C=2	6	6	3	No-converge	3	5
C=3	5	5	3	No-converge	3	4
C=4	5	5	5	No-converge	3	4
C=5	5	5	5	No-converge	7	4
C=6	5	5	5	No-converge	4	4
C=7	5	5	5	No-converge	4	4
C=8	4	4	4	No-converge	5	6
C=9	4	4	4	No-converge	5	6

C=10	4	4	5	No-converge	9	6

Table 2.Experimental result: cpu time of algorithms

	cpu time (second)					
C: number of cluster	**FHNN by own**	**FCM**	**Gk**	**GG**	**k-means**	**FHNN by [8]**
lena's picture						
C=2	0.1475	0.1875	0.51563	No-converge	0.20313	0.45313
C=3	0.11063	0.14063	0.46875	No-converge	0.26563	0.4375
C=4	0.10188	0.15625	1.6719	No-converge	0.26563	1.4219
C=5	0.1125	0.28125	3.2656	No-converge	1.3281	2.5938
C=6	0.15	0.23438	6.8906	No-converge	3.1094	6.0156
C=7	0.18125	0.28125	11.313	No-converge	0.79688	9.4531
C=8	0.1125	0.3125	24.219	No-converge	2.2344	13.281
C=9	0.15938	0.35938	23.406	No-converge	2.7031	17.813
C=10	0.28438	0.48438	27.281	No-converge	1.3438	14.188
Cameraman's picture						
C=2	0.10063	0.125	0.25	No-converge	0.26563	0.25
C=3	0.01875	0.20313	0.67188	No-converge	0.40625	0.57813
C=4	0.00313	0.17188	4.6406	No-converge	0.6875	2.5781
C=5	0.05	0.21875	6.3281	No-converge	0.98438	5.875
C=6	0.15	0.23438	10.891	No-converge	1.3125	8.9531
C=7	0.14375	0.32813	6.6563	No-converge	3.1094	5.2188
C=8	0.12813	0.32813	6.9531	No-converge	1.6875	4.4531
C=9	0.175	0.35938	24.234	No-converge	1.7344	17.047
C=10	0.28438	0.48438	44.906	No-converge	5.0781	35.453
Phantom						
C=2	0.025	0.10938	0.10938	No-converge	0.15625	0.10938
C=3	0.025	0.125	0.17188	No-converge	0.15625	0.10938
C=4	0.07188	0.15625	0.3125	No-converge	0.17188	0.15625
C=5	0.01875	0.20313	0.39063	No-converge	0.46875	0.20313
C=6	0.06563	0.23438	0.46875	No-converge	0.35938	0.21875
C=7	0.06563	0.28125	0.54688	No-converge	0.40625	0.26563
C=8	0.15	0.25	0.53125	No-converge	0.54688	0.48438
C=9	0.19688	0.29688	0.64063	No-converge	0.625	0.54688
C=10	0.1125	0.32813	0.79688	No-converge	1.2344	0.59375

6. CONCLUSIONS

In this paper, a new objective function for image segmentation is proposed. This new method is based on FHNN and provides a faster speed by comparison with other ways.

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