STUDY OF IMAGE SEGMENTATION USING ARTIFICIAL INTELLIGENCE

Tripti Dongare-Mahabare

Department of Computer Science Pratibha College of Commerce & Computer Studies, Chinchwad Pune
E-mail : tru.neel@gmail.com Mobile-9595193221

Nilambari Kale

Department of Computer Science Pratibha College of Commerce & Computer Studies, Chinchwad Pune
E-mail : nilambari.mate@gmail.com mobile-9730685554

Abstract :
Segmenting an image to meaningful parts is a fundamental operation in image processing. Image segmentation is the process of partitioning a digital image into multiple segments. Segmentation partitions an image into distinct regions containing each pixels with similar attributes. To be meaningful and useful for image analysis and interpretation, the regions should strongly relate to depicted objects or features of interest. Meaningful segmentation is the first step from low-level image processing transforming a grey scale or color image into one or more other images to high-level image description in terms of features, objects, and scenes. The success of image analysis depends on reliability of segmentation, but an accurate partitioning of an image is generally a very challenging problem. In this paper, various image segmentation methods using artificial intelligence are explained.

Keywords: **Neural, network, Pixels, Segmentation, self organizing map**

Introduction:
Image segmentation is a process of dividing an image into different regions such that each region is homogenous. Most of segmentation algorithms are based on two characters of pixel gray level: discontinuity around edges and similarity in the same region. There are three main categories in image segmentation: Edge-based segmentation; Special theory based segmentation, feature based segmentation.
1) Edge based segmentation:
2) Special theory based segmentation:
   A. Fuzzy Techniques
   B. Physics based techniques
   C. Neural Network technique
3) Feature based Segmentation

Segmentation of tissues and structures from medical images is the first step in many image analysis applications developed for medical diagnosis. Development of treatment plans and evaluation of disease progression are other applications. These applications stem from the fact that diseases affect specific tissues or structures, lead to loss, atrophy (volume loss), and abnormalities. Consequently, an accurate, reliable, and automatic segmentation of these tissues and structures can improve diagnosis and treatment of diseases. Manual segmentation, although prone to rater drift and bias, is usually accurate but is impractical for large datasets because it is tedious and time consuming. Automatic segmentation methods can be useful for clinical applications if they have: 1) ability to segment like an expert; 2) excellent performance for diverse datasets; and 3) reasonable processing speed. Artificial Neural Networks (ANNs) have been developed for a wide range of applications such as function approximation, feature extraction, optimization, and classification. In particular, they have been developed for image enhancement, segmentation, registration, feature extraction, and object recognition. Among these, image segmentation is more important as it is a critical step for high-level processing such as object recognition. Multi-Layer Preceptor (MLP), Radial Basis Function (RBF), Hopfield, Cellular, and Pulse-Coupled neural networks have been used for image segmentation. These networks can be categorized into feed-forward (associative) and feedback (auto-associative) networks. MLP, Self-Organized Map (SOM), and RBF neural networks belong to the feed-forward networks while Hopfield, Cellular, and Pulse-Coupled neural networks belong to the feedback networks. This chapter is organized as follows. Section 2 explains methods that benefit from feedback networks such as Hopfield, Cellular, and Pulse-Coupled neural networks for image segmentation. In Section 3, we review the methods that use feedforward networks such as MLP and RBF neural networks. Then, we present our

recent method. In this method, deep brain structures are segmented using Geometric Moment Invariants (GMIs) and MLP neural networks.

Neural Network technique

Neural network based segmentation is totally different from conventional segmentation Algorithms. In this algorithm, an image is firstly mapped into a neural network where every neuron stands for a pixel. Then, we extract image edges by using dynamic equations to direct the state of every neuron towards minimum energy defined by neural network. Neural network based segmentation has three basic characteristics: 1) highly parallel ability and fast computing capability, which make it suitable for real time application; 2) unrestricted and nonlinear degree and high interaction among processing units, which make this algorithm able to establish modeling for any process; 3) satisfactory robustness making it insensitive to noise. However, there are some drawbacks for neural network based on segmentation, such as: 1) some kinds of segmentation information should be known beforehand; 2) initialization may influence the result of image segmentation; 3) neural network should be trained using learning process beforehand, the period of training may be very long, and we should avoid overtraining at the same time.

ANN are computational models inspired by biological neural networks, and are used to approximate functions that are generally unknown. Particularly, they are inspired by the behavior of neurons and the electrical signals they convey between input (such as from the eyes or nerve endings in the hand), processing, and output from the brain (such as reacting to light, touch, or heat). The way neurons semantically communicate is an area of ongoing research. Most artificial neural networks bear only some resemblance to their more complex biological counterparts, but are very effective at their intended tasks (e.g. classification or segmentation).Some ANNs are adaptive systems and are used for example to model populations and environments, which constantly change.Neural networks can be hardware- (neurons are represented by physical components) or software-based (computer models), and can use a variety of topologies and learning algorithms.

There are various types of artificial neural networks (ANN).
feedback Neural Networks:
- ➢ Cellular Neural Network
- ➢ Pulse-coupled Neural Network

Feed-forward Neural network :
- ➢ Radial Basis Function Network(RBF)
- ➢ Kohonen self organizing network

- ➢ Leaning Vector Quantization
- ➢ Recurrent Neural Network
- ➢ Modular Neural Network
- ➢ physical Neural Network etc

In this paper we focus on Hopfield Neural Network, kohonen's self organizing network & Radial Basis Function network (RBF).

Image segmentation using feedback Neural Networks :

Feedback or recurrent networks include feedback loops. These networks are very powerful and can get extremely complicated. Hopfield, Cellular, and Pulse-Coupled neural networks described in this section belong to this category of networks.

Hopfield Neural Network

Hopfield Neural Network (HNN), introduced by Hopfield, (1982), consists of a pool of neurons with connections between each unit. Every neuron connects to other neurons with a weight in the network. All neurons are both input and output neurons. The output is a binary value (0,1 or -1,1). In the original form of HNN, the state of each neuron is determined by (Hopfield, 1982),

$$V_i \to 1 \;\; \text{if} \;\; \sum_{i \neq j} T_{ij} \, V_j > U_i \qquad \text{Eq.-1}$$

$$V_i \to 0 \;\; \text{if} \;\; \sum_{i \neq j} T_{ij} \, V_j < U_i \qquad \text{Eq.-2}$$

where Vi is the output of neuron i and Ui is a threshold value. Tij is the strength of the connection between neurons i and j . HNN has a scalar value associated with the given state of the network, called energy, E, of the network. It is defined as

$$E = -1/2 \; \sum_{i \neq j} \sum T_{ij} \, V_j < U_i \qquad \text{Eq.-3}$$

The constraint $T_{ij} = T_{ji}$ i (i.e., symmetric weights) guarantees that the energy function decreases monotonically (Hopfield, 1982; Amartur et al., 1992). In this condition, initial values of neurons lead the network to converge at a local minimum. In some version of HNN, a bias for each neuron is considered and the network energy is determined by

$$E = -1/2 \; \sum \sum T_{ij} \, V_j < U_i - \sum_{K} I_k \, V_k \qquad \text{Eq.-4}$$

where k I is a bias term. The energy function minimization is obtained by solving a set of motion equations (Amartur et al., 1992)

$\partial U_i / \partial t = -\partial E / \partial V_i$ 　　　Eq.-5

where U i is the input of the i-th neuron. If the input-output function decreases monotonically and the motion equations are satisfied, the energy function decreases as time passes and converges at a local minimum. The energy function is nonconvex and has more than one local minimum. A primary application of HNN is an associative memory. The network is able to save a given pattern by choosing a proper set of weights. From image segmentation point of view, HNN consists of N M× neurons with the pixels as the rows and the classes as the columns. HNN is used as a map between the image pixels and their labels (i.e., assigning N pixels to M classes). The assignment of the pixels minimizes the energy function. The criterion function or weights can be based on a metric measure between a pixel and a class. In (Amartur et al., 1992), generalized distance measure between the k-th pixel and the centroid of class ` is determined by

$R_{kl} = |X_k - X_l| A_l^{-1}$ 　　　Eq..-6

where Xk is the P-dimensional feature vector of the k-th pixel, Ai is a positive definite weighting matrix, and Xl is the P-dimensional centroid for class l . The objective function to minimize is given by

$$E = -1/2 \sum_{k=1}^{N} \sum_{l=1}^{N} R_{kl} \, V_{lk}^2 \qquad \text{Eq.-7}$$

where R_{kl} is a symmetric distance measure. By substitution (7) into (5), the neuron dynamics can be described by

$$\frac{dU_{kl}}{dt} = -R_{kl} V_{kl}$$

Eq.-8

In (Amartur et al., 1992), the winner-takes-all neuron is used to construct the input-output function for the k-th pixel.

$$V_{kn(t+1)} = \begin{array}{ll} 1 & \text{if } U_{kn} = MAX(U_{kl}) \\ 0 & \text{Otherwise} \end{array}$$

The algorithm for clustering an image is as follows: 1. Initialize the inputs of the neurons randomly. 2. Using (9), calculate the output of the neurons. Assign pixels to classes. 3. Compute the centroid and the covariance matrix for class l as described in (Amartur et al., 1992). 4. Solve equation (8) using Euler's approximation. 5. If there is a significant change in the input of each neuron, repeat from step 2), else, terminate. If the number of clusters is large, the network may over-classify the image into many disjoint regions. In this condition, a similarity or dissimilarity measure should be used to merge them. Fig. 1 shows an example of clustering a magnetic resonance image (MRI) of the head (Amartur et al., 1992). This network is easily implemented in hardware and its high speed makes it appropriate for real-time applications. The maximum operator generates a crisp classification. To generate a fuzzy classification, integrated a fuzzy c-means strategy with the HNN and introduced a Fuzzy Hopfield Neural Network (FHNN). They modified the energy function to include the fuzzy parameters. In this network, all of the neurons on the same row compete and eventually the neuron with the maximum membership to a given
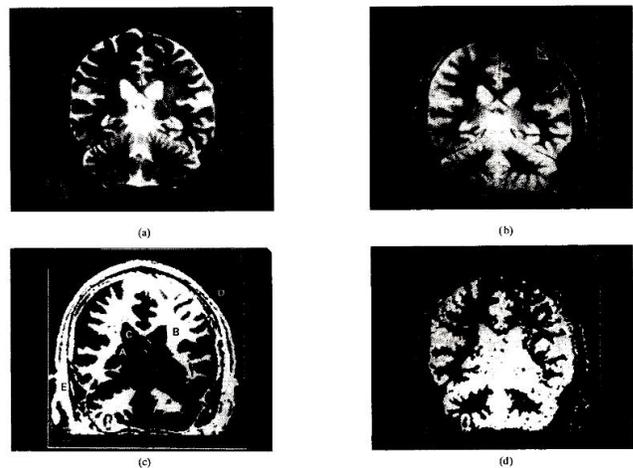

Fig-1

Fig. 1. Magnetic resonance images of the head of a normal subject: (a) T2-weighted at level 1; (b) proton density-weighted at level 1; (c) classified into 5 clusters; and (d) classified into 7 clusters (From Amartur et al., 1992 with permission). class wins. In this approach, there is no need to determine sensitivities associated with the weighting factors that are difficult to determine. Another technique was proposed by Cheng et al., (1996) as Competitive Hopfield Neural Network (CHNN) where the competitive learning rule, Winner-Takes-All (WTA), was utilized to update the weights.

(Chang and Chung, 2001) describe another difficulty of the HNN: the original HNN cannot incorporate contextual information into the segmentation process. They also mention that the robustness of the HNN to noise is low. To overcome this limitation, they introduce Contextual-Constraint-based Hopfield Neural Cube (CCBHNC). The network benefits from a three-dimensional architecture. They incorporated the pixel's feature and its surrounding contextual information into the third dimension.

Image segmentation using feed-forward Neural Networks :

KOHONEN'S SELF ORGANIZING MAP :-
The artificial neural network introduced by the Finnish professor Teuvo Kohonen in the 1980s is sometimes also known as the Kohonen map or network. It contains of components, namely nodes or neurons. Each of these nodes has some weight vector of the same dimension as the input space associated with it. SOM is used for visualizing low dimensional views of a higher dimensional data set 2.1. Architecture of Self Organizing Map (SOM)
The number of neurons in the first neural layer can be chosen in a task specific manner. Each neuron in the first neural layer has its own weight vector which is dimensionally equal to the input layer. Each neuron is connected to its adjacent neuron by a suitable neighborhood relation which determines the topology of the map. This neighborhood function is assigned by a special function also known as the topological neighborhood.
Components of Self Organizing Map Self-organizing process involves four major components
1) Initialization: All the connection weights of the nodes are initialized with small random values.
2) Competition: For each input neuron ,the neuron at the output layer will determine the value of a function called discriminate function, The discriminate function, which forms the basis of the competition, is computed by the neurons for each input pattern. The neuron with the smallest value of the discriminate function is declared as the winner.
3) Cooperation: The winner neuron determines the spatial location of the topological neighborhood.
4) Adaptation: The excited neurons, i.e. the neighboring nodes of the winner neuron decrease the value of their individual discriminate function according to the input pattern through suitable adjustments associated with the connection weights.
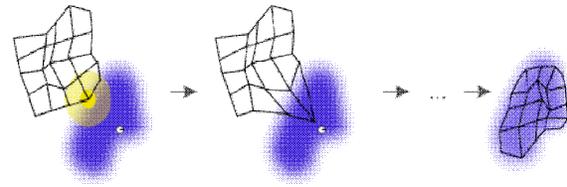
Algorithm

1. Randomize the map's nodes' weight vectors
2. Grab an input vector $\mathbf{D(t)}$
3. Traverse each node in the map
   1. Use the Euclidean distance formula to find the similarity between the input vector and the map's node's weight vector
   2. Track the node that produces the smallest distance (this node is the best matching unit, BMU)
4. Update the nodes in the neighborhood of the BMU (including the BMU itself) by pulling them closer to the input vector
   1. $\mathbf{W_v}(s + 1) = \mathbf{W_v}(s) + \Theta(u, v, s)\, \alpha(s)(\mathbf{D}(t) - \mathbf{W_v}(s))$
5. Increase s and repeat from step 2 while $s < \lambda$

A variant algorithm:

1. Randomize the map's nodes' weight vectors
2. Traverse each input vector in the input data set
3. Traverse each node in the map
4. Use the Euclidean distance formula to find the similarity between the input vector and the map's node's weight vector
5. Track the node that produces the smallest distance (this node is the best matching unit, BMU)
6. Update the nodes in the neighborhood of the BMU (including the BMU itself) by pulling them closer to the input vector

$\mathbf{W_v}(s + 1) = \mathbf{W_v}(s) + \Theta(u, v, s)\, \alpha(s)(\mathbf{D}(t) - \mathbf{W_v}(s))$

7. Increase s and repeat from step 2 while $s < \lambda$

Interpretation :

Self-Organizing Map Segmentation Process Initially, all weight vectors of the first neural layer are set to random values. After that some input vectors D(t) from the input space are selected and set as an input for the neural network. Then the difference between the neuron vectors Wv and the input vectors is computed by traversing each node in the map using the Euclidean distance formula. The node with the least difference between the input vector and neuron vector is selected. This node is the winner neuron in correspondence to which the neighboring neurons adjust themselves such that they are closer to the input vector using the following formula: Wv(s + 1) = Wv(s) + Θ(u, v, s) α(s)(D(t) - Wv(s)) Then Wv(s+1) and Wv are compared for detection of any significant changes. If there exists any change then again the neuron vectors are updated such that they are closer to the input vector. This process is carried out till the last iteration is reached.

Radial Bias Function:

In the field of mathematical modeling, a **radial basis function network** is an artificial neural network that uses radial basis functions as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and neuron parameters. Radial basis function networks have many uses, including function approximation, time series prediction, classification, and system control. They were first formulated in a 1988 paper by Broomhead and Lowe, both researchers at the Royal Signals and Radar Establishment.This is becoming an increasingly popular neural network with diverse applications and is probably the main rival to the multi-layered preceptor. Much of the inspiration for RBF networks has come from traditional statistical pattern classification techniques
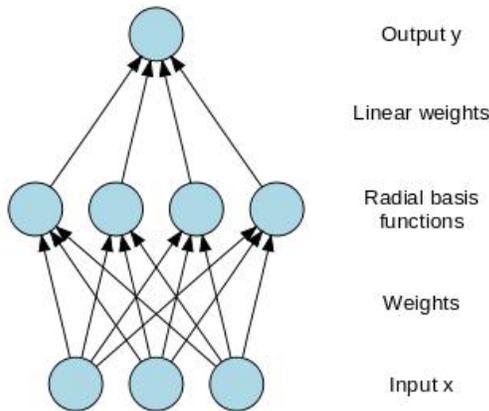
Radial basis function (RBF) networks typically have three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer. The input can be modeled as a vector of real numbers $\mathbf{x} \in \mathbb{R}^n$. The output of the network is then a

scalar function of the input vector, $\varphi : \mathbb{R}^n \rightarrow \mathbb{R}$, and is given by

$$\varphi(\mathbf{x}) = \sum_{i=1}^{N} a_i \rho(||\mathbf{x} - \mathbf{c}_i||)$$

where N is the number of neurons in the hidden layer, $\mathbf{c}_i$ is the center vector for neuron i, and a_i is the weight of neuron i in the linear output neuron. Functions that depend only on the distance from a center vector are radially symmetric about that vector, hence the name radial basis function. In the basic form all inputs are connected to each hidden neuron. The norm is typically taken to be the Euclidean distance and the radial basis function is commonly taken to be Gaussian

$$\rho\left(||\mathbf{x} - \mathbf{c}_i||\right) = \exp\left[-\beta ||\mathbf{x} - \mathbf{c}_i||^2\right]$$

The Gaussian basis functions are local to the center vector in the sense that i.e. changing parameters of one neuron has only a small effect for input values that are far away from the center of that neuron. RBF networks are universal approximates on a compact subset of $\mathbb{R}^n$. This means that an RBF network with enough hidden neurons can approximate any continuous function with arbitrary precision.
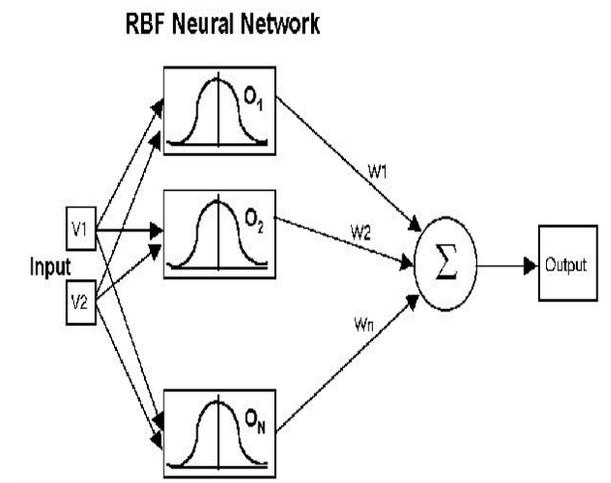
Conclusion:

There are several methods for image segmentation based on artificial neural networks. The networks were categorized into feedback and feed-forward networks. Among the feedback networks, Hopfield networks have been used. Among the feed-forward neural networks, Self Organizing Map (Kohenen), Radial Basis Function neural networks have been utilized.

The Hopfield network was described as a map between the image pixels and their labels. The network is easily

implemented in hardware and used in real-time applications. On the other hand, the network is fully connected and it is not applicable for 3D or huge 2D medical image segmentation due to its large number of parameters. In addition, for object recognition, it is not essential that each pixel connects to all other pixels. Indeed, it may be ineffective to incorporate information of all other pixels to label a pixel.

A feed-forward network is usually utilized for dimension reduction. As discussed, The Kohonen Self-Organising Algorithm was programmed to use medical images as input signals. The use of an annular Self-Organising Map allowed segmenting the external shape of a human head out of database of Magnetic Resonance images. Through this process of segmentation, the information describing certain structures of the image is discarded thus compressing the information required to describe the segmented structure. It has been used for color reduction of medical images. The next network discussed was the RBF neural network. This type of neural network is usually useful for function approximation and classification.

RBF network have become very popular, and are serious rivals to the MLP. RBF trains faster than a MLP.

Their main features are:

1. They are two-layer feed-forward networks.
2. The hidden nodes implement a set of radial basis functions (e.g. Gaussian functions).
3. The output nodes implement linear summation functions as in an MLP.
4. The network training is divided into two stages: first the weights from the input to hidden layer are determined, and then the weights from the hidden to output layer.
5. The training/learning is very fast.
6. The networks are very good at interpolation

References :

[1] Artificial Neural Networks - Methodological Advances and Biomedical Applications Edited by Prof. Kenji Suzuki ISBN 978-953-307-243-2 Hard cover, 362 pages Publisher InTech Published online 11, April, 2011 Published in print edition April, 2011

[2] Amartur, S. C.; Piraino, D. & Takefuji, Y. (1992). Optimization neural networks for the segmentation of magnetic resonance resonance images. *IEEE Transactions on Medical Imaging,* 11(2): 215-220.

[3] Angelini, E. D.; Jin, Y. & Laine, A. (2005). State-of-the-art of levelset methods in segmentation and registration of medical imaging modalities. *The Handbook of Medical Image Analysis 3*.

[4] Bishop, C. M. (2006). Pattern Recognition and Machine Learning, *Springer*.

[5]Chang, C. Y. & Chung, P. C. (2001). Medical image segmentation using a contextual-constraint-based Hopfield neural cube. *Image and Vision Computing*, 19(9-10): 669-678.

[6]Chang, P. L. and W. G. Teng (2007). Exploiting the self-organizing map for medical image segmentation, *20th IEEE international Symposium on Computer-Based Medical Systems (CBMS'07)*, Maribor, 281:288.

[7] Cheng, K.-S.; Lin, J.-S. & Mao, C.-W. (1996). Application of competitive Hopfield neural network to medical image segmentation. *IEEE Transactions on Medical Imaging* 15(4): 560-561.

[8] Chua, L. O. & Yang, L. (1988a). Cellular neural networks, *IEEE international Symposium, Circuits and Systems*.

[9] Chua, L. O. & Yang, L. (1988b). Cellular neural networks: Applications. *IEEE transactions on circuits and systems*, 35(10): 1273-1290.

[10] Chua, L. O. & Yang, L. (1988c). Cellular neural networks: Theory. *IEEE transactions on circuits and systems*, 35(10):1257-1272.

[11] Alamgir Nyma, Myeongsu Kang, Yung-Keun Kwon, Cheol-Hong Kim, and Jong-Myon Kim "A Hybrid Technique forMedical Image Segmentation" Article ID 830252,Journal of Biomedicine and Biotechnology Hindawi Publishing Corporation Volume 2012.

[12] Ravi S and A M Khan, "Operators Used in Edge Detection: A Case Study", International Journal of Applied Engineering Research, ISSN 0973-4562 vol. 7 No 11, 2012.

[13] Bryan S. Morse, Lecture 18: Segmentation (Region Based), Brigham Young University, 1998.

[14] http://www.engineersgarage.com/articles/image-processing-tutorial-applications.

[15]http://en.wikipedia.org/wiki/Image_segmentation

[16] Sameena Banu, Assistant Professor " The Comparative Study on Color Image Segmentation Algorithms" International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com Vol. 2, Issue4, July-August 2012, pp.1277-1281.