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Image Segmentation Using a RBF Approach of Neural Network

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Abstract: ***Radial Basis function Neural Networks forms a class of neural networks which is much more advantageous then other methods of neural networks such as faster learning, easy networks & structures & better approximations & classifications. The system consist of a multilayer perceptron (MLP)-like network that performs image segmentation by RBF technique of the input image using labels automatically pre-selected by a fuzzy clustering technique. The proposed architecture is feedforward, the learning is unsupervised. The proposed system is capable to perform automatic multilevel segmentation of images, based solely on information contained by the image itself.***

Keyword — Image segmentation, Multilayer perceptron, unsupervised, Fuzzy clustering.

I. INTRODUCTION

Image segmentation algorithm is a crucial step in image processing and analysis. The goal of segmentation is to separate an image into some regions of feature and to pick up the interesting objects. Image segmentation is nothing but the grouping of pixels into individual clusters in such a way that the pixels from the same cluster are more similar to each other than pixels from different clusters.[1] In non-fuzzy or hard clustering, data is divided into crisp clusters, where each data point belongs to exactly one cluster. Fuzzy clustering algorithm compares the intensity in a relative way and groups them into clusters. The grouped clusters are not with crisp boundaries.[2]

Radial Basis function Neural Networks forms a class of neural networks which is much more advantageous then other methods of neural networks such as faster learning, easy networks & structures & better approximations & classifications. In this paper, we propose a system capable to perform multilevel segmentation of images in an automatic/unsupervised way. No *a priori* assumptions whatsoever are made about the image (type, features, contents, stochastic model, etc.). Such an "universal" algorithm is most useful for applications that are supposed to work with different (and possibly initially unknown) types of images (e.g., searching for images on the Internet or in the photo archive of a magazine). The proposed system can be readily employed, "as is," or as a basic building block by a more sophisticated image segmentation algorithm (that incorporates additional "knowledge" into different parts of the system).The proposed neuro-fuzzy segmentation system is self organizing. It consists of a multilayer perceptron (MLP)-like network that performs image segmentation by adaptive thresholding of the input image using labels automatically pre-selected by a fuzzy clustering technique. The proposed architecture is feed forward, but unlike the conventional MLP, the learning is unsupervised. The output status of the network is described as a fuzzy set. Fuzzy entropy is used as a measure of the error of the segmentation system. Because this measure handles only one aspect of the quality of the segmentation, and because no satisfactory quality measures were proposed in the literature, the results are analyzed mainly by visual inspection and comparison with results obtained by other algorithms.

One of the main roadblocks toward full automation of the segmentation system is the problem of automatically choosing the correct number of labels. This parameter, of crucial importance to most labeling methods, is usually very hard to determine automatically, and in most cases it is left as a parameter which has to be provided by the user[3-4]. Some methods of employing cluster validity measures to solve this problem were tested, and some preliminary results are presented in this paper.[5-6]

Neural-Networks:-

Neural networks (NNs) are aimed at emulating the biological nervous system with the hope of achieving human-like performance artificially by capturing the key ingredients responsible for the remarkable capabilities of the human nervous system [10]. Interaction among the neurons is very high in NNs making them suitable for collective decision making. The main characteristics of NNs, namely, adaptively, fault tolerance, robustness and optimality play important roles particularly in the field of pattern classification. It is well-known that both neural networks and fuzzy logic are intelligent techniques in information processing technology, which are frequently used for complex system modeling and data processing. Both techniques have distinctive features and present numerous advantages.[11]Fuzzy logic provides a framework to incorporate a knowledge base and to deal with imprecise data, whereas neural networks are endowed with various advantages such as parallelism, learning ability and speed of processing. Both techniques have their own limitations. Fuzzy logic is unable to design its fuzzy rules according to the training data to build a reconfigurable system able to identify the desired behavior, while the non-interpretability of results presents a major drawback of neural networks. Owing to these problems, many researchers have combined neural networks and fuzzy logic synergistically as a single system, called hybrid neuro-fuzzy system (NFS), which brings both advantages from one part and overcomes the drawbacks from another part. Both NNs and fuzzy systems are adaptive in the estimation of the input-output function without any precise mathematical model. NNs handle numeric and quantitative information while fuzzy systems can handle symbolic and qualitative data. Apart from this, in a fuzzy classifier patterns are assigned with a degree of belonging to different classes. Thus the partitions in fuzzy classifiers are soft and gradual rather than hard and crisp. Therefore, an integration of neural and fuzzy systems should have the merits of both and it should enable one to build more intelligent decision making systems.[12-13]

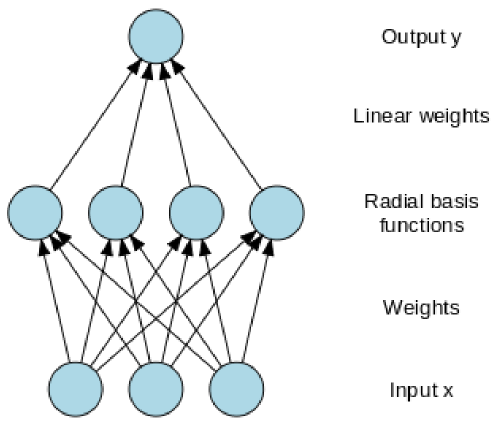
II. FUZZY CLUSTURING: -

Cluster analysis is found to be one of the useful tools for data analysis. It is a method for finding clusters of a data set with most similarity in the same cluster and most dissimilarity between different clusters[13]. Image segmentation can be done with the help of fuzzy clustering Since Zadeh proposed fuzzy sets that introduced the idea of partial memberships described by membership functions; it has been successfully applied in various areas. Especially, fuzzy sets could allow membership functions to all clusters in a data set so that it is very suitable for cluster analysis. Fuzzy clustering algorithm compares the intensity in a relative way and groups them into clusters[14-16] The unique feature of the RBF network is the process performed in the hidden layer.

The idea is that the patterns in the input space form clusters. If the centres of these clusters are known, then the distance from the cluster centre can be measured. Furthermore, this distance measure is made non-linear, so that if a pattern is in an area that is close to l. Beyond this area, the value drops dramatically. The notion is that this area is radially symmetrical around the cluster centre, so that the non-linear function becomes known as the radial-basis function. Cluster centre it gives a value close to 1.

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 perceptron .

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, $\varphi : \mathbb{R}^n \to \mathbb{R}$, 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

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

The Gaussian basis functions are local to the center vector in the sense that

$$\lim_{||x|| \to \infty} \rho(\left\Vert \mathbf{x} - \mathbf{c}_i \right\Vert) = 0$$

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 approximators on acompact subset of $\mathbb{R}^n$. [4] This means that an RBF network with enough hidden neurons can approximate any continuous function with arbitrary precision.

General flowchart.

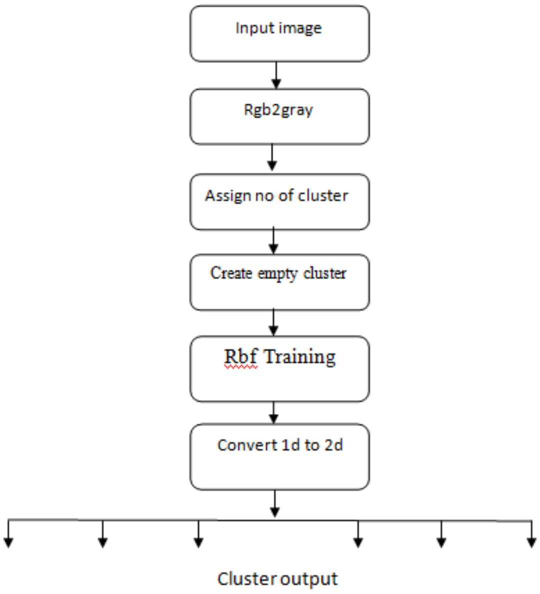
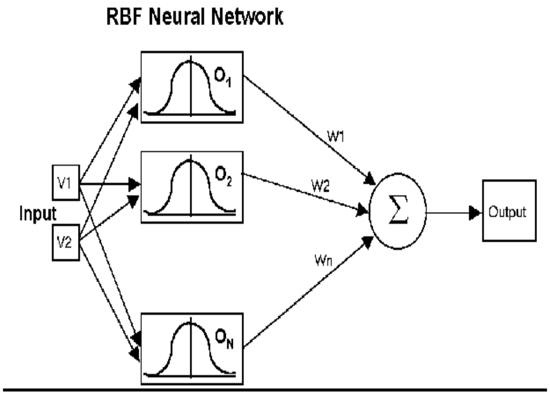


Fig. 1. General flowchart.

III. RBF Network Architecture



RBF networks have three layers:

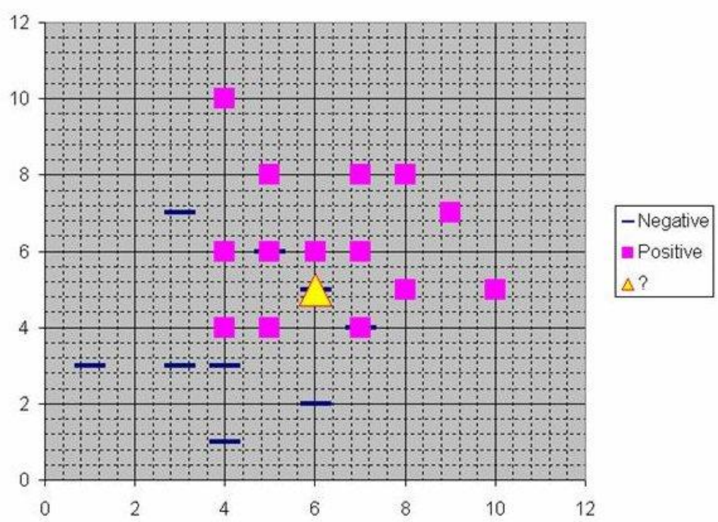
1. Input layer – There is one neuron in the input layer for each predictor variable. In the case of categorical variables, N-1 neurons are used where N is the number of categories. The input neurons (or processing before the input layer) standardizes the range of the values by subtracting the median and dividing by the interquartile range. The input neurons then feed the values to each of the neurons in the hidden layer.
2. Hidden layer – This layer has a variable number of neurons (the optimal number is determined by the training process). Each neuron consists of a radial basis function centered on a point with as many dimensions as there are predictor variables. The spread (radius) of the RBF function may be different for each dimension. The centers and spreads are determined by the training process. When presented with the x vector of input values from the input layer, a hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the RBF kernel function to this distance using the spread values. The resulting value is passed to the summation layer.
3. Summation layer – The value coming out of a neuron in the hidden layer is multiplied by a weight associated with the neuron (W1, W2, ...,Wn in this figure) and passed to the summation which adds up the weighted values and presents this sum as the output of the network. Not shown in this figure is a bias value of 1.0 that is multiplied by a weight W0 and fed into the summation layer. For classification problems, there is one output (and a separate set of weights and summation unit) for each target category. The value output for a category is the probability that the case being evaluated has that category.[22]

Training RBF Networks

The following parameters are determined by the training process:

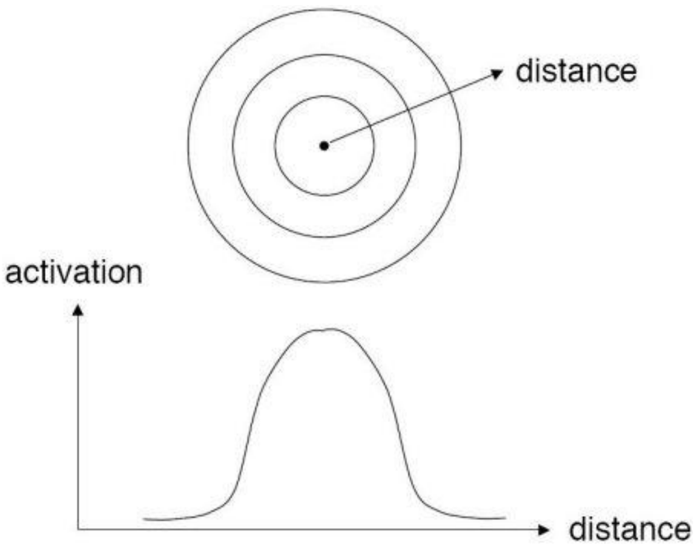
1. The number of neurons in the hidden layer.
2. The coordinates of the center of each hidden-layer RBF function.
3. The radius (spread) of each RBF function in each dimension.
4. The weights applied to the RBF function outputs as they are passed to the summation layer.[23]

Various methods have been used to train RBF networks. One approach first uses K-means clustering to find cluster centers which are then used as the centers for the RBF functions. However, K-means clustering is a computationally intensive procedure, and it often does not generate the optimal number of centers. Another approach is to use a random subset of the training points as the centers

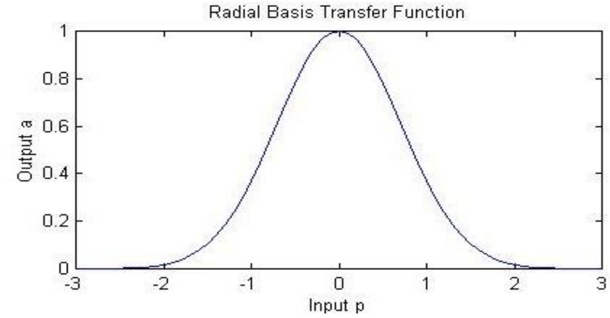


Assume that each case in the training set has two predictor variables, *x* and *y*. The cases are plotted using their *x,y* coordinates as shown in the figure. Also assume that the target variable has two categories, positive which is denoted by a square and negative which is denoted by a dash The nearest neighbor classification performed for this example depends on how many neighboring points are considered. If 1-NN is used and only the closest point is considered, then clearly the new point should be classified as negative since it is on top of a known negative point. On the other hand, if 9-NN classification is used and the closest 9 points are considered, then the effect of the surrounding 8 positive points may overbalance the close negative point.

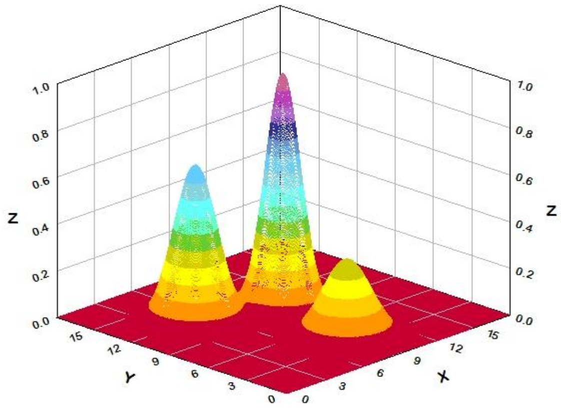
An RBF network positions one or more RBF neurons in the space described by the predictor variables (x,y in this example). This space has as many dimensions as there are predictor variables. The Euclidean distance is computed from the point being evaluated (e.g., the triangle in this figure) to the center of each neuron, and a radial basis function (RBF) (also called a kernel function) is applied to the distance to compute the weight (influence) for each neuron. The radial basis function is so named because the radius distance is the argument to the function. The further a neuron is from the point being evaluated, the less influence it has.



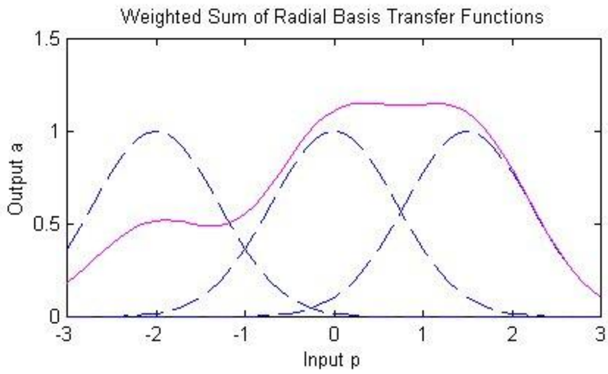
Different types of radial basis functions could be used, but the most common is the Gaussian function:



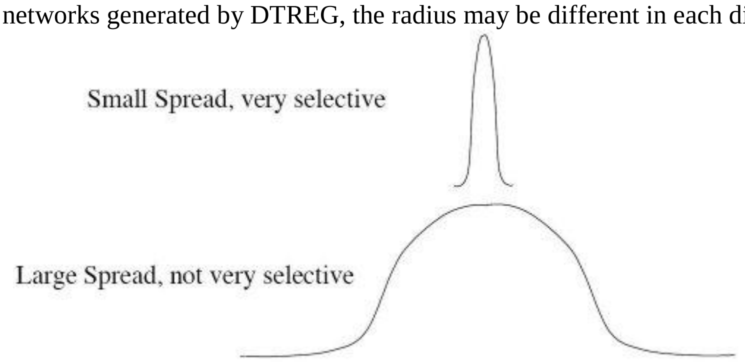
If there is more than one predictor variable, then the RBF function has as many dimensions as there are variables. The following picture illustrates three neurons in a space with two predictor variables, *X* and *Y*. *Z* is the value coming out of the RBF functions:



The best predicted value for the new point is found by summing the output values of the RBF functions multiplied by weights computed for each neuron.



The radial basis function for a neuron has a center and a radius (also called a spread). The radius may be different for each neuron, and, in RBF networks generated by DTREG, the radius may be different in each dimension.

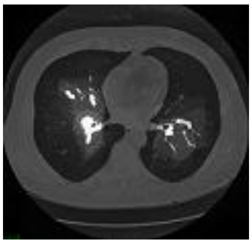


With larger spread, neurons at a distance from a point have a greater influence.

Various methods have been used to train RBF networks. One approach first uses K-means clustering to find cluster centers which are then used as the centers for the RBF functions. However, K-means clustering is a computationally intensive procedure, and it often does not generate the optimal number of centers. Another approach is to use a random subset of the training points as the centers[24]

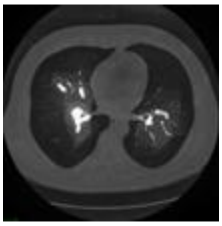
IV. OUTPUT

The output for six different images has been studied on the basis MSE, PSNR, Processing time & Area, few of them are shown below:-

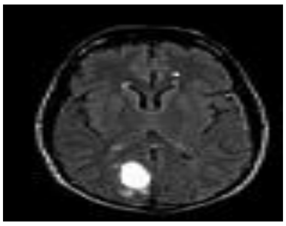


CANCER1

CANCER2

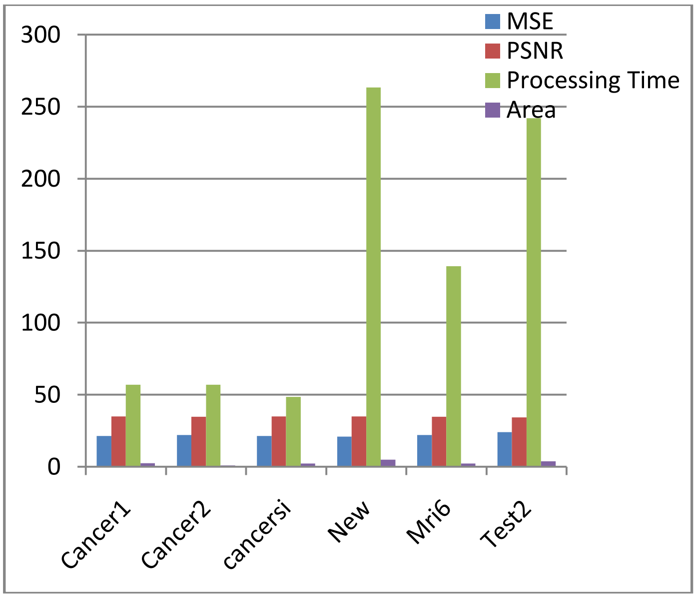


CANCERSI



MRI6

Image name	MSE	PSNR	Processing Time	Area
Cancer1	21.417	34.8232	56.9695	2.376
Cancer2	21.9781	34.7109	56.9959	0.875589
cancersi	21.3609	34.8346	48.4122	2.12844
New	20.9998	34.9087	263.318	4.96011
Mri6	22.0468	34.6151	139.304	2.25562
Test2	24.0468	34.3202	241.905	3.8439



V. Conclusion:-

Statistical feed-forward networks such as the RBF network have become very popular, and are serious rivals to the MLP. Essentially well tried statistical techniques being presented as neural networks.
Learning mechanisms in statistical neural networks are not biologically plausible – so have not been taken up by those researchers who insist on biological analogies. RBF trains faster than a MLP
Another advantage that is claimed is that the hidden layer is easier to interpret than the hidden layer in an MLP. Although the RBF is quick to train, when training is finished and it is being used it is slower than a MLP, so where speed is a factor a MLP may be more appropriate.

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

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