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Comparison of Simple Clustering by Self-Organizing Maps Using Neural Network Clustering Tool

B.P. Bhuvana

Department of ECE, Bharath University, Chennai-73, India

Abstract: Clustering is used to group the similar objects together. This can be employed in medical field so that the tumor cells can be detected. Self-Organising maps are used as clustering algorithm. In this paper two different two dimensional array are considered and the results have been c comparedby using neural network clustering tool.

Key words: SOM · Neural Network

INTRODUCTION

Clustering is the process by which objects are grouped together to form groups such that the objects in the same group will have similar characteristics. Objects which are in different groups will have entirely different characteristics. In this paper we will be using self-organizing maps for clustering process. Let us consider the clustering of flowers with different two dimensional arrays. Self-organizing maps (SOMs) are used for classifications. These classifications will have topological information. Self-organizing maps can be created with any desired level of detail. They are particularly well suited for clustering data in many dimensions and with complexly shaped and connected feature spaces. They are well suited to cluster flowers. There a re four flower attributes and these will act as inputs to the SOM, which will map them onto a 2-dimensional layer of neurons.

Image and sound are analog signals that can be processed by the biological system. Artificial Neural Networks is used to depict the character of biological neurons. Cyril Prasanna Raj P proposed a neural network architecture with new technology for weight storage and with backpropogation algorithm in analog domain for signal processing applications [1]. Mauro Tucci and Marco Raugi presented a new approach for self organising maps. Here a neuron act as finite impulse response (FIR) and during sequential learning process the co-efficient of filters are updated [2].

Analog device have device mismatch, charge leakage and nonlinear transfer function. GonzalaCarrajal presented an analysis of these effects on the residual error by LMS algorithm [3]. Miguel Figueroa described adaptive signal processing in mixed signal VLSI based on anti hebbian learning.

Neural network is used for face recognization based applications. This system usually uses a dimensionality-reduction network. The co-efficient can be learned or programmed to perform principal component analysis (PCA) and linear discriminant analysis (LDA) for dimensionality reduction [4]. Yuzo Hirai and KuninoriNishizawa fabricated principal component analysis (PCA) learning network by asynchronous PDM in a FPGA circuits. Differential equations and the circuits are used to express the generalizedhebbian algorithm [5].

Chris Diorio, Paul Hasler developed a complimentary pair of four terminal silicon synapses for analog learning applications. A non-volatile memory is used. Electron tunneling and hot electron injection allow bidirectional memory updates [6]. Chun-Hsien Chen developed neural network architecture for syntax analysis. Artificial Neural Networks can be used for symbol processing applications. A new approach is proposed for lexical analysis, stack and parse tree construction [7].

Digital perturbative learning in analog VLSI neural network was proposed by Vincent F Koosh. He used two feed forward neural networks. First uses analog synapses and second uses a computer for controlling global

Corresponding Author: B.P. Bhuvana, Department of ECE, Bharath University, Chennai-73, India.

operations [8]. MomchilMilew proposed an analog implementation of artificial neural network with quadratic non-linearity of synapses [9].

We have selected a specific application to apply neural networks in analog circuits. A pattern was assumed by Widrow and Hoff. It is an adaptive algorithm. Filter co-efficient are adjusted by LMS for minimizing the cost function. Recursive least square algorithm uses matrix operations, hence operations. But LMS doesn't use such operations; hence it uses less time and resources. LMS algorithm is simple and less complicated. It also uses gradient based steepest decent method. It does not require correlation function calculation and matrix inversions.For understanding the concepts of LMS algorithm. Let us consider a linear Perceptron. Here the weights are updated so as to reduce the error. This error is the difference between the output and the external reference [10].

MATERIALS ASD METHODS

Self Organising Map: Here the self-organizing map is used to compute the class vectors of each of the training inputs. These classfications cover the feature space populated by the known flowers and can now be used to classify new flowers accordingly. The network output will be a 64x150 matrix, where each ith column represents the jth cluster for each ith input vector with a 1 in its jth element.

The function vec2ind returns the index of the neuron with an output of 1, for each vector. The indices will range between 1 and 64 for the 64 clusters represented by the 64 neurons.SOM topology plots the self-organizing maps topology of 64 neurons positioned in an 8x8 hexagonal grid. Each neuron has learned to represent a different class of flower, with adjecent neurons typically representing similar classes.

SOM hits calculates the classes for each flower and shows the number of flowers in each class. Areas of neurons with large numbers of hits indicate classes representing similar highly populated regions of the feature space. Wheras areas with few hits indicate sparsely populated regions of the feature space [11].

SOM neighbour connections shows the neuron neighbor connections. Neighbors typically classify similar samples.

SOM neighbor weight distances shows how distant (in terms of Euclidian distance) each neuron's class is from its neighbors. Connections which are bright indicate highly connected areas of the input space. While dark connections indicate classes representing regions of the feature space which are far apart, with few or no flowers between them.

Long borders of dark connections separating large regions of the input space indicate that the classes on either side of the border represent flowers with very different features [12].

SOM planes shows a weight plane for each of the four input features. They are visualizations of the weights that connect each input to each of the 64 neurons in the 8x8 hexagonal grid. Darker colors represent larger weights. If two inputs have similar weight planes (their color gradients may be the same or in reverse) it indicates they are highly correlated.

Random Initialization: The choice of initial weights shows whether the neural net reaches a minimum error and if it reaches minimum error then how fast it converges. Weight update between any two units depend on both the derivative of the upper unit activation function and the lower unit activation function.

Hence, it should be noted that the initial weights which makes activations or the derivative of activation function zero should be avoided. Initial weight values should not be too large also. A common method to initialize the weight is to assign random values between -0.5 and 0.5. These values can be either positive or negative.

Training of Neural Net: Aim of the neural net is to achieve a balance between the correct response to training pattern and the good response to the new input pattern and also it is not mandatory to continue the process of training till the mean square error reaches the minimum value [13].

Hecht-Nielsen suggested two sets of data during the training process. They are as follows, a set of training patterns and a set of training -testing patterns. These are disjoint sets. Based on the training patterns weights are adjusted. But the error is calculated by the training-testing data. Training continues as long as the error in training-testing decreases. When the error is increased, net memorizes the training patterns and training is terminated at this point.

Number of Training Pairs: Consider P as the number of training patterns available, W as the number of weights to be trained and e is the expected accuracy of classification.

Some of the questions which are asked regarding the number of training pairs include "how can a net classify the percentage of testing and training patterns correctly?" if there is enough testing pattern available, then the net will generalise properly. Training patterns are determined by

$$\frac{W}{P} = e$$

Data Representation: In some cases, input and output vectors same range values in some components. This is because of the fact that a single factor in the weight correction expression is the activation of the lower unit whose activation function is zero. From this it is clear that learning may be improved if the inputs can be represented in the bipolar form and bipolar sigmoid function is used [4].

In the applications of the neural network, data may be represented in the form of continuous valued variable or a set or ranges. Consider an example the temperature of a food can be represented by the actual temperature or by the ranges of temperature like: hot, room temperature, chilled and frozen. This can be represented in neural network with the former case stating a single neuron could be used in general and in later case four neurons each with bipolar values could be appropriate.

Neural Network Implementation: Artificial Neural Network can be built using analog, digital or hybrid electronic hardware. Neurocomputing algorithms can be implemented in dedicated or general purpose. One of the commercial neurocomputer involves simulation of error back-propagation. In conventional programmable host computer, neurons are trained. The digital circuitry performs subsequent transfer and storage of weights which result from the training [14].

However, through analog computation information stored in the network is recalled within the electronic circuitry. Fast recall is performed by the network based on some features. Those features are the analog computation mode and parallel form of information processing. Numerical simulation is done in off chip in the neurocomputer. Digital transfer and data storage circuitry and a dedicated analog neural network perform a recall [15-18].

The most commonly encountered operations are scalar and outer product vector multiplication and matrix vector multiplication [19-22]. These operations are performed are as a series of multiply and add operations. Generation of the non-linear activation function involves additions and subtractions of matrices and vectors and ordinary multiplications and they, are less frequent, but are also indispensible for most learning and recall task.. Efficiency of training can be improved by the following reasons [5].

- Programmable computers have dedicated hardware architectures.
- Parallel architectures of densely connected neural nodes contains multiply and multiply-add procesors.
- By using generalization property of networks, training data volume data is reduced.
- Design of Neurocomputing IC is done by analog, digital or digital/analog arrays.

Sequence of steps are illustrated in fig 4 showing the problem-algorithm-model flowchart. Alternatively, the users problem can be transferred directly to the artificial neural system model for execution but sometimes artificial neural system model is done through modelling of the algorithm after neural processing of algorithm. Solution is obtained by processing the artificial neural system model [6].

RESULTS

Matlab 7.12.0 have been used for clustering the flower with 10 two dimensional array and 20 two dimensional array and the results of the Self Organizing Map Topology, Self Organizing Map Neighbour connections, Self Organizing Map neighbor weight distances, Self Organizing Map Hits, Self Organizing Map weight positions are comared and the results are shown below.

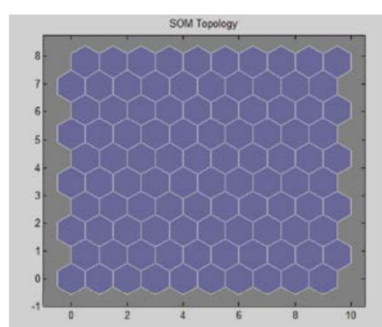

Fig. 1:

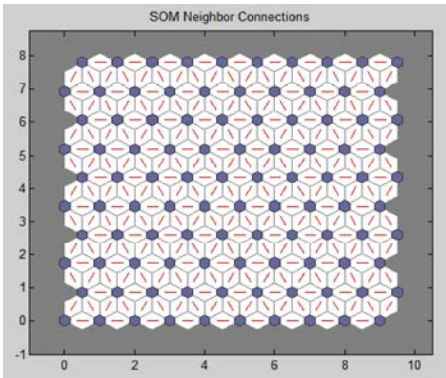

Fig. 2:

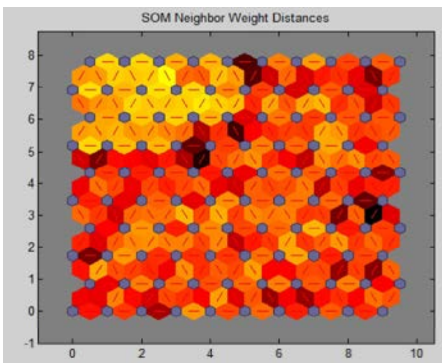

Fig. 3:

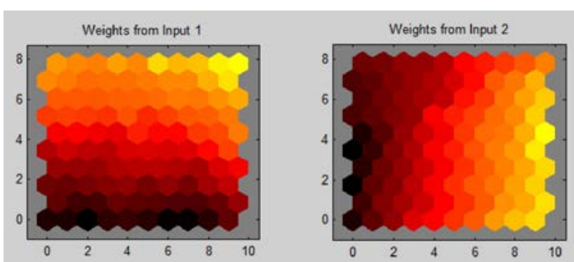

Fig. 4:

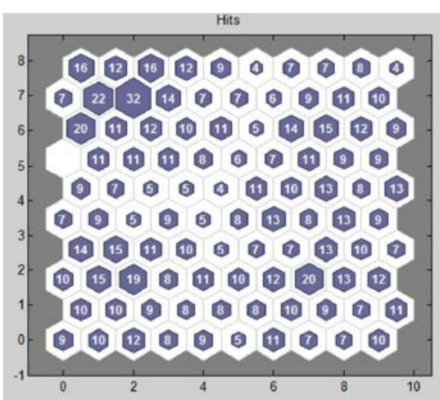

Fig. 5:

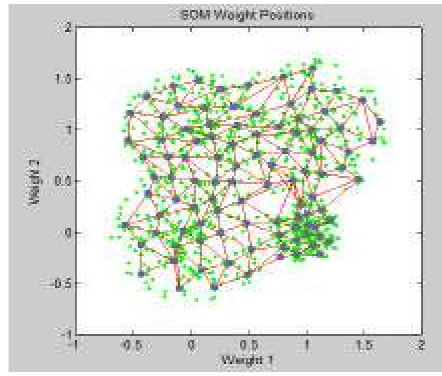

Fig. 6:

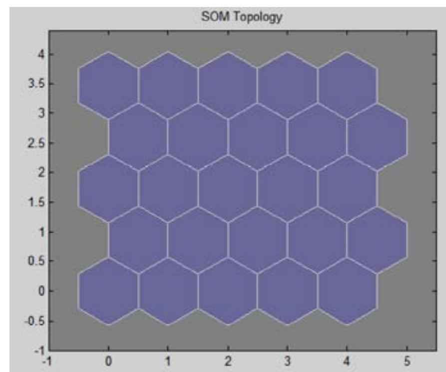

Fig. 7:

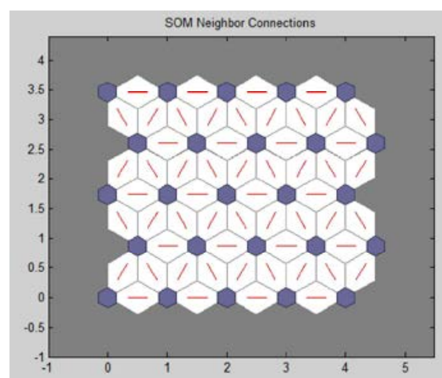

Fig. 8:

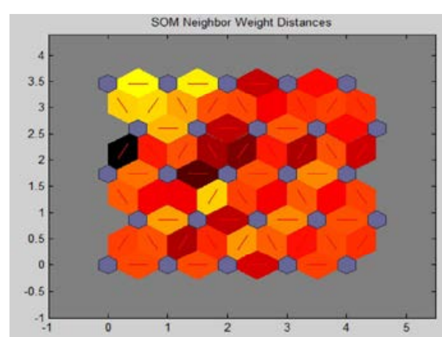

Fig. 9:

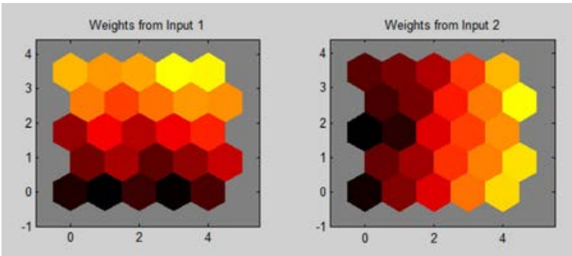

Fig. 10:

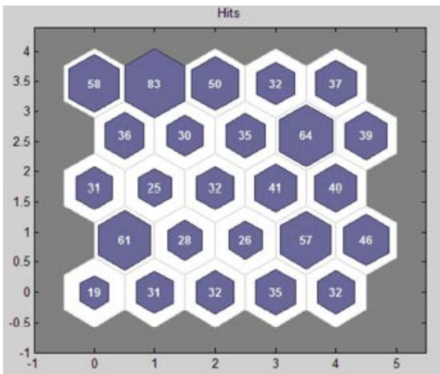

Fig. 11:

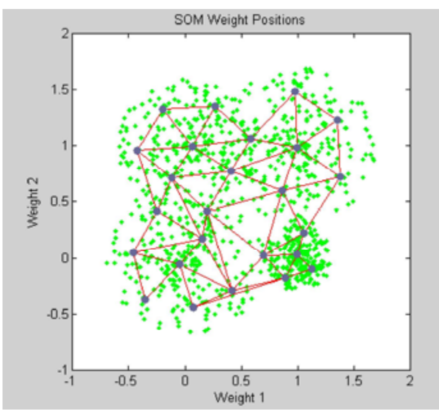

Fig. 12:

DISCUSSION

The work done in this paper evaluates the comparison of the clustering techniques with various two dimensional arrays. This could be extended to the comparison of various medical images also [23-25].

CONCLUSION

Here, it is clearly shown that whenthe number of two dimensional array increases, topology increases and hence the weight of the neurons also increase. Hence there is a variation in the weight positions also.

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