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Using Self Organizing Feature Maps for Classification in RGB Images

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***Abstract*—**Artificial neural networks have gained a lot of interest as empirical models for their powerful representational capacity, multi input and output mapping characteristics. In fact, most feed-forward networks with nonlinear nodal functions have been proved to be universal approximates. In this paper, we propose a new supervised method for color image classification based on self-organizing feature maps (SOFM). This algorithm is based on competitive learning. The method partitions the input space using self-organizing feature maps to introduce the concept of local neighborhoods. Our image classification system entered into RGB image. Experiments with simulated data showed that separability of classes increased when increasing training time. In additional, the result shows proposed algorithms are effective for color image classification.

***Keywords*—**Classification, SOFM, neural network, RGB images.

I. Introduction

In recent years, automatic image classification has been increasingly investigated [1]-[3]. However, the image classification and retrieval techniques are still immature due to many reasons. The approaches majority of image classification have addressed classification task using low-level image features such as color, texture, etc. Most of the works in this field were proposed [4]-[6] which concentrate on semantic classes such as indoor/outdoor, people/non-people, city, landscape, sunset, forest, etc. These are more general, consumer-level, semantic classes compared to the business-use oriented semantic classes that are used by other researchers. Another pertinent work concerns the separation of computer-generated graphic images, such as presentation slides, from photographic images [7]-[9]. The greater part of the approaches addressed image classification deals with pure color images and presumes homogeneity in the color content of the image scene, either explicitly or implicitly. However, real images bring out a wide range of heterogeneity in the color content. This variation of color information induces varying degrees of uncertainty in the information content. The ambiguity in image information emerging from the admixtures of the color components has often been dealt with the soft computing paradigm.

Artificial neural network (ANN) architectures have been increasingly employed to deal with many tasks of image processing especially image classification and retrieval. The neural classifier has the advantage of being fast (highly parallel), easily trainable and capable of creating arbitrary partitions of feature space [10]. However a neural network model, in the standard form, is unable to correctly classify images into more than two classes [11]. This is due to the fact that each of the component single neuron employs the standard bi-level activation function. Since the bi-level activation function produces only binary responses, the neurons can generate only binary outputs. So, in order to produce multiple color responses either an architectural or a functional extension to the existing neural model is required.

In this paper, a new approach for color image classification based on Self Organizing Feature Maps (SOFM) [12]-[14] model is presented. Self-Organizing Maps (SOFM) is a neural network procedure in which a layer of neurons is initialized with random weights, and subsequently organized by inspection of the data to be analyzed. The organization procedure uses progressive adjustment of weights based on data characteristics and lateral interaction such that neurons with similar weights will tend to spatially cluster in the neuron layer. The remainder of the paper is organized as follows. Section II reviews Self organizing Maps. Proposed algorithm is discussed in Section III. Section IV presents the simulation results of the proposed color image classification method and Section V closes with a conclusion

II. Background on Self Organizing Feature Maps

The principal goal of a SOFM developed by [15] is to transform an incoming signal pattern of arbitrary dimension into a one- or two- dimensional discrete map, and to perform this transformation adaptively in a topological ordered fashion. Typically, each input pattern presented to the network one at a time consists of a localized region, or "spot," of activity against a quiet background. Each such presentation causes a corresponding localized group of neurons in the output layer of the network to become active [13], introducing the concept of a neighborhood. A brief description of the SOFM from [16] follows to illustrate this concept of local neighborhood. Let, X denote a spatially continuous input space, the topology of which is defined by the metric relationship of the vectors $x \in X$. Let A denote a spatially discrete output space, the topology of which is endowed by arranging a set of neurons as (N) the computation nodes of a lattice. Let Q denote a nonlinear transformation called a feature map, which maps the input space X onto the output space A as shown by $Q: X \rightarrow A$. This may be viewed as an

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abstraction that defines the location of a winning neuron i(x) developed in response to an input vector x Given an input vector x the SOFM algorithm proceeds by first identifying a best-matching or winning neuron i(x) in the output space A in accordance with the feature map Q The synaptic weight vector Wi of neuron may then be viewed as a pointer for that neuron i(x) into the input space X. The ability of a self-organizing feature map to Q: 1) provide a good approximation of the input space 2) exhibit topological ordering (spatial location of a neuron in the lattice corresponds to a particular domain or feature of input patterns) and 3) provide density matching1 (regions in the input space X that have high probability density, pdf(x), are mapped onto larger domains of output space A makes it an excellent candidate to introduce the definition of a local neighborhood into feed forward neural networks. This does not preclude the use of other clustering algorithms. However, traditional clustering algorithms such as those driven by the standard - nearest-neighbor rule [17] do not exhibit density matching property and may lead to neighborhoods with significantly different populations (i.e., number of data points). This will influence the accuracy of estimation of covariance matrices for residuals in these neighborhoods, critical for accurate color image classification, as discussed later.

III. Proposed Algorithm

The proposed system is an intelligent for color image classification. This system contains two sequential steps: generate random color image and color image classification using SOFM algorithm.

A. Generate Random Color Image

In image processing, different models such as RGB, CMY and HIS are defined for each pixel of image. Each of these models has different application. One of the most application models is RGB which shows based on Cartesian model. For showing color image by this model, we need three numbers between zero and one. The first number shows the percent of red color(x), the second number shows the percent of green color(y) and last number shows the percent of the blue color (z) in making desired color. As an example, we should use the coordinate (0, 0, 0) and (1, 1, 1) for shows black and white colors respectively [18]. In this paper, input image of the SOFM algorithm is consisted of blue, green and red colors images which are generated randomly in this image.

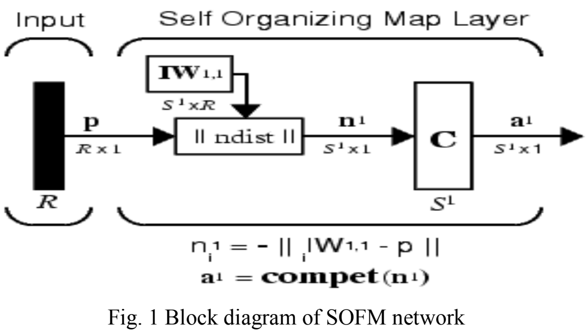

Fig. 1 Block diagram of SOFM network

B. Color Image Classification Using SOFM Algorithm

Fig. 1 indicates the block diagram of SOFM network [19]. This network contains two layers. The first layer is related to input models and dimension of R*1. In this paper, R is represents the number of existed classes in the image. Second layer contain self-organizing feature map. In this layer contain neurons and competitive layer.

Training of network coefficients is performed using:

$$W_{i,j}(new) = W_{i,j}(old) + a(N)T(N)(P_j - W_{i,j}(old)) \qquad (1)$$

Wij is defined as network coefficient in the SOFM algorithm. For starting the algorithm Wij are chosen randomly as shown in the result. Pj denotes the samples which are chosen in each step of network training of input image. In this paper j represents the number of existed classes in the input image and N represents the number of repetitions which is trained using SOFM network. T and a(N) are Also training coefficients which are obtained using:

$$a(N) = a_0 e^{(-\frac{N}{T_a})} \qquad (2)$$

$$T(N) = e^{(-\frac{I^2}{S(N)})} \qquad (3)$$

where S(N) is calculated by:

$$S(N) = S_0 e^{(-\frac{N}{T_s})} \qquad (4)$$

where T_a and T_s are obtained experimentally. S_0 is also calculated by:

$$S_0 = \frac{NPI}{3} \qquad (5)$$

where NPI is Neighborhood Prim Iteration. Another kind of neighborhood is rectangular neighborhood which is shown in Fig. 3 which oneness, dual and third neighborhoods rectangular are shown. In this paper rectangular neighborhood is used where I is defined as neighborhood. Neighborhood shows the distance between the wined neurons and the neighborhood neurons. In Fig. 2 circular neighborhood are shown. Fig. 2 (a) represents oneness circular neighborhood and Fig. 2 (b) represent third circular neighborhood. We should take attention on choosing the kind of neighborhood and the number of neighborhood. Lowering the number of neighborhood leads to of less neurons in adjacent to neighborhood of wined neuron. So network is converging very soon and less neuron are being trained. If the number of neighborhood chosen very big, the number of neighborhood in adjacent to winner neurons increased. Therefore, the coefficient which have been trained before, are being varied certainly by a new input. So this network needs more time for training. At the first in the executing of the SOFM algorithm, the coefficient of training network is chosen randomly for each model. Then, a pixel is chosen randomly from the input image. This pixel is an input of SOFM network. Therefore:

$$Pattern = [P1 \quad P2 \quad .....P_j] \tag{6}$$

We then apply that on the network after normalizing the pattern matrix as:

$$A = \sum_{i=1}^{j} P_i W_i \tag{7}$$

After considering A, we calculate settling of wined neurons by:

$$[u \quad v] = find\ (A = \max(A)) \tag{8}$$

In (8), u and v are considered as the place of row and Column of wined neurons respectively. It is possible that many neurons are wined in this network. So for only choosing one neuron from the wined neurons, we choose the neuron which is in the center of the wined neurons. This work is a tasteful work. In this paper we select the wined neurons using:

$$R = \frac{\min(u) + \max(u)}{2} \tag{9}$$

$$C = \frac{\min(v) + \max(v)}{2} \tag{10}$$

In (9) and (10), R and C represent the place of row and column of wined neuron respectively. In the next step of SOFM algorithm, coefficient the wined neuron and its neighborhood should be trained (The number of neighborhood of wined neuron is usually determined experimentally). The coefficient of Wj is corrected by the use of equation 1. Then, SOFM algorithm repeated by new training coefficient again. This algorithm is executed according to the number of repetition which is considering for it. If the number of repetition algorithm increased, the coefficient of Wj is trained better. After finishing SOFM algorithm, output of coefficient Wj represent one class in the input image.

IV. Result

To evaluate our novel method, random color images are used in experiment. Fulfillment of this system is performed using the MATLAB software. In Fig. 4 a random color image of pixel 500*500 is shown. This image based on RGB image and colors locations red, green and blue are selected randomly. In Fig. 5, the color image consists of square pixel 10*10. So each square is red, green or blue colors. Therefore we have 2500 square of pixel 10*10 in this image. In this paper, the image is designed a way that 50% are red pixels, 30% are blue pixel and 20% are green pixels.

We have 2500 square of 10*10. Therefore, 2500 neurons are utilized to settle them in a 50*50 matrix. According to this point, the input image has three classes (red, green and blue). Therefore for each class, we consider a 50*50 matrix as the coefficient matrix (W1, W2 and W3). First, we choose the random coefficients. In Figs. 4 and 5, input image and the Matrix of coefficient of W1, W2 and W3 before training and after training (the number of repetition equal N=300000) are shown respectively.

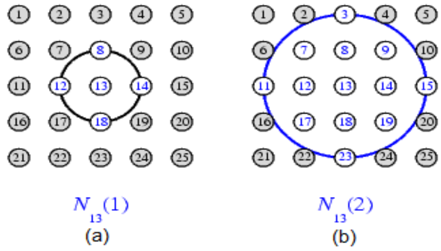

Fig. 2 Circular neighborhood in neuron 13

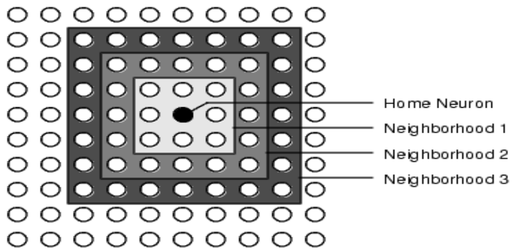

Fig. 3 Rectangular neighborhood in home neuron

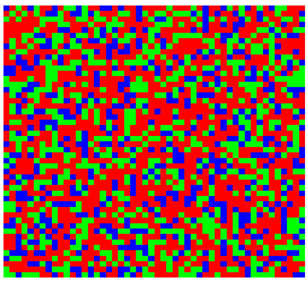

Fig. 4 Input image of SOFM algorithm

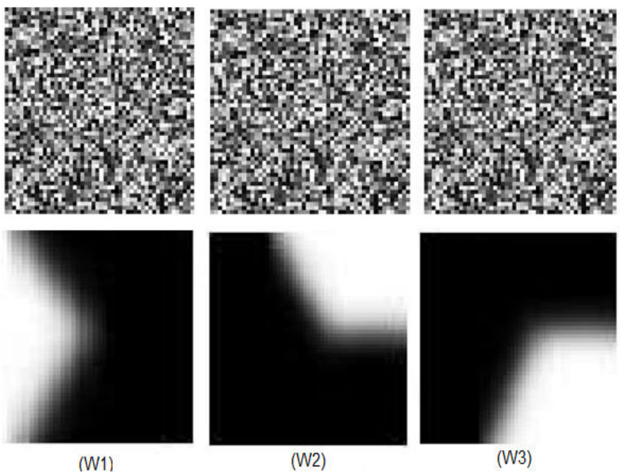

Fig. 5 Up-coefficient before training, bottom- final coefficient after training

In this paper, initial and final rate of a are selected 0.01 and 0.9 respectively. According to (5) and according to use of 26 neighborhoods, we have chosen primary amount of S as 0.8667. The last amount of S is also as 0.01. Ta and Ts are selected 44477 and 66666 respectively by substituting the initial and last amounts of a and S in equation 2 and 4 respectively (for N=300000). In Fig. 6 the output of SOFM algorithm according to different repetition are shown. According to Fig. 8, it has been considered that the number of repetition of coefficient training (Wj) is being trained better and as a better classification is confirm.

In Figs. 7 and 8 are shown the coefficients of W1, W2 and W3 before and after training for the number of repetition respectively. The results these figures show that the reliability of network is increased by increasing the number of repetition training algorithm.

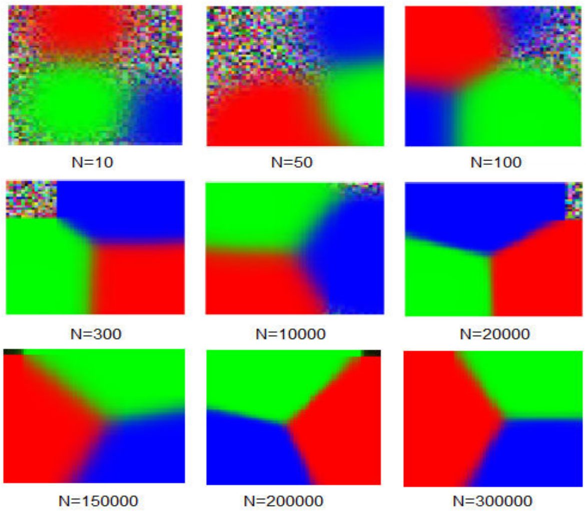

Fig. 6 Output SOFM network for different N

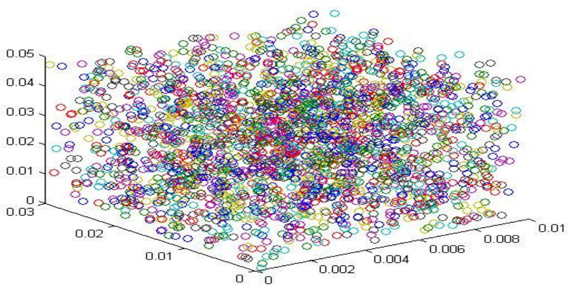

Fig. 7 Initial coefficient before training

V. Conclusion

In this paper, we have proposed a color image classification based on Self Organizing Feature Map (SOFM). In this algorithm, we perform the classification for the images which to form of the three main colors red, green and blue. We conclude based on the experiments where the training coefficients are the main factors in color image classification performance. The experimental results have portrayed the effectiveness of the proposed algorithm in color image classification. For future, with using our algorithm, we can be classified for images which more than three classes.

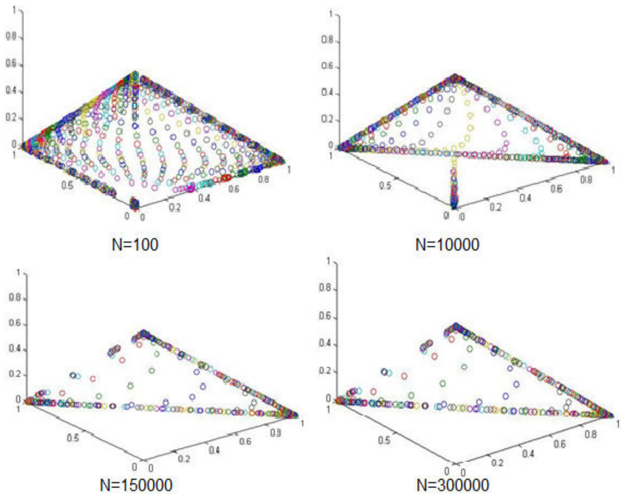

Fig. 8 Training coefficient for different N

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