Color Image Segmentation upon a New Unsupervised Approach using Amended Competitive Hebbian Learning

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Abstract: This paper proposes a new unsupervised color image segmentation procedure based on the competitive concept, divided into three processing stages. It begins by the estimation of the probability density function, followed by a training competitive neural network with Mahalanobis distance as an activation function. This stage allows detecting the local maxima of the pdf. After that, we use the Competitive Hebbian Learning to analyze the connectivity between the detected maxima of the pdf upon Mahalanobis distance. The so detected groups of Maxima are then used for the segmentation. Compared to the K-means clustering or to the clustering approaches based on the different competitive learning schemes, the proposed approach has proven, under a real and synthetic test images, that does not pass by any thresholding and does not require any prior information on the number of classes nor on the structure of their distributions in the dataset.

1 INTRODUCTION

The aim of automatic classification is to partition a set of observations into groups or classes such as observations belonging to the same class are more similar than those belonging to different classes (Eddarouich and Sbihi, 2007).

For the multidimensional data classification methods (Muthanna et al., 2010; Hammouche et al., 2005; Verikas et al., 1996), cluster analysis techniques attempt to separate a set of multidimensional observations into groups or clusters which share some properties of similarity. The objects are generally represented by N-dimensional vectors of observed features. The statistical approach in cluster analysis postulates that the input patterns are drawn from an underlying probability density function (pdf), which describes the distribution of the data points through the data space. Regions of high local density, which might correspond to significant classes in the population, can be found from the peaks or the modes of the density function estimated from the available patterns (Devijver and Kittler, 1982). Then, the key problem is to partition the data space with a multimodal pdf into subspaces over which the pdf is unimodal (Mizoguchi and Shimura, 1976).

Among the most common applications of automatic classification is image segmentation. Color image segmentation is one of the most important pre-processing step towards image understanding, image compression and coding. It is a process that consists of partition the image into disjoint region as sets of connected pixels that are homogenous with respect one or more color characteristics (Uchiyama and Arbib, 1994).

Generally, most algorithms of segmentation treated are based on threshold selection or on parameters adjustment which may change the its results.

Considering the analogy between clustering and segmentation, the color image segmentation is achieved by pixel classification according to color features. It is generally assumed that homogeneous regions in the image correspond to clusters of color points in the color space. The sample of observations is composed of image pixels represented as data points scattered in a color space; it determines a partition of these points into subgroups in a way that makes points within a group more similar than points in different groups. In an unsupervised context, the number of these subgroups is not a priori known and has also to be determined.

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Amongst the non-classical methods, the application of artificial neural networks (ANN) is prominent. In recent years, motivated by the remarkable characteristics of the human visual system (HVS), research has applied ANNs to various problems in classification (Yeo et al., 2005). ANNs have several advantages over many conventional computational algorithms, among which the most important are parallelism, adaptability to different data sets and optimal performance.

Many clustering procedures based on modes detection concepts, have been proposed. In some of them, modes are considered as local maxima of the estimated probability density function and are detected by hill climbing procedures using some gradient search technique (Fukunagal and Hostler, 1975). As these procedures are based on differential operators, they face some difficulties where noise is present in the data set. In practical situations, they are known to generate a greater number of modes than the true pdf. Another approach is based on the analysis of the convexity properties of the underlying pdf. Modes are then considered as concave regions of this function and are detected by means of a test which determines, locally, the convexity of the multivariate pdf (Vasseur and Postaire, 1980; Moussa, Sbihi and Postaire, 2008). Although this approach yields more robust results than the previous one, it remains sensitive to local irregularities in the pattern distribution, especially for small data sets.

In this context, we are going to present a new unsupervised approach for the segmentation of color images based on the detection of the modes of multivariate probability density function (pdf) without using either differential operators or any procedures of filtering

The remainder of the paper is organized as follows. Section 2 presents the different steps of the proposed approach. Section 3 is consecrated to other results and discussion. The paper ends with a conclusion and perspectives.

2 THE MODES DETECTION PROCEDURE

The new algorithm of the modes detection is carried out in three processing stages. The first one consists in estimating the underlying pdf using a non-parametric estimator. In the second stage, we use an artificial neural network with competitive training (CNN) to extract the local maxima of the pdf. In the third stage, we develop a new technique for the detection of the interneural connection.

2.1 The Estimation of Underlying Probability Density Function

Let $\Gamma = \{X_1, X_2, ..., X_Q\}$, be the set of Q N-dimensional observations of a random variable X with a probability density function P(X).To estimate this underlying density function when what is available is only a set $X_q = \{x_{q,1}, x_{q,2}, ..., x_{q,n}, ..., x_{q,N}\}$, q=1,2,...,Q of Q observations, the analyst may use non-parametric techniques.

The Parzen (1962) window method proves well adapted to the proposed procedure in this paper. However, this estimation procedure needs prohibitive calculus when the dimension of the space is very important. So, we have opted for the fast estimation algorithm which is proposed by Postaire and Vasseur (1982).

First, the range of variation of each component of these observations is normalized to the interval [0, R], where R is an integer such as $R \geq 2$, by means of the transformation defined as:

$$y_{n,q} = \frac{\left(x_{n,q} - \min_q x_{n,q}\right)}{\left(\max_q x_{n,q} - \min_q x_{n,q}\right)} * R \quad (1)$$

Each axis of the so normalized data space is then partitioned into R exclusive intervals of unit width. This discretization defines a set of $\Re^N$ hypercube of unit side length. Each hypercube noted $H(X)$, is a site defined by its N coordinates $x_1, x_2, ..., x_n, ..., x_N$ which are the integer parts of the coordinates of its center X.

To be more specific, let $Y_q = [y_{1,q}, y_{2,q}, ..., y_{n,q}, ..., y_{N,q}]$, q=1, 2, Q be the Q observations in the normalized space. Each observation Yq is found inside a non-empty hypercube with the coordinates $x_n = \text{int}(y_{n,q})$, *n=1, 2, N*, where $\text{int}(y_{n,q})$ designates the integer parts of $y_{n,q}$. If several observations fall in the same hypercube, this one appears many times on the list of non–empty hypercubes. Furthermore, the number of times the hypercube H(X) appears in that list indicates the number of data points *q[H(X)]* which falls in this hypercube. Subsequently, the value of the local density estimated is:

$$p(X) = \frac{q[H(X)]}{Q} \tag{2}$$

Since the volume of *H(X)* is equal to unity.

So, this fast procedure allows only the estimation of the underlying probability density function at the centers of the non-empty hypercubes whose number never exceeds the number Q of available observations. At the centers of the hypercube cells, which are not on that list, the density estimates are known to be null. At the end of this fast algorithm, all the available information for clustering is in the discrete set $\underline{X}$ of estimated values of the underlying probability density function $p(X)$.

2.2 The Extraction of Local Maxima by Neural Network

Assimilating the modes to the local maxima of the pdf, the proposed approach uses the Neural Networks with Competitive Training (NNCT) (Eddarouich and Sbihi, 2007).

In the training algorithm, we work only on the pdf by presenting, sequentially, the centers of the non-empty hypercubes of the set **X** to the network, instead of the *Q* observations.

The neural network is composed of two layers: the input layer and the output layer (Cf. Fig.1). The first one is made of N units I_n, n=1,2,...,N, such that unit I_n is solicited by the attribute X_N of the non-empty hypercube H(X) when this one is presented to the network. However, each output neuron materializes an hypercube which represents the site of one local maximum of the pdf in the set **X**, and presents its weight by the mean vector $\mu_k(X)$, k=1,2,…,K. The number of the output neuron is first initialized arbitrary.

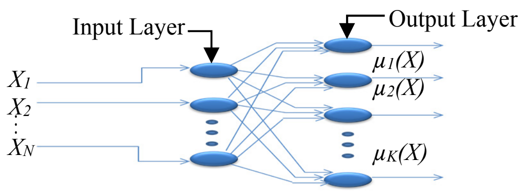


Figure 1: Competitive neural network.

During the training phase, The output neurons enter into competition with each other by comparing the distance D[μ_k(X), H(X)], k=1,2,…,K, between the input hypercube H(X) and each output neuron μ_k(X), the winner is the closest one to the hypercube, then we compare the values of the pdf associated to the winner neuron μ_g(X) and to H(X). The distance measure used in this learning algorithm is Mahalanobis distance that gives best results for the non Gaussian distribution (Timouyas et al., 2012) instead of Euclidian distance as in the (NNCT).

The following algorithm describes the different steps of the learning phase:

Training Algorithm:

Initialization Phase:

- Initialize the mean vectors $\mu_k(X)$; *k*=1, 2, K, of the K output neural, with an arbitrary choice of K non-empty hypercubes from the set X,
- Initialize the coefficients of the training function α_0 and τ . The choice of these parameters is not a real problem. We should only give a very important value to τ for the algorithm to search the sites of the local maxima before its convergence (Eddarouich and Sbihi, 2007).

Processing Phase:

1) Present to the network, with an arbitrary pulling, a non-empty hypercube H(X),
2) Search for the winner neuron *g* defined by calculating the distance that separate μ_k(X) and H(X) and seeking for the minimal distance:

$$D[\mu_k(X), H(X)] = \sqrt{(\mu_k(X) - H(X)) \sum\nolimits^{-1} (\mu_k(X) - H(X))} \tag{3}$$

Σ^{-1}. Inverse of covariance matrix.

3) Compare the fdp(μ_g(X)) and fdp(H(X)):
If fdp(μ_g(X)) < fdp(H(X)) update the parameters of the winner neuron as follow:

$$\begin{cases} \mu_g(X) = \mu_g^{t-1}(X) - \alpha(t)(H(X) - \mu_g^{t-1}(X) \\ fdp\left(\mu_g(X)\right) = fdp(H(X)) \end{cases} \tag{4}$$

Where t is the number of iterations and $\alpha(t)$ is a one of "search then converge" learning functions defined as:

$$\alpha(t) = \frac{\alpha_0}{1 + {}^{t}/_{\tau}} \tag{5}$$

Then go to step1. Else, go directly to step1,

4) Stopping criteria: after the processing of all hypercubes, compare $\mu_k^t(X)$ to $\mu_k^{t-1}(X)$ for k∈K.

If$(\mu_k^t(X) \neq \mu_k^{t-1}(X)) \forall \quad k = 1, 2, ..., K$, pass to the next iteration and go to step 1.

Else, end of the processing.

2.3 Detection of Significant Modes of Pdf

As the modes that are detected during the learning phase perfectly mark modal regions and are divided into a number equal to the number of classes present in the sample, we thought about connecting each groups of the closest modes in such a way that we get a map which preserves the shape and structure of the classes.

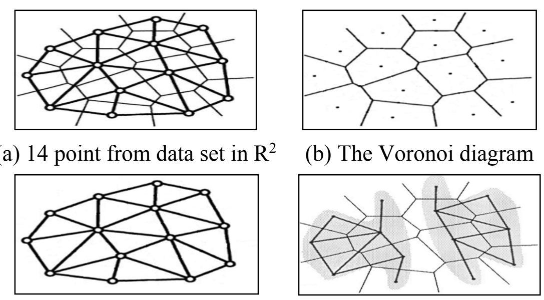
One of the perfect methods which forms topology preserving maps is Competitive Hebbian Learning (CHL) proved by Martinetz (1993). The basic principle which governs the change of interneural connection strength been formulated by Hebb (1949). According to Hebb's postulate, a presynaptic unit i increases the strength of synaptic link to a postsynaptic unit j if both units are concurrently active (Martinetz, 1993).

CHL is usually not used on its own but in conjunction with other method derived as Neural Gas plus Competitive Hebbian Learning (Martinetz, 1993) and Growing Neural Gas (Fritzke, 1995).

Let $F=\{H(X_1),H(X_2),...,H(X_K)\}$, be the set of K hypercubes which represent the sites in $\underline{X}$ of the K detected local maxima; the output of CNN. In this phase, we are going to seek the interneural connection of these modes using a new method of Competitive Hebbian Learning adapting Mahalanobis distance as measure of resemblance.

The clustering in CHL is based on three concepts. Firstly, the Vector Quantization (VQ), which is searching for centroids as density points of nearby lying samples, it can be also directly used as prototype-based clustering method: each centroid is then associated to one prototype. By aiming to minimize the expected squared quantization error (Gray, 1984).

The second and third concepts are Voronoi diagram and the Delaunay triangulation illustrated below:



(a) 14 point from data set in R^2 (b) The Voronoi diagram

(c) The Delaunay triangulation (d) The induced Dt

Figure 2: The detection of the induced Dt by masking the Delaunay triangulation with the data set.

The Voronoi diagram V_F of a set $F=\{H(X_1),H(X_2),...,H(X_K)\}$ of hypercubes $H(X_i) \in R^N$ is given by K N-dimensional polyhedra, the Voronoi polyhedra V_i, which is defined as follows: The Voronoi polyhedron V_i of a hypercube $H(X_i) \in F$ is given by the set of hypercubes $v \in R^N$ which are close to $H(X_i)$ than any other $H(X_j) \in F$ for $i \neq j$ (Martinetz and schulten, 1994) :

$$V_i = \{v \in R^N \mid \|v - H(X_i)\| \leq \|v - H(X_j)\| \; \forall j\} \quad (6)$$

The dual graph of Voronoi diagram is Delaunay triangulation Dt (Delaunay, 1934), it's the connection of all pairs $H(X_i)$, $H(X_j) \in F$, where the circumcircles of the triangles consisting of each of 3 hypercubes of the set, such that no hypercube in F is inside.

The Dt is also the graph where hypercubes with a common Voronoi edge V_i and V_j are connected by an edge, that is (Martinetz & schulten, 1994):

$$Dt(F) = \{i, j = 1, \dots, K \mid V_i \cap V_j \neq \emptyset\} \quad (7)$$

To generate the induced Delaunay triangulation (Fig. 2(a)), competitive Hebbian learning, given the K modes detected by CNN as prototypes in R^N, successively adds connections among them. The method does not change the weight of prototypes, but only generates topology according to these prototypes. For each mode $H(X_k)$, its two closest prototypes are connected by an edge using Mahalanobis distance (3) as measure of resemblance instead of Euclidian distance, it works as an activation function for competition between neurons. This leads to the induced Delaunay triangulation, which is limited to those regions of the input space R^N.

3 RESULTS AND DISCUSSION

To illustrate the behavior of the procedure, we present two examples. The first one is a synthetic image constituted of 4 regions of colors in different shapes. The three RGB components, coded on 256 levels, constitute the axes of the coordinates of the representation space of the image pixels (fig. 3(a)).

The proposed procedure of the pdf modes detection of the observations sample in figure 3.b permits to extract the six related regions with the resolution parameter R=30.

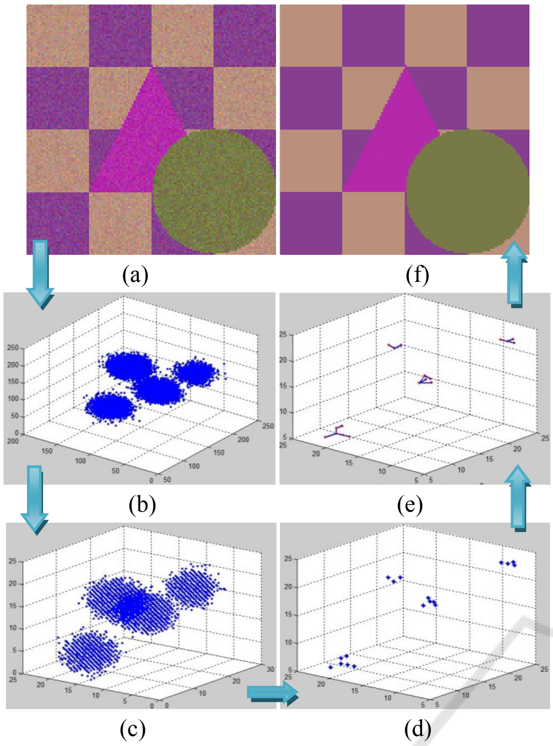


Figure 3: (a) Original color image; (b) Pixels in the RGB color space; (c) Estimation of the underlying pdf; (d) Prototypes in the RGB color space; (e) Prototypes connected by edges; (f) Segmented color image.

This figure provides the clear idea about the different steps of the proposed method. Below we illustrate separately the 4 classes of the image:

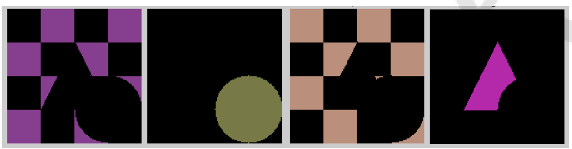


Figure 4: the four classes of the image.

As shown, the proposed technique success to detect the four groups of connected neurons presenting the four classes in the image (fig. 3(e)) and have been used to get the segmented image (fig. 3(f)).

Now, we will apply the approach on a real color image, with a significant overlapping degree, constituted of five homogeneous regions with different shapes:

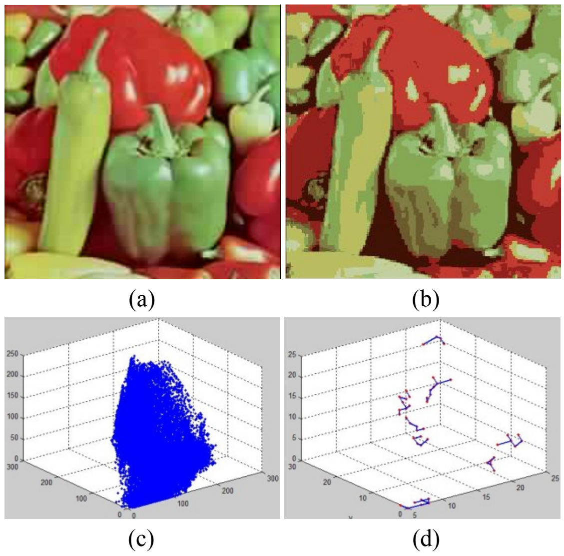


Figure 5: (a) Original pepper image; (b) Segmented pepper image; (c) Pixels in the RGB color space; (d) Prototypes connected by edges defining 8 classes in 8 iterations.

Despite the difficulty of the treatment of this image where the various clusters present a significant overlapping degree in the RGB color space (fig.5(c)), the use of the Mahalanobis Metric as criterion of resemblance, allows the proposed approach to give more powerful results compared to the Neuromemetic approach.

In order to prove the approach's efficiency more, we evaluate the homogeneity in the image compared to K-means result applying on the same image by the experimental parameters exposed below:

Table 1: Statistical parameters of the two methods.

Parameters	K-Means	Proposed method
avg voxel intensity	45.764	47.0573
Std Dev	21.6	19.3433
Coeff Var	47.21%	41.106%

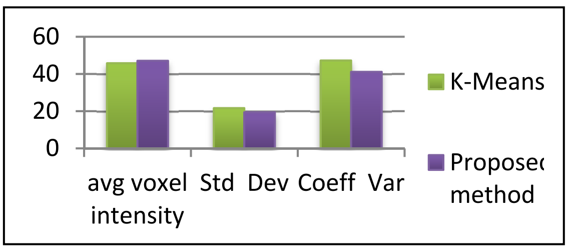


Figure 6: Comparison of statistical parameters.

The image segmented by the suggested procedure is most consistent because of its lower standard deviation and higher average voxel intensity, which is clearly proved by its lower coefficient of variance compared to the K-means result. Hence, the proposed procedure demonstrates its accuracy in color image segmentation, knowing that this method has all advantages of artificial neural network mentioned before.

In spite of that, The Mahalanobis Distance has a higher execution time than Euclidian Distance because of its processing complexity but the nearest-neighbor search can be performed in only O(LogN) instead of O(N) time by exploiting the Delaunay triangulation (Knuth, 1973). Also, with this so reduced number N of neurons, the proposed detection of modes procedure stays faster than this phase in both Neuromimetic and Neuromorphological procedures (Timouyas et al., 2014). Although, our aim to further minimize the execution time of the new approach in overall.

4 CONCLUSIONS

In this paper, a new approach of unsupervised color image segmentation has been introduced, based essentially on neural network concepts.

In order to conceive an unsupervised classification procedure, we have searched to connect the detected local maxima, by CNN, in such away, every connected set of neurons represents a class, using the Competitive Hebbian Learning.

The proposed procedure permits good unsupervised image color segmentation without resorting to any thresholding and does not require any priori information about the number of classes nor about the structure of their distributions in the sample.

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