

One-Dimensional Kohonen Networks and Their Application to Automatic Classification of Images

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Abstract - We describe an application of 1-Dimensional Kohonen Networks to the classification of color 2D images which has been evaluated in Popocatepetl Volcano's images. The Popocatepetl, located in the limits of the State of Puebla in México, is active and under monitoring since 1997. We address the question if our application of the Kohonen Network classifies according to the total intensity color of an image or, if it classifies according to the connectivity, i.e. the topology, between the pixels that compose an image. To support the hypothesis that our system classifies according to the topology of the pixels in the images, we will present two approaches based a) in the evaluation of the classification given by the network when the pixels in the images are permuted; and, b) when an additional metric to the Euclidean distance is introduced.

Index Terms – 1-Dimensional Kohonen Networks, Automated Image Classification, Metrics on Euclidean Spaces, Non-Supervised Classification.

INTRODUCTION

It is well known the use of 1-Dimensional Kohonen Networks in non-supervised classification of data with an elevated redundancy degree [5]. On the other hand, non-supervised image classification is an important vision task where images with similar features are grouped in classes. Many processing tasks (description, object recognition or indexing, for example) are based on such preprocessing [9]. In this paper, we consider these ideas in order to apply Kohonen Networks to provide solutions to automatic classification of images. The paper is organized as follows: Section I describes basic concepts of 1-Dimensional Kohonen Networks, Section II describes some procedures to take in account in order to avoid training bias, Section III describes procedures and applications related to the classification of 2D color images through Kohonen networks results and discussion, Section IV presents conclusions and future work.

I. FUNDAMENTALS OF THE 1-DIMENSIONAL KOHONEN NETWORKS

A. Classifying Points Embedded in a n -Dimensional Space Through a 1-Dimensional Kohonen Network

A Kohonen Network with two layers, where the first one corresponds to n input neurons and the second corresponds to m output neurons ([4], [8]) can be used to classify points embedded in a n -dimensional space in m categories. The input points have the form $(x_1, \dots, x_i, \dots, x_n)$. The total number of connections of neurons in the input layer to neurons in the output layer will be $n \times m$ (See Figure 1). Each neuron j , $1 \leq j \leq m$, in the output layer,

will have associated a n -dimensional weight vector which describes a representation of class C_j . All these vectors have the form:

$$\text{Output neuron 1: } W_1 = (w_{1,1}, \dots, w_{1,n})$$

\vdots

$$\text{Output neuron } m: W_m = (w_{m,1}, \dots, w_{m,n})$$

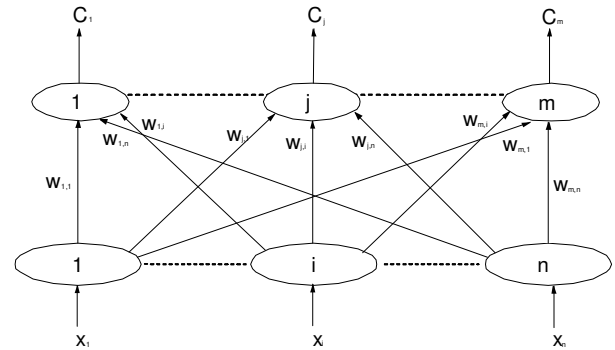


Fig 1. Topology of a 1-dimensional Kohonen Network [5].

B. Training the 1-dimensional Kohonen Network

A set of training points are presented to the network T times. According to [5], all values of weight vectors can be initialized with random values. In that neuron whose weights vector W_j , $1 \leq j \leq m$, is the most similar to the input point P^k is chosen as winner neuron, for each t , $0 < t < T$. Such selection is based on the squared Euclidean distance. The selected neuron will be that with the minimal distance between its weight vector and the input point P^k :

$$d_j = \sum_{i=1}^n (P_i^k - w_{j,i})^2 \quad 1 \leq j \leq m \quad (1)$$

Once the j -th winner neuron in the t -th presentation has been identified, its weights are updated according to:

$$w_{j,i}(t+1) = w_{j,i}(t) + \frac{1}{t+1} [P_i^k - w_{j,i}(t)] \quad 1 \leq i \leq n \quad (2)$$

When the T presentations have been achieved, the final values of the weights vectors correspond to the coordinates of the 'gravity centers' of the points, or clusters of the m classes.

II. REDISTRIBUTION IN THE n -DIMENSIONAL SPACE OF KOHONEN NETWORK'S TRAINING SET

To avoid training bias, the training data used for the experiments presented here needs to be redistributed. Consider a set of points distributed in a 2D subspace defined by rectangle $[0,1] \times [0,1]$. Moreover, this set of points is embedded in a sub-region delimited, for example, by rectangle $[0.3,0.6] \times [0.3,0.6]$ (Figure 2).

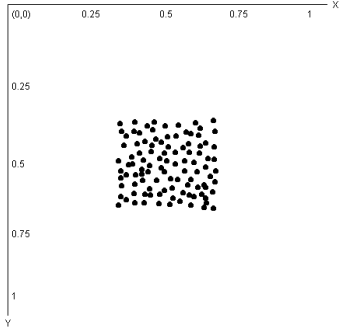


Fig. 2. A set of points embedded in $[0.3,0.6] \times [0.3,0.6] \subset [0,1] \times [0,1]$.

Because the points are not uniformly distributed in the 2D space, we can expect important repercussions during their classification process. For example, for a number of classes, we can obtain some clusters that coincide with other clusters or classes without associated training points. Next we present a simple methodology to distribute uniformly the points of a training set for the general case of a n -dimensional space.

Consider a unit n -dimensional hypercube H where points are embedded in their corresponding minimal orthogonal bounding *hyper-box* h such that $h \subseteq H$. The point with the minimal coordinates $P_{\min} = (x_{1_{\min}}, x_{2_{\min}}, \dots, x_{n-1_{\min}}, x_{n_{\min}})$ and the point with the maximal coordinates $P_{\max} = (x_{1_{\max}}, x_{2_{\max}}, \dots, x_{n-1_{\max}}, x_{n_{\max}})$ will describe the main diagonal of h . We proceed to apply to each point $P = (x_1, x_2, \dots, x_{n-1}, x_n)$ in the training set, including P_{\min} and P_{\max} , the geometric transformation of translation given by:

$$x'_i = x_i - x_{i_{\min}} \quad 1 \leq i \leq n \quad (3)$$

By this way, we will get a new *hyper-box* h' and the points that describe the main diagonal of h' will be $P'_{\min} = \underbrace{(0, \dots, 0)}_n$

$P'_{\max} = (x'_{1_{\max}}, x'_{2_{\max}}, \dots, x'_{n-1_{\max}}, x'_{n_{\max}})$. See Figure 3.

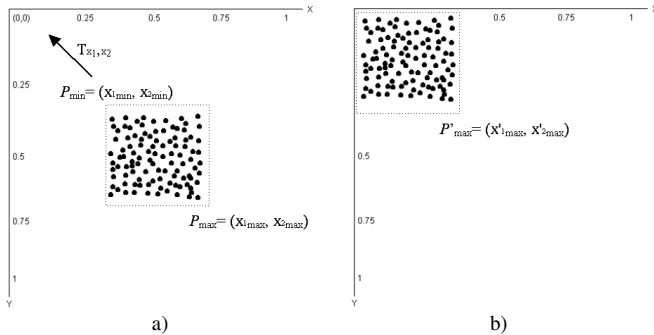


Fig. 3. a) A training set and its minimal orthogonal bounding *hyper-box* h .
b) Translation of h and the training points such that P'_{\min} is the origin of the 2D space.

The second part of the distribution procedure consists in the extension of the current *hyper-box* h' to the whole n -dimensional hypercube H . The scaling of a point $P = (x_1, x_2, \dots, x_{n-1}, x_n)$ is given by multiplying their coordinates by factors S_1, S_2, \dots, S_n each one related with x_1, x_2, \dots, x_n respectively in order to produce the new scaled coordinates x'_1, x'_2, \dots, x'_n [6]. Because the goal is to extend the bounding *hyper-box* h' and the translated training points to the whole unit hypercube H , by scaling the point

$P'_{\max} = (x'_{1_{\max}}, x'_{2_{\max}}, \dots, x'_{n-1_{\max}}, x'_{n_{\max}})$ we must obtain the new point $\underbrace{(1, \dots, 1)}_n$. That is to say, we define the set of n equations:

$$1 = x'_{i_{\max}} \cdot S_i \quad 1 \leq i \leq n \quad (4)$$

Starting from these equations we obtain the scaling factors to apply to all points included in the bounding *hyper-box* h' (see Figure 4):

$$S_i = \frac{1}{x'_{i_{\max}}} \quad 1 \leq i \leq n \quad (5)$$

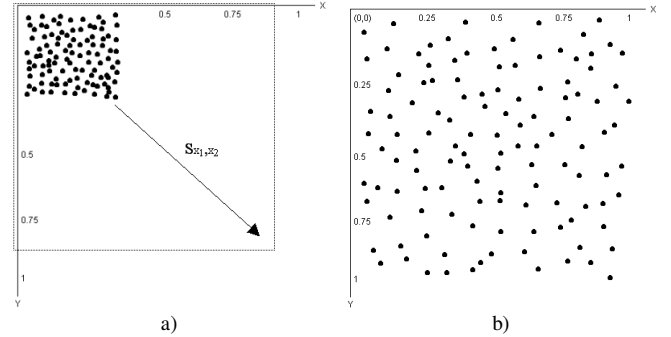


Fig. 4. a) Applying to the translated training set scaling factors such that it will be (b) redistributed to the whole 2D space.

Finally, each one of the coordinates in the original points of the training set must be transformed in order to be redistributed in the whole unit n -dimensional hypercube $[0,1]^n$ through:

$$x'_i = (x_i - x_{i_{\min}}) \cdot \left(\frac{1}{x'_{i_{\max}}} \right) \quad 1 \leq i \leq n \quad (6)$$

III. IMAGE CLASSIFICATION THROUGH 1-DIMENSIONAL KOHONEN NETWORKS

A. Representing Images through Vectors in \mathcal{R}^n

Let m_1 (rows) and m_2 (columns) be the dimensions of a two-dimensional image. Let $n = m_1 \cdot m_2$. Each pixel in the image has associated a 3-dimensional point (x_i, y_i, RGB_i) such that $RGB_i \in [0, 16777216]$, $1 \leq i \leq n$, where RGB_i is the color value associated to the i -th pixel (assuming that the color of pixels are based in the color model RGB). The color values of the pixels will be normalized such that they will be in $[0.0, 1.0]$ through the transformation:

$$normalized_RGB_i = \frac{RGB_i}{16777216} \quad (7)$$

Basically, we will define a vector in the n -Dimensional space by concatenating the m_1 rows in the image considering for each pixel its normalized color RGB value. By this way each image is now associated to a vector in the n -dimensional Euclidean space. Due to the color values normalization the scalar values in such vectors will be in $[0,1]$. By this way, a set of training images to be applied in a Kohonen Network will be embedded in a unit n -Dimensional hypercube once they have been transformed to their respective associated vectors.

B. Classifications Results

Our training set contains 148 images selected from *CENAPRED* [3] files. These images represent some of the Popocatepetl volcano

fumaroles during the year 2003. The volcano is located in the limits of Puebla state in México; and it is active and under monitoring since 1997. The selected images have an original resolution of 640×480 pixels and 24-bits color under format compression JPG.

We present the results obtained by three 1-Dimensional Kohonen Networks with different topologies (in each case, we applied a scaling to the 148 original images):

- Network Topology τ_0 :
 - Images Resolution: 112×64
 - Input Neurons: $n = 112 \times 64 = 7,168$
 - Output Neurons (classes): $m = 20$
 - Presentations: $T = 10$
- Network Topology τ_1 :
 - Images Resolution: 56×32
 - Input Neurons: $n = 56 \times 32 = 1,792$
 - Output Neurons (classes): $m = 30$
 - Presentations: $T = 1,000$
- Network Topology τ_2 :
 - Images Resolution: 260×180
 - Input Neurons: $n = 260 \times 180 = 46,800$
 - Output Neurons (classes): $m = 25$
 - Presentations: $T = 500$

The set of 148 training points (images) were presented a number of times according to the corresponding topologies. The training procedures were applied as described at Section II. All the weights vectors were initialized to 0.5.

Figure 5 shows the classification of the training images using the three proposed topologies. The figures show the distribution of the 148 training images in each one of the classes.

C. Intensity Based Classification Vs. Classification Based in the Topology of Pixels in the Images

One of the problems to consider is related with the question if our implementations of the Kohonen Networks classify according to the total intensity color of an image or well, if they classify according to the connectivity, i.e. the topology, between the pixels that compose an image. In order to give arguments that support our hypothesis that our procedures get the classification according to the topology of the pixels in the images, we have developed two approaches:

- An approach (section III.C.1) based in a classification of the training images but when their pixels are attached to a specific permutation. If our implementation classifies by color intensity, then we can expect a distribution of the images in the classes which would be similar to the distributions presented before permutation, as in Figure 5.
- An approach (section III.C.2) based in the distances between the weights vectors associated to each output neuron. The clusters themselves are 2D color images if we apply in an inverse way the procedure described in section III.A. In this approach we will use an additional metric that guarantee the comparison of images only by their color intensity. According to the Kohonen Network training algorithm, the clusters (classes representatives) have been distributed uniformly in an unit n -Dimensional hypercube. Such distribution implies, in an implicit way, the fact that each cluster has itself specific characteristics that allow distinguishing its respective class among other classes. By applying the new proposed metric, we can expect that the distances provided by it indicate us a considerable proximity between clusters, hence, they have similar color intensities. Moreover, this last result should

establish a considerable distinct distribution respect to the distribution indicated by the Euclidean metric. In the case that Kohonen Network classifies only by color intensity, then the clusters distribution reported by both metrics should be similar.

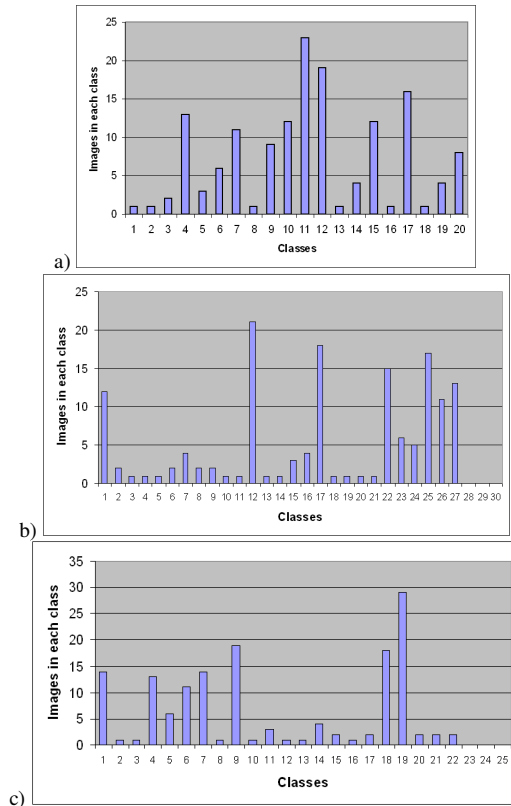


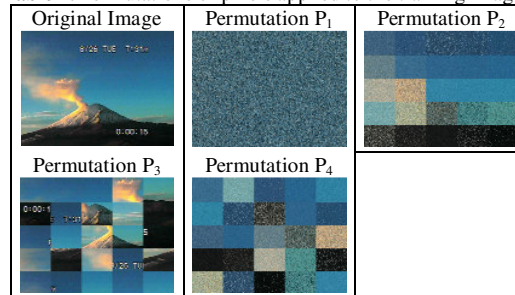
Fig. 5. Classification of the 148 training images according to Network Topology a) τ_0 , b) τ_1 and c) τ_2 .

C.1 Permutation of Pixels in the Training Images

(See Table 1 for examples of the permutations we describe here.)

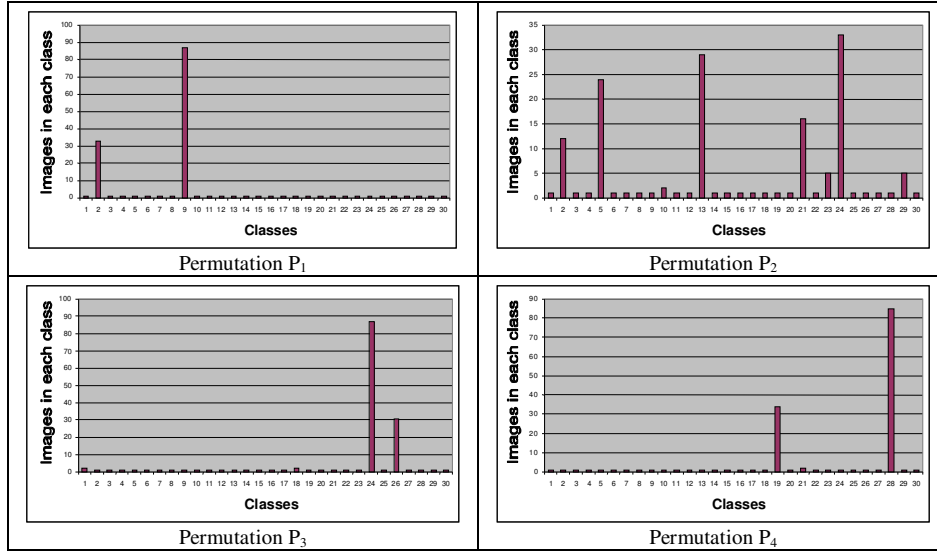
- P_1 : Random permutation of all the pixels in the image.
- P_2 : Division of the image in 25 rectangular regions and random permutation of the pixels in each region.
- P_3 : Division of the image in 25 rectangular regions and random permutation of such regions.
- P_4 : Division of the image in 25 rectangular regions, random permutation of the pixels in each region and random permutation of the regions.

Table 1. Permutations of pixels applied to the training images.



Consider to network topology τ_1 . In the cases of permutations P_1 , P_3 and P_4 , we can observe in their corresponding charts (Table 2)

Table 2. Distribution of the training images in the classes of network topology τ_1 .



grouped the 80% of training images. The results using permutation τ_2 differs from others by the property that the 80% of training images are grouped in seven classes with more than 5 images each one. From an informal point of view, permutation P_2 can be considered visually as a permutation that preserved, compared with the remaining permutations, the connectivity of the pixels respect to the original training images. This is because if we increment the number of rectangular regions (more regions than those in permutation P_2) and permute its corresponding pixels, as the number of regions increase the corresponding image will approximate to the original image. In fact, the original images can be seen as images divided in regions with only one pixel each one; obviously, the permutation of the pixel in each region leave to the image in its original state.

C.2 Analysis Based in an Additional Metric over \mathfrak{R}^+

Definition 1 ([1] & [2]): Let $x, y \in \mathfrak{R}^+$. Let ρ be the function described as

$$\rho(x, y) = \begin{cases} 1 - \frac{x}{y} & \text{if } x < y \\ 1 - \frac{y}{x} & \text{if } y < x \\ 0 & \text{if } x = y \end{cases} \quad (8)$$

Such function is in fact a metric over \mathfrak{R}^+ . See [7] for more details.

Let I be an image. We know that each one of its pixels p_i will have associated a vector (x_i, y_i, RGB_i) , $i \in [1, n]$, $RGB_i \in [0, 16777216]$. Lets assume that the dimensions of each pixel are equal to one. We will define to the Total Intensity of I , denoted by $T(I)$, as follows:

$$T(I) = \sum_{i=1}^n RGB_i \quad (9)$$

Let I_A and I_B be two images with the same geometrical dimensions. Let $T(I_A)$ and $T(I_B)$ be their corresponding Total

the fact that once the training process has finished two classes

Intensities. Because $T(I_A), T(I_B) \in \mathfrak{R}^+$ we can determine its distance through metric ρ .

Now, we will define the similarity between images I_A and I_B according to the value of $\rho(T(I_A), T(I_B))$. Let $0 \leq \epsilon < 1$ be an arbitrary value such that we establish

$$I_A \text{ is similar to } I_B \Leftrightarrow \rho(T(I_A), T(I_B)) < \epsilon$$

A classification based in metric ρ will not take in account the connectivity between the pixels in the images. For example, for the images presented in Figure 6 we have that $\rho(T(I_A), T(I_B)) = 0$.



Fig. 6. An example where $\rho(T(I_A), T(I_B)) = 0$. I_B is image I_A applying permutation P_3 .

The Kohonen Network we implemented uses as part of its processes of training and classification the Euclidean metric over \mathfrak{R}^n . Because each one of the representatives of the classes (clusters) in the network are themselves vectors in \mathfrak{R}^n , then we can determine the Euclidean distance between any pair of clusters.

We define a false color map that represents the distribution of the clusters in the subspace $[0, 1]^n$. The maximal Euclidean distance between any two clusters will be $d_{max} = \sqrt{n}$ and the minimal distance will be $d_{min} = 0$. Every Euclidean distance between two clusters will be associated with a color in the grayscale through $\frac{d}{d_{max}} \cdot 256$. By this way if $d = 0$ then it will have associated the black color while if $d = d_{max}$ then it will have associated the white color.

Moreover, we will define a false color map that represent the distances between the clusters in the subspace $[0, 1]^n$ under our metric ρ . For any clusters a and b , $\rho(a, b)$ will be associated with the grayscale through $\rho(a, b) \cdot 256$. If $\rho(a, b) = 0$ then $a = b$ and therefore such distance will be represented through the black color. On the other hand, $\rho(a, b) \cdot 256 \rightarrow 256$ while $\rho(a, b) \rightarrow 1$.

Consider Network Topology τ_0 . The false color maps associated to the distances between the clusters under the Euclidean metric and ρ metric are presented in Table 3. It can be observed in the map under metric ρ that the 47% of the distances between clusters are less than 0.20. This indicates that according this metric an important number of clusters are similar with $\epsilon = 0.20$ (the mean distance in this metric is 0.2542 with variance 0.0373 and standard deviation 0.1933). In the other hand, for topology τ_0 , $n = 7168$, hence, $d_{\max} = \sqrt{7168} = 84.66$. Analogously we consider the number of distances whose value is less than the 20% of d_{\max} . By this way, the map based in the Euclidean metric reports that only the 19% of the distances between clusters are lower than 16.9328 (the mean distance under Euclidean metric was 24.2119 with variance 94.7531 and standard deviation 9.7341). In conclusion, both metrics report different distributions of the clusters which make visible the differences between a classification based in topology of pixels, by the Kohonen Network, and a classification based in color intensities of the images.

IV. CONCLUSIONS

According to the results provided by the approaches discussed in sections III.C.1 and III.C.2 we can infer that image classification based in a 1-Dimensional Kohonen Network groups an image set according to features based in the connectivity between pixels, i.e., their topology. As part of future work, we will analyze in a detailed way the images contained in each one of the resulting classes and their respective neighborhoods in order to determine some features shared by these images. By identifying these features, in our images domain, we will analyze the possible application of our classifications in the prediction of events of Popocatepetl volcano. Another objective, with respect to future work, considers the comparison of non-supervised classification, with other techniques that allow the automated retrieval and classification of images such as Case Based Reasoning (CBR) and Image Based Reasoning (IBR).

REFERENCES

1. Aguilera, Antonio; Lázzeri Menéndez, Santos Gerardo & Pérez-Aguila, Ricardo. Image Based Reasoning Applied to the Comparison of the Popocatepetl Volcano's Fumaroles. Proceedings of the IX Ibero-American Workshops on Artificial Intelligence, Iberamia 2004, pp. 3-8. November 22 to 23, 2004. National Institute of Astrophysics, Optics and Electronics (INAOE), Puebla, México.
2. Aguilera, Antonio; Lázzeri Menéndez, Santos Gerardo & Pérez-Aguila, Ricardo. A Procedure for Comparing Color 2-Dimensional Images Through their Extrusions to the 5-Dimensional Colorspace. Proceedings of the 15th International Conference on Electronics, Communications, and Computers CONIELECOMP 2005, pp. 300-305. Published by the IEEE Computer Society. February 28 to March 2, 2005. Puebla, México.

3. CENAPRED (Centro Nacional de Prevención de Desastres), México. Web Site: <http://www.cenapred.unam.mx> (April 2003).
4. Davalo, Eric & Naïm, Patrick. Neural Networks. The Macmillan Press Ltd, 1992.
5. Hilerá, José & Martínez, Victor. Redes Neuronales Artificiales. Alfaomega, 2000. México.
6. Pérez Aguila, Ricardo. The Extreme Vertices Model in the 4D space and its Applications in the Visualization and Analysis of Multidimensional Data Under the Context of a Geographical Information System. Thesis for the Master's Degree in Sciences. Universidad de las Américas - Puebla. Puebla, México, 2003.
7. Pérez Aguila, Ricardo; Gómez-Gil, Pilar & Aguilera, Antonio. Non-Supervised Classification of 2D Color Images Using Kohonen Networks and a Novel Metric. Progress in Pattern Recognition, Image Analysis and Applications; 10th Iberoamerican Congress on Pattern Recognition, CIARP 2005; Proceedings. Lecture Notes in Computer Science, Vol. 3773, pp. 271-284. Editors: Lazo, M. & Sanfeliu, A. Springer-Verlag Berlin Heidelberg. November 15 to 18, 2005. La Havana, Cuba.
8. Ritter, Helge; Martinetz, Thomas & Schulten, Klaus. Neural Computation and Self-Organizing Maps, An introduction. Addison-Wesley Publishing Company, 1992.
9. Zerubia, Josiane; Yu, Shan; Kato, Zoltan & Berthod, Mark. Bayesian Image Classification Using Markov Random Fields. Image and Vision Computing, 14:285-295, 1996.

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Table 3. False Color Maps that show the distances between clusters in Network Topology τ_0 .

Distances according to Euclidean Metric	Distances according to ρ Metric
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