IMPLEMENTATION OF AN ARTIFICIAL NEURAL NETWORK FOR THE SEGMENTATION OF TEXTURE IMAGES.

A. Mosquera, D. Cabello, M. J. Carreira and M. G. Penedo.
Departamento de Electrónica y Computación. Facultad de Física.
Universidad de Santiago de Compostela.
15706 Santiago de Compostela. SPAIN.

Abstract: In this work we describe the implementation of an artificial neural network, an extension of Hopfield's model, for the segmentation of textured images. We use a Markov random field in order to model the textures in the image. The problem is approached in terms of the minimization of a cost function that is projected onto the network. It provides a locally optimal solution to the problem of the classification of M*M pixels into K classes (textures). The experimental results obtained on artificial and natural images show the validity of the architecture we propose.

Keywords: *Image analysis, texture modeling, Markov random field, textured image segmentation, artificial neural network, Hopfield network.*

1. INTRODUCTION.

Image segmentation is an important problem in artificial vision, image analysis, etc. It consists in the partition of an image into a set of elementary regions characterized by the fact that some property is constant. Many objects in the real world present textured surfaces; the information texture provides is determinant in order to obtain a correct segmentation of the image. There are currently a large number of segmentation methods based on statistics obtained from the values of the gray levels of the pixels in the image. In our approach we will use the concept of Markov random field as a model for the image textures, [1,2].

The inherent parallelism that both the problems of image processing and neural network architectures present have increased the interest in their use for the solution of difficult computational problems, such as the segmentation problem, [3,4]. In most cases, these neural networks are designed so as to minimize an energy function given by the architecture of the network itself, [5]. Its parameters are thus obtained from the cost function we want to minimize for the solution of the problem. In practical cases, the networks must have the lowest possible number of connections. In this context, Markov's random field plays an important role as it limits the dependencies of each pixel to a small set of neighbors.

In this work we describe the implementation of an artificial neural network for the segmentation of textured images which is an extension of Hopfield's model [5]. The problem is approached in terms of the minimization of a cost function that is projected onto the network. This function provides a locally optimal solution for the problem of the classification of M*M pixels into K classes (textures). The results obtained, both on artificial images, a visualization of Markov's field, and on natural images extracted from Brodatz's album [6] prove the validity of the architecture we propose.

2. IMAGE MODEL.

The use of Markov's random field model in image processing applications has been investigated by many authors, and in the literature there is a detailed discussion of its use in images where textures are present, [1,2,7]. In this work we will use a second order Markov random field in order to model the probability density of the image intensities matrix.

In a Markov field model, the intensity of the pixels of an image is a linear combination of the intensities of neighboring pixels. We denote as Ω the set of points in the image of dimension M*M, $\Omega = \{ (i,j) \,;\, 0 \leq i,j \leq M-1 \}$, and s is a two dimensional vector such that $s \in \Omega$. If we assume that the observations y(s) of a texture are Gaussian and have a zero mean value, Markov's random field model can be described by means of the following equation:

$$y(s) = \sum_{r \in N_s} \theta_r \, y(s+r) + e(s) \tag{1}$$

where e(s) is a sequence of Gaussian noise with a null mean value, N_s is the neighbor vector considered and θ_r is the parameter vector of the model. This implies that:

$$p(y(s) \,/\, y(r),\, r \neq s) = p(y(s) \,/\, y(s+r),\, r \in N_s) \tag{2}$$

That is, $\{y(\cdot)\}$ is strictly a Markov field with respect to its neighbors.

The unknown parameters $\{\theta, \upsilon\}$ can be estimated for each pixel of a given image by means of the equations

$$\theta^* = \left[\sum_{\Omega'} q(s)q^t(s)\right]^{-1}\left[\sum_{\Omega'} q(s)y(s)\right]$$
$$\nu^* = \frac{1}{M^2}\sum_{\Omega'}\left[y(s)-\theta^{*t}q(s)\right]^2 \qquad (3)$$

where q(s) is the neighbor vector of y(s) and the sums extend to parameter estimation windows of size Ω'. These equations constitute a maximum probability estimation for the parameters of the model, [8].

3. NEURAL NETWORK FOR TEXTURE CLASSIFICATION.

Once the image model has been established and its parameters estimated in each position using (3), we will approach the segmentation problem by means of the implementation of an artificial neural network which minimizes an energy function obtained from the parameters given by the image model we consider.

The neural network we use is made up of K layers, each one of them consists in a matrix of M*M neurones, where K is the number of possible textures existing in the image and M the dimensionality of the image. We assume that the elements (neurones) of the network are binary and are indexed as (i,j,l), where (i,j) indicates the position in the image and l the layer. The (i,j,l)-th neurone is ON if its output V_{ijl} is 1, and this will indicate that pixel (i,j) of the image belongs to texture l, assuming that each pixel has a single label. Let $T_{ijl:i'j'l'}$ be the weight associated with the interconnection between neurones (i,j,l) and (i',j',l') and I_{ijl} the input of neurone (i,j,l) and let us use a network with symmetric connections, $T_{ijl:i'j'l'}=T_{i'j'l':ijl}$, and without feedback, that is $T_{ijl:ijl}=0$. Then, the general expression of the energy of the network is:

$$E=-\frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{l=1}^{K}\sum_{i'=1}^{M}\sum_{j'=1}^{M}\sum_{l'=1}^{K} T_{ijl:i'j'l'}V_{ijl}V_{i'j'l'}-\frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{l=1}^{K} I_{ijl}V_{ijl} \qquad (4)$$

The use of this network means obtaining a set of states of the neurones so that its energy is a minimum. In order to employ the spontaneous process for the minimization of the energy of the neural network, we will formulate the segmentation problem as a minimization of an error function which is the sum of two terms. The first term corresponds to a quadratic error of the assignment of an image point to a given texture and the second favors the assignment of neighboring points to the same texture. This error function is given by

$$e=\frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{l=1}^{K}\left[\theta_{ij}-\hat{\theta}_{l}\right]^{2}V_{ijl}-\frac{\lambda}{2}\sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{l=1}^{K}\sum_{(i',j')\in N_{s}}V_{ijl}V_{i'j'l} \quad (5)$$

where θ_{ij} is the M*M matrix of parameter vectors estimated using (3), $\hat{\theta}_l$ is the characteristic parameter vector of each layer (texture), N_s is the neighbor vector considered and λ is a weight factor.

From equations (4) and (5) we can identify the parameters of the network, these parameters will be

$$I_{ijl}=-[\theta ij-\hat{\theta}_{l}]^{2}$$

$$T_{ijl:i'j'l'}=\begin{cases}\lambda & \text{if } (i',j')\in N_{s} \text{ and } l'=l\\ 0 & \text{other case}\end{cases} \quad (6)$$

We have implemented a relaxation algorithm in order to minimize the energy of the network. This energy can be written as

$$E=\sum_{i=1,j=1,l=1}^{M,M,K}E_{ijl}=\frac{-1}{2}\sum_{i=1,j=1,l=1}^{M,M,K}U_{ijl}\,V_{ijl} \quad (7)$$

where U_{ijl} is the potential of the (i,j,l)-th neurone. By identifying terms with expression (4), we can obtain the expression of the potential of a neurone, which is given by

$$U_{ijl}=\sum_{i'=1,j'=1,l'=1}^{M,M,K}T_{ijl:i'j'l'}\,V_{i'j'l'}+I_{ijl} \quad (8)$$

For our network and taking into account the values of its parameters, equation (6) is

$$U_{ijl}=\lambda\sum_{(i',j')\in N_{s}}V_{i'j'l}-(\theta_{ijl}-\hat{\theta}_{l})^{2} \quad (9)$$

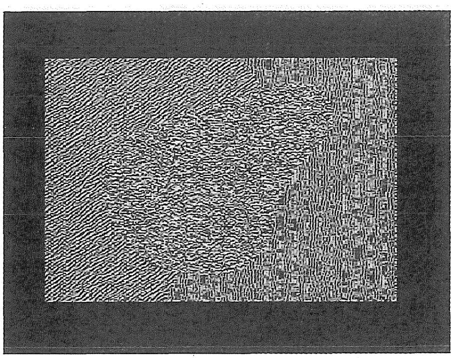
In the relaxation algorithm, in order to generate a new state of the neural network, we assume that each pixel has a single label, which means that only one neurone is active in each column. The new state of the network is calculated by means of the "Winner-takes-all" method over each column so that the neurone with the highest potential is turned ON and the rest are OFF. This process is assumed as simultaneous for all the columns of the network. This scheme makes the system converge to a stable state, generally a local minimum of the function we want to minimize.

Before applying the network to a general image, it is necessary for it to know what textures it may find, that is, it is necessary for it to undergo a learning process. This process consists in the calculation of the Markov field parameters characterizing the texture. These parameters are going to be the ones characterizing each layer of the neural network.

3. RESULTS.

In order to test the validity of the artificial neural network and of the relaxation algorithm we propose, we have generated images which are a composition of different textures and attempted their segmentation. Figure 1.a shows a composition of textures which were artificially generated as a visual representation of Markov random fields with different values of the parameters. Figure 1.b, on the other hand, shows a composition of natural textures (beach sand, water and wood grain) extracted from Brodtaz's album [6]. Both images have 256*256 pixels, 256 levels of gray and present a combination of three different textures; the network necessary in order to segment them will have three layers. The parameters $\hat{\theta}_l$ characterizing each texture/layer of the network are estimated from 25*25 pixel samples for the textures of figure 1.a and from 49*49 pixel samples for those of figure 1.b.

An important aspect in the segmentation process is the determination of the optimum window size Ω' for the estimation, using (3), of the parameter vector θ_{ij} (local properties). This window must be large enough for the estimation of the parameters to be correct and small enough for us to be able to detect small regions of the image. Its size will be determined automatically by means of the analysis of the codifference matrices obtained as a generalization of the operation of binary images erosion to multiple gray level images using a structural element. The distance between the minima of the codifference matrices sum function provides information about the size of the 'motif' of the texture, [9]. This method fixed a window size Ω' of 9*9 pixels for figure 1.a and of 17*25 for figure 1.b. Also, in this last case, we have generalized the concept of neighborhood, taking as closest neighbors to a



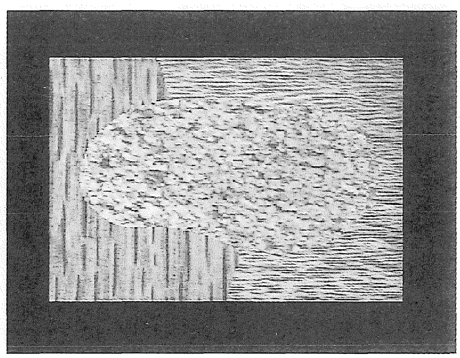


Figure 1. Texture composition images. (a): artificially generated textures, (b): natural textures.

given pixel those located at a distance of half the size of the motif. This implies that in the second term of equation (5), N_s includes the neighbors we consider and all the pixels inside them.

The value of parameter λ is not critical in the segmentation process. Within a small interval, higher values lead to more compact segmentations; outside this interval, its value does not affect the results obtained very much. In the examples considered we have taken values in the interval (1,3).

The results obtained when applying the network to the image of figure 1.a considering $\lambda = 1$, starting from a random distribution of neurone activation and after 40 iterations are shown in figure 2; in figure 2.a the regions obtained appear as masks with different levels of gray and in figure 2.b, we show their contours superimposed on the original image. As we can see, the boundaries obtained coincide with those perceived on the original image.

Figure 3 shows the segmentation obtained for the image of figure 1.b. From left to right and from top to bottom, figures 3.a and 3.b show the results provided by the network and the deterministic relaxation algorithm considered, $\lambda = 2$, starting again from a random distribution of the activation of the neurones and after 40 iterations. In order to compare, figures 3.b and 3.c show the segmentation provided by a minimum distance classifier, taking into account three classes whose characteristic patterns are parameters $\hat{\theta}_l$, assigning to each pixel the class (texture) which is closest in the property space and transferring this information to the image space. As we can observe, the network presents a better performance, reducing segmentation errors. We can conclude by pointing out the validity of

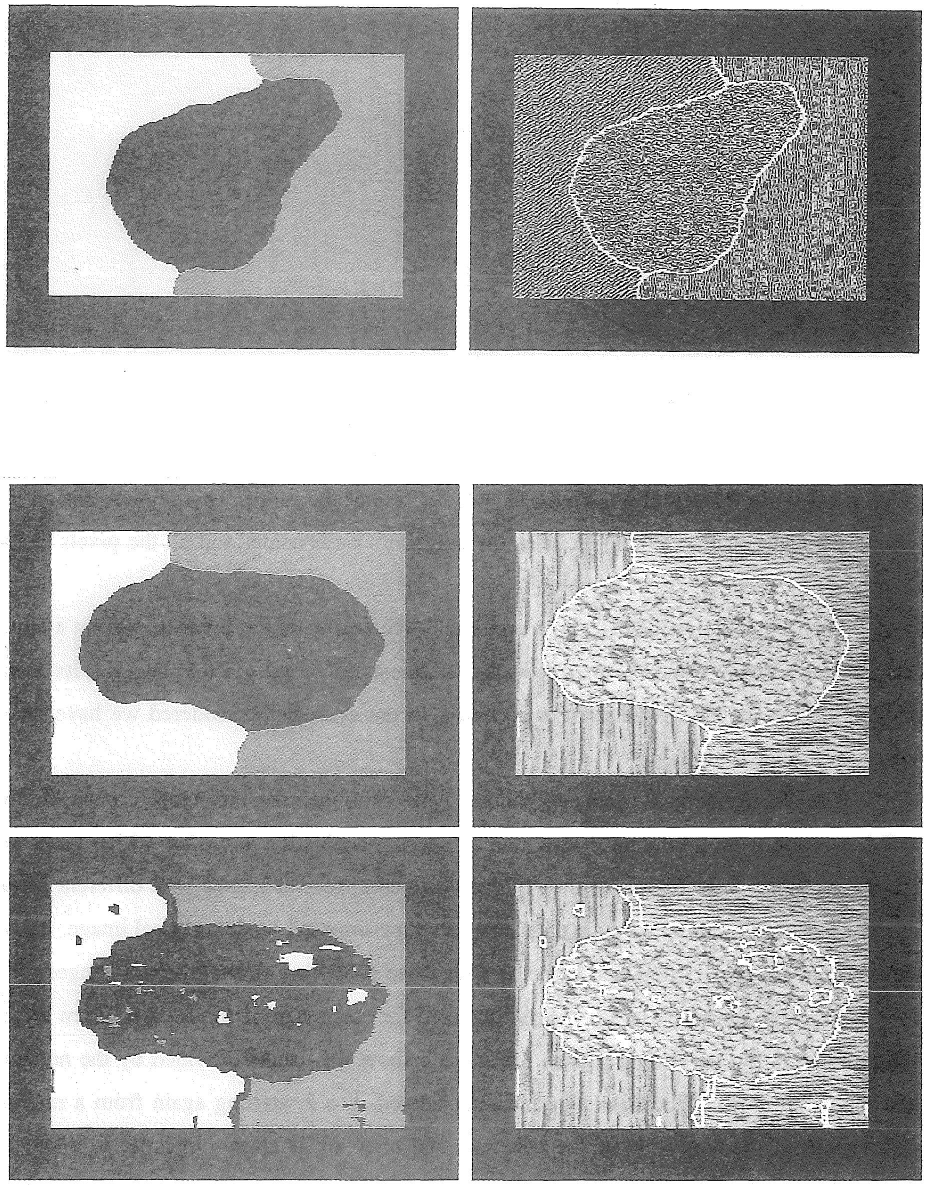


Figure 3. Segmentation of natural textures. (a),(b): results obtained using the neural network, (c),(d): results obtained using ca minimum distance classificer.

the architecture we propose, which provides almost optimal results for the problem of the segmentation of texture images.

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