Representing 2D objects. Comparison of several self-organizing networks

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Abstract: Self-organizing networks have been generally considered as topology preserving of an input space. However, following recent definitions of topology preservation, not every self-organizing model has this quality. In this work, we study the topology preservation capability of four different self-organizing models: Self-Organizing Maps, Growing Cell Structures, Neural Gas and Growing Neural Gas. We use the topographic product to determine if these networks preserve the topological features of several bidimensional objects. We conclude that neuronal gases obtain better results since they can modify the topology of the network during the learning phase. Also, within these, the Growing Neural Gas has a smaller complexity than the Neural Gas, reason why it is candidate to be used in the representation of 2D objects. In future works, we will employ this network to represent 2D objects and to extract geometrical features.

Key-Words: Self-Organizing Networks, Topology Representing Networks, Topology Preservation, Topographic Product, Object Representation.

1 Introduction

Researchers have usually considered self-organizing networks as topology preserving models, since it has been thought that as consequence of the competitive learning similar patterns are mapped onto adjacent neurons and, vice versa, neighboring neurons activate or code similar patterns. In fact, in many cases they are also named as topology preserving feature maps.

However, this is not true in a great number of cases. Martinetz y Schulten [1] have formally defined what is a Topology Representing Networks and its relationship with computational geometry structures as the Voronoi Diagram and the Delaunay Triangulation. So that, several models are outside this category, for instance, Self-Organizing Maps (SOM).

This is the basic problem that the diverse attempts to characterize the geometry of bidimensional objects by means of a self-organizing network [2] have presented. Because they basically use the SOM model, they have only obtained good results when the object has a similar structure to the predefined network topology, which limits considerably its performance.

In this paper, we study the topology preservation capability of several self-organizing models, when having as input the bidimensional shape of an object. Then, we will obtain the self-organizing networks that perform the best representation of an object in order to extract geometrical features from it.

2 Measuring topology preservation

Different measures [3][4][5][6][7] have been developed to quantify the degree of topology preservation of an input space by a self-organizing network. Between all of them, we have applied the topographic product [8], which is the one that has been more widely used [9][10][11].

2.1 Topographic product

The main idea of this measure is to compare the neighbourhood relation between two neurons with respect to its position in the map on the one hand ($Q_2(j,k)$) and according to its reference vectors on the other ($Q_1(j,k)$):

$$Q_1(j,k) = \frac{d^V\left(w_j, w_{n_k^A(j)}\right)}{d^V\left(w_j, w_{n_k^V(j)}\right)} \tag{1}$$

$$Q_2(j,k) = \frac{d^A\left(j, n_k^A(j)\right)}{d^A\left(j, n_k^V(j)\right)} \tag{2}$$

where j is a neuron, w_j is its reference vector, n_K^V is the k th closest neighbour to j in the input space V following a distance d^V and n_K^A is the k th closest neighbour to j in the network A according to a distance d^A.

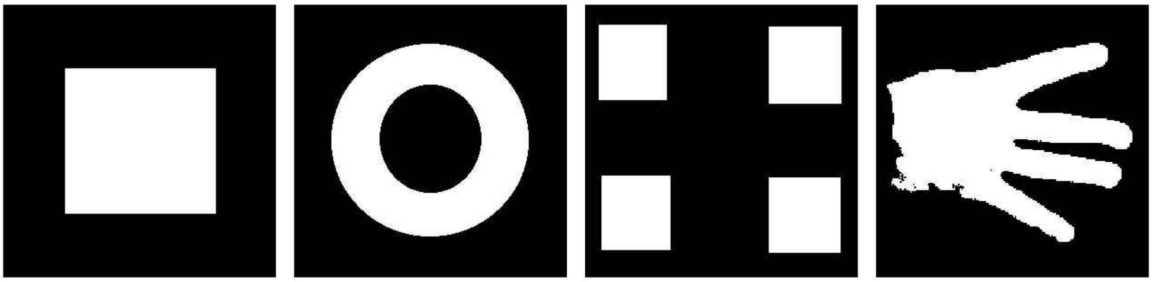

Fig. 1. Input manifolds (bidimensional objects)

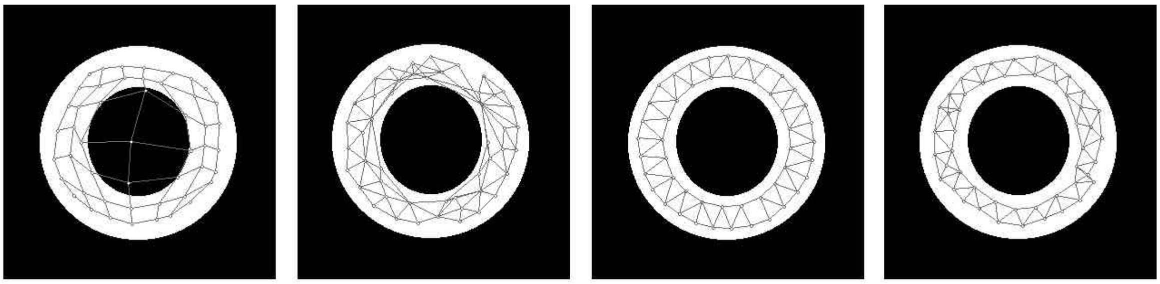

Fig. 2. Final adaptation of the different self-organizing models

Combining (1) and (2) we obtain a measure of the topological relationship between neurons j and its k closest neigbours:

$$P_3(j,k)=\left(\prod_{l=1}^{k} Q_1(j,l)\cdot Q_2(j,l)\right)^{1/2k} \qquad (3)$$

To extend this measure to every neuron in the network and all the possible neighbourhood orders and, since we are only interested in obtaining deviations of this measure from 1, the topographic product P is defined as

$$P=\frac{1}{N(N-1)}\sum_{j=1}^{N}\sum_{k=1}^{N-1} log\left(P_3(j,k)\right) \qquad (4)$$

3 Comparative study of the topology preservation of different self-organizing models

In order to study the topology preservation capability of diverse self-organizing models, we have chosen networks with different characteristics, according to its dimensionality (fixed or variable) and the number of units during the learning process (fixed or variable) (Table 1).

<table>
<tr><td colspan="2"></td><td colspan="2">Number of units</td></tr>
<tr><td colspan="2"></td><td>Fixed</td><td>Variable</td></tr>
<tr><td rowspan="2">Dimens.</td><td>Fixed</td><td>Self-Organizing Maps (SOM)</td><td>Growing Cell Structures (GCS)</td></tr>
<tr><td>Variable</td><td>Neural Gas (NG)</td><td>Growing Neural Gas (GNG)</td></tr>
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Table 1. Self-organizing networks studied

We have performed the learning of diverse input manifolds (Fig. 1) by the four different self-organizing models, choosing for each one of them typical parameters applied in the literature.

Learning of the Self-Organizing Map (SOM) has been performed following the algorithm in [12], with parameters $N=100$, $t_{max}=100\cdot 10000$, $s_i=5$, $s_f=1$, $a_i=0.8$, $a_f=0.1$.

The Growing Cell Structures (GCS) developed by Fritzke [13] employs parameters $N=100$, $e_b=0.1$, $e_n=0.01$, $a=0$, $l=10000$, $h=0$.

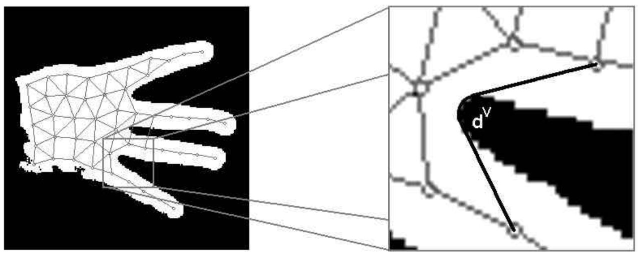

Fig. 3. Distance in the input space

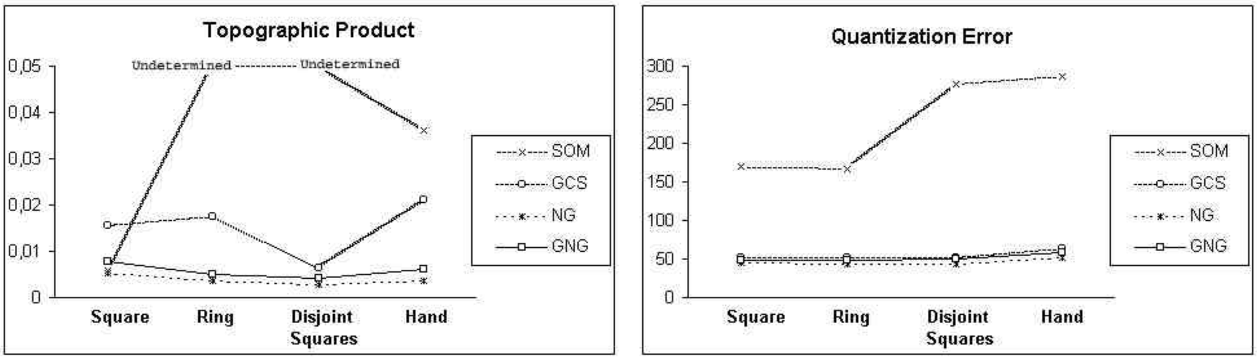

Fig. 4. Topographic product and quantization error for the different manifolds and self-organizing models

Following [14], the Neural Gas (NG) with competitive Hebbian learning makes use of parameters $N = 100$, $t_{max} = 100 \cdot 10000$, $l_i = 100$, $l_f = 0.01$, $e_i = 0.5$, $e_f = 0.005$, $e_f = 0.005$, $T_f = 200$.

Growing Neural Gas (GNG) [15] is adapted with parameters $N = 100$, $l = 10000$, $e_1 = 0.1$, $e_2 = 0.01$, $a = 0$, $b = 0$.

We have performed five learning processes for each one of the possible cases (four models and four input manifolds). As Fig. 2 shows, the quality of the adaptation of the different networks to the manifolds varies significantly. Once made this learning, we calculate the topographic product, in order to measure the topology preservation in each one of the cases.

Unlike the normal use that topographic product has in the literature where the distance in the input space d^V is the Euclidean distance between neurons, we define this distance measure as the length of the shortest path between those neurons within the manifold (Fig. 3). If there is not a path between them, $d^V = \infty$.

In Fig. 4 we show the average results for the topographic product and the quantization error for each one of the instances. As we have previously supposed, SOM are not good topology preserving networks, even in same cases it is not possible to calculate the topographic product because some neuron lies outside the manifold. Both neural gases, NG and GNG, that adapt its topology during the learning phase, are the ones that obtain the best results. Only in those cases where the input manifold has a similar shape to the topology of the fixed dimensionality networks, its topographic product is comparable to the other models. This is because topographic product only considers the network topology without taking into account the input manifold, since it is considered that a correct learning of the input space has been performed. However, this is not real, since SOM characterize worse the input space, obtaining a greater quantization error (Fig. 4), calculated as:

$$E = \sum_{\forall x \in V} \left\| w_{f_w(x)} - x \right\|^2 \cdot p(x) \qquad (5)$$

4 GNG vs. NG

Neural Gas and Growing Neural Gas have a similar behaviour with the different input manifolds. However, learning complexity of the NG is much greater than the one of the GNG, due to the ordering process of all the reference vectors for each one of the input patterns x, obtaining very superior learning times (Table 2).

Self-organizing model	Learning time (in seconds)
SOM	135
GCS	29
NG	535
GNG	32

Table 2. Learning times.

Due to the decaying parameters of the NG, if its learning were interrupted in the same time that GNG ends its learning (32 seconds), the adaptation process would not have finished (Fig. 5). So, the results of the topographic product would be quite worse, even undetermined. This question is very important if we

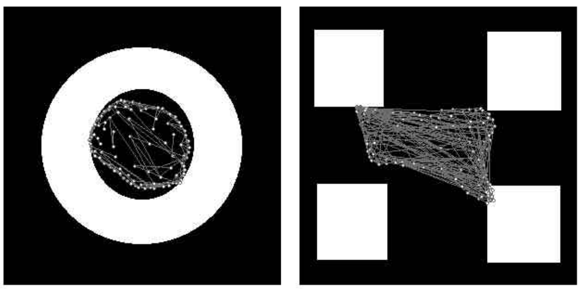

Fig. 5. Incomplete learning of the NG

want to apply the results of this work to a real-time system, when the learning process could be interrupted by a temporal event.

However, if the system knows the deadline in advance it can modify the parameters of the NG, for instance the number of input patterns l, to finish in time. In our study, if the NG ends in those 32 seconds, the topographic product is very close to the one achieved with the GNG (Fig. 6).

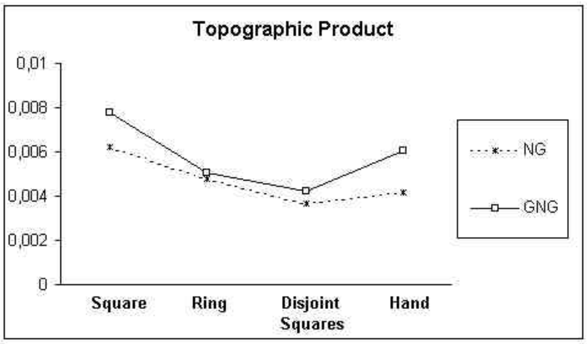

Fig. 6. Comparing topographic product of NG and GNG with same deadline.

5 Conclusion

In this paper we have presented a study of the topology preserving capabilities of four different self-organizing networks. Between several measures, we have chosen topographic product that gives a good idea of the correctness of the adaptation process performed. We show that networks with a variable topology, NG and GNG, adapt better to any one of the input manifolds than networks with a pre-established topology, SOM and GCS. Neural gases do not have the same behaviour when applying them to real-time systems, because NG has a greater complexity than GNG.

This work will lead us to obtain good representations of bidimensional objects, in order to characterize them in later classification o recognition processes. This is a new application of self-organizing neural networks, because they are usually used as classifiers not as features.

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