Representing Non–Rigid Objects with Neural Networks

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INTRODUCTION

Self-organising neural networks try to preserve the topology of an input space by means of their competitive learning. This capacity has been used, among others, for the representation of objects and their motion. In this work we use a kind of self-organising network, the Growing Neural Gas, to represent deformations in objects along a sequence of images. As a result of an adaptive process the objects are represented by a topology representing graph that constitutes an induced Delaunay triangulation of their shapes. These maps adapt the changes in the objects topology without reset the learning process.
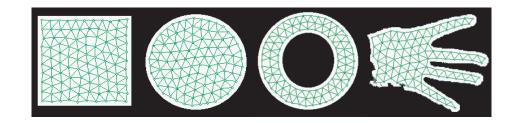
BACKGROUND

Self-organising maps, by means of a competitive learning, make an adaptation of the reference vectors of the neurons, as well as, of the interconnection network among them; obtaining a mapping that tries to preserve the topology of an input space. Besides, they are able of a continuous re-adaptation process even if new patterns are entered, with no need to reset the learning.

These capacities have been used for the representation of objects (Flórez, García, García & Hernández, 2001)] (Figure 1) and their motion (Flórez, García, García & Hernández, 2002) by means of the Growing Neural Gas (GNG) (Fritzke, 1995) that has a learning process more flexible than other self-organising models, like Kohonen maps (Kohonen, 2001).

These two applications, representation of objects and their motion, have in many cases temporal constraints, reason why it is interesting the acceleration of the learning process. In computer vision applications the condition of finalization for the GNG algorithm is commonly defined by the insertion of a predefined number of neurons. The election of this number can affect the quality of the adaptation, measured as the topology preservation of the input space (Martinetz & Schulten, 1994).

Figure 1. Representation of two-dimensional objects with a self-organising network

In this work GNG has been used to represent two-dimensional objects shape deformations in sequences of images, obtaining a topology representing graph that can be used for multiple tasks like representation, classification or tracking. When deformations in objects topology are small and gradual between consecutive frames in a sequence of images, we can use previous maps information to place the neurons without reset the learning process. Using this feature of GNG we achieve a high acceleration of the representation process.

One way of selecting points of interest in 2D shapes is to use a topographic mapping where a low dimensional map is fitted to the high dimensional manifold of the shape, whilst preserving the topographic structure of the data. A common way to achieve this is by using self-organising neural networks where input patterns are projected onto a network of neural units such that similar patterns are projected onto units adjacent in the network and vice versa. As a result of this mapping a representation of the input patterns is achieved that in post-processing stages allows one to exploit the similarity relations of the input patterns. Such models have been successfully used in applications such as speech processing (Kohonen, 2001), robotics (Ritter & Schulten, 1986), (Martinez, Ritter, & Schulten, 1990) and image processing (Nasrabati & Feng, 1988). However, most common approaches are not able to provide good neighborhood and topology preservation if the logical structure of the input pattern is not known a priori. In fact, the most common approaches specify in advance the number of neurons in the network and a graph that represents topological relationships between them, for example, a two-dimensional grid, and seek the best match to the given input pattern manifold. When this is not the case the networks fail to provide good topology preserving as for example in the case of Kohonen's algorithm.

REPRESENTATION AND TRACKING OF NON-RIGID OBJECTS WITH TOPOLOGY PRESERVING NEURAL NETWORKS

This section is organized as follows: first we provide a detailed description of the topology learning algorithm GNG. Next an explanation on how GNG can be applied to represent objects that change their shapes in a sequence of images is given. And finally a set of experimental results using GNG to represent different input spaces is presented in.

The approach presented in this paper is based on self-organising networks trained using the Growing Neural Gas learning method (Fritzke, 1995), an incremental training algorithm. The links between the units in the network are established through competitive hebbian learning (Martinetz, 1994). As a result the algorithm can be used in cases where the topological structure of the input pattern is not known a priori and yields topology preserving maps of feature manifold (Martinetz & Schulten, 1994).

Recent studies has presented some modifications of the original GNG algorithm to improve the robustness of the cluster analysis (Cselényi, 2005), (Cheng & Zell, 2000), (Qin & Suganthan, 2004), (Toshihiko, Iwasaki & Sato, 2003), but none of them use the structure of the map as starting point to represent deformations in a sequence of objects shapes.

Growing Neural Gas

With Growing Neural Gas (GNG) (Fritzke, 1995) a growth process takes place from a minimal network size and new units are inserted successively using a particular type of vector quantisation (Kohonen, 2001). To determine where to insert new units, local error measures are gathered during the adaptation process and each new unit is inserted near the unit which has the highest accumulated error. At each adaptation step a connection between the winner and the second-nearest unit is created as dictated by the competitive hebbian learning algorithm. This is continued until an ending condition is fulfilled, as for example evaluation of the optimal network topology based on some measure. Also the ending condition could it be the insertion of a predefined number of neurons or a temporal constrain. In addition, in GNG networks learning parameters are constant in time, in contrast to other methods whose learning is based on decaying parameters.

In the remaining of this Section we describe the growing neural gas algorithm and ending condition as used in this work. The network is specified as:

A set N of nodes (neurons). Each neuron $c \in N$ has its associated reference vector $w_c \in R^d$. The reference vectors can be regarded as positions in the input space of their corresponding neurons.

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