Growing Neural Forest-Based Color Quantization Applied to RGB Images

Jesús Benito-Picazo, Department of Computer Languages and Computer Science, University of Málaga, Málaga, Spain
Ezequiel López-Rubio, Department of Computer Languages and Computer Science, University of Málaga, Málaga, Spain
Enrique Domínguez, Department of Computer Languages and Computer Science, University of Málaga, Málaga, Spain

ABSTRACT

Although last improvements in both physical storage technologies and image handling techniques have eased image managing processes, the large amount of information handled nowadays constantly demands more efficient ways to store and transmit image data streams. Among other alternatives for such purpose, the authors find color quantization, which consists of color indexing for minimal perceptual distortion image compression. In this context, artificial intelligence-based algorithms and more specifically, Artificial Neural Networks, have been consolidated as a powerful tool for unsupervised tasks, and therefore, for color quantization purposes. In this work, a novel approach to color quantization is presented based on the Growing Neural Forest (GNF), which is a Growing Neural Gas (GNG) variation where a set of trees is learnt instead of a general graph. Experimental results support the use of GNF for image quantization tasks where it overcomes other self-organized models including SOM, GHSOM and GNG. Future work will include more datasets and different competitive models to compare to.

KEYWORDS

Color Quantization, Self-Organization, Tree-Structured Model, Unsupervised Learning

1. INTRODUCTION

Color quantization is a process used to reduce the number of distinct colors used for representing a digitally sampled image. It consists of selecting a small but representative set of indexed colors (codebook) for coding the original digital image with minimum perceptual distortion. Considered as a useful lossy compression method to find an acceptable set of colors for representing a digital image, it has been used as a method to properly adapt images to video adapters with low color displaying capabilities as well as reducing the storage requirements and the transmission bandwidth while maintaining an acceptable image fidelity.

The quality of the codebook will be determined by the error between the original image and the resultant image. An optimal codebook aims to minimize this error, which is usually measured by a mean square error criterion.

There are several well-known codebook design algorithms such as k-means algorithm (Linde, Buzo, & Gray, 1980), fuzzy c-means (Bezdek, 1981), competitive learning (Hertz, Krogh, & Palmer, 1991), self-organizing map (Kohonen, The self-organizing map, 1990), and their variants. The Self-Organizing Map (SOM) (Kohonen, 1982) was the starting point for the development of many self-organizing models (López-Rubio, 2010a), (López-Rubio, 2010b), (López-Rubio, Palomo-Ferrer,
Ortiz-de-Lazcano-Lobato, & Vargas-González, 2011). Some of them try to face some drawbacks of the original SOM regarding its pre-established network architecture, i.e. topology and number of neurons (Kohonen, 2013), (López-Rubio, Growing Hierarchical Probabilistic Self-Organizing Graphs, 2011). The Growing Hierarchical Self-Organizing Map (GHSOM) (Rauber, Merkl, & Dittenbach, 2002) represents a hierarchical extension of the SOM to reflect hierarchical data, where the entire architecture of the neural network is automatically determined during the unsupervised learning process. The Growing Neural Gas (GNG) (Fritzke, 1995) constitutes a successful self-organizing neural network model that solves the fixed-network architecture problem of the SOM. The GNG is based on the Neural Gas (NG) model (Martinetz, 1991), but the GNG provides a neuron growth and removal mechanism to automatically determine the number of neurons during the unsupervised learning process according to the input data.

Initially proposed in (Palomo & López-Rubio, 2016b), the Growing Neural Forest (GNF) model was featured as an improvement of the GNG in which a spanning tree for each connected component (subgraph) of the overall graph is computed. This way, only those units which are connected to the winning unit in a spanning tree are updated. Hence, the GNF will learn a set of trees (forest) so that each tree represents a connected data cluster, meaning such a better adaptation to input data than the GNG.

As many self-organizing models were successfully applied in the past to color quantization (Dekker, 1994), (Papamarkos, 1999), (Xiao, Leung, Lam, & Ho, 2012), (Palomo & Domínguez, 2013), in this work the GNF has also been used for competing with those in order to remark its validity for this application.

The reminder of the paper is organized as follows1. The GNF model is explained in Section 2. Experimental results on color quantization are detailed in Section 3. Section 4 concludes this paper.

2. THE MODEL

In this section, a brief summary of the Growing Neural Forest self-organizing model is provided. Please refer to (Palomo & López-Rubio, 2016b) for more details. A Growing Neural Forest (GNF) comprises a graph with an adaptive number of nodes (neurons) and edges (links). The nodes and the edges are inserted and removed from the graph as necessary along the adaptation procedure. The current number of neurons is noted \( H \). Let the training set be \( S \), where \( S \subseteq \mathbb{R}^D \), and \( D \) is the input space dimension. Every neuron \( i \in \{1, \ldots, H\} \) contains a prototype \( w_i \in \mathbb{R}^D \) and an error variable \( e_i \in \mathbb{R}, e_i \geq 0 \). Every connection is associated to an age, which is a natural number. Let the set of connections be \( A \subseteq \{1, \ldots, H\} \times \{1, \ldots, H\} \), so that no links are allowed between a neuron and itself, \((i, i) \notin A\). Here \( A \) is defined as an undirected graph, i.e. \((i, j) \in A\) if and only if \((j, i) \in A\).

Given the current set of links, the \( Q \) connected components of the graph are called subgraphs, so that the number of subgraphs is less or equal than the number of neurons, \( Q \leq H \). Each subgraph has an associated spanning tree. Hence, a forest is formed from the set of the \( Q \) spanning trees. Let \( \tilde{A} \subseteq \{1, \ldots, H\} \times \{1, \ldots, H\} \) be the set of links of the spanning trees, where \( \tilde{A} \subseteq A \). Since \( A \) is an undirected graph, \( \tilde{A} \) is undirected too. Figure 1 depicts a possible GNF structure.

The learning rule for the GNF is based on the Growing Neural Gas (Fritzke, 1995). It finds a spanning tree for each connected component (subgraph) of the overall graph, so that only those neurons which are linked to the winning neuron in a spanning tree are modified. The learning algorithm is given by these steps:

1. Start with two neurons \( (H = 2) \) joined by a link, so that the graph contains only one subgraph which comprises both neurons. The link set \( A \) only contains the connection between both
A Key Point Selection Shape Technique for Content Based Image Retrieval System


[www.igi-global.com/article/a-key-point-selection-shape-technique-for-content-based-image-retrieval-system/171131?camid=4v1a](www.igi-global.com/article/a-key-point-selection-shape-technique-for-content-based-image-retrieval-system/171131?camid=4v1a)