# IMAGE COMPRESSION AND FEATURE EXTRACTION WITH NEURAL NETWORK

Dinesh K. Sharma, University of Maryland Eastern Shore dksharma@umes.edu
Loveleen Gaur, BLS Institute of Management gaurloveleen@yahoo.com
Daniel Okunbor, Fayetteville State University diokunbor@uncfsu.edu

#### ABSTRACT

The need to transmit data over Internet is increasing at a very fast pace, which requires techniques that can considerably reduce the size of images so that they occupy less space and bandwidth for transmission. In this paper, we have used Kohonen's self organizing map (SOM) network, which is a class of neural networks, for image compression and feature extraction. Moreover, a global processing technique is used for training the Kohonen's network that can considerably, reduce the size of images. JPEG images were used for the experimentation.

# 1. INTRODUCTION

Following the rapid development of information and communication technologies, more and more information has to be processed, stored, and transmitted in high speed over networks. The need for data compression and transmission is increasingly becoming a significant topic in all areas of computing and communications. Computing techniques that would considerably reduce the image size that occupies less space and bandwidth for transmission over networks form an active research. Image compression deals with reducing the amount of data required to represent a digital image (Haykin, 2003).

Several compression techniques have been developed, such as Differential Pulse Code Modulation, Discrete Cosine Transform (Gersho and Gray, 1992), Discrete Fourier Transform, and numerous vector quantization (VQ) methods (Amerijckx et. al., 2003). VQ technique has been used widely (Gray, 1984; Gersho and Gray, 1992). VQ has fairly good performance in both compression ratio and extracted image quality. The principle of the VQ technique is simple. At first, the image is split into square blocks of n´n pixels, for example 4 4, 6 6 or 8 8; each block is a vector. After dividing the original image into blocks, the VQ encoder is used to search each block throughout the codebook for the codeword that is similar to the image block. The index values of the code words closest to the blocks are recoded as the compressed image. When decompressing the image, the VQ decoder uses these index values to recover the corresponding blocks to reconstruct the image. Although, VQ is a powerful technique, it however suffers from high computational complexity.

Kohonen's self-organized map (SOM) is another image compression technique that achieves the same efficiency at that of the VQ scheme (Amerijckx et. al., 1998). SOM has many applications, including but not limited to, classification and exploration of collections of text documents, image compression and pattern recognition (Chen et al., 1994; Pei and Lo, 1988). Kurnaz et al. (2001) presented an incremental self-organized map for the segmentation of ultrasound images. Elements of the feature vectors were formed by the Fast Fourier Transform of image intensities in square blocks. Zheng (1994) described the concept of groupings based on certain rules such as proximity and similarity of image segmentation based on SOM. Katoh et al. (1998) used SOM for recognizing

human emotions through facial expressions. By inputting various images of facial expressions into SOM and changing the interconnection weights, they were able to classify image features.

In this paper, we present an image compression technique using SOM employing global processing. Global processing technique processes every pixel of an image without utilizing blocks as it is generally implemented in the conventional SOM. The proposed technique places emphasis on the fourth property of the feature map e.g. feature extraction. In this respect, the data from an input space obtained from nonlinear distribution, is processed using the SOM to select the set of best approximating features.

## 2. KOHONEN'S SELF ORGANIZING MAPS

Kohonen invented the self organizing map (SOM) in the early 1980s. Kohonen's SOM is a widely-used artificial neural network (ANN) model based on the idea of self-organized or unsupervised learning (Kohonen, 2001). The SOM network is a data visualization technique, which reduces the dimensions of data through a variation of neural computing networks. It is a nonparametric approach that makes no assumptions about the underlying population distribution and is independent of prior information (Kohonen, 2001). The problem that data visualization attempts to solve is that humans simply cannot visualize high dimensional data so techniques must be created to help us understand high dimensional data.

In SOM, the neurons are placed at the nodes of a lattice e.g. usually one or two dimensional. The neurons become selectively tuned to various input patterns (Stimuli) or classes of update patterns in the course of a competitive learning process. The location of the neurons so tuned (i.e. winning neurons) become ordered with respect to each other in such a way that a meaningful coordinate system for different input features is created over the lattice. A SOM is therefore characterized by formation of a topographic map of the input pattern in which the spatial location of the neurons in the lattice is indicative of intrinsic statistical features contained in the input pattern (Haykin, 2003; Zheng, 1994).

SOMs are based on competitive learning in which the output neurons of the network compete among themselves to be activated or fired, with the result that only one output neuron, or one neuron per group, is on at any one time. An output neuron that wins the competition is called a winning neuron (Haykin, 2003). One way of inducing a winning neuron is to use lateral inhibitory connections (i.e., negative feedback paths) between them. SOM provides a way of representing multidimensional data in much lower dimensional spaces - usually one or two dimensions. The brain is organized in such a way that topologically ordered computational maps (defined by an array of neurons representing slightly differently tuned processors or filters) represent different sensory inputs. Consequently, the neurons transform input signals into a place-coded probability distribution that represents the computed values of parameters by sites of maximum relative activity within the map (Knudsen, 1987).

#### 3. METHODOLOGY

As mentioned earlier, the Kohonen's SOM is based on an unsupervised learning that only requires the input data with the main objective of reducing high dimensional input space to lower dimensional output. In addition to these important characteristics, the algorithm is simple and easy to understand. In this paper, we use SOM for segmenting images. Image processing using segmentation is treated as a classification problem, in which segmentation is achieved by pixel classification using SOM (Kong and Guan, 1994). Kong et al. (2002) used SOM for performing image segmentation in two steps, coarse segmentation to obtain the global clustering information of the image followed by pixel based classification scheme that utilizes the local features to refine segmentation. Iivarinen et al. (1996) used SOM to estimate the distribution of features extracted

from faulty-free samples. Visa (1992) implemented image segmentation based on SOM and texture measures. The proposed SOM algorithm for image compression using SOM employing global processing is divided into six steps as depicted in the chart below.

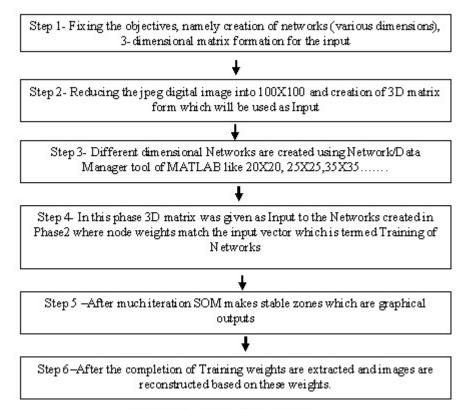


Figure 1: Flowchart of the methodology

## 4. EXPERIMENTS

The above six-step methodology is applied to an image compression problem. First, we acquired a digital image from the Internet (Stallman, 2001). This image was in jpeg format. The size of the image was reduced from its original size of 2835X2050 pixels to 100X100 pixels. Initially, gray values of pixels were extracted in a matrix form. Subsequently, a three-dimensional matrix was formed in which two dimensions were concerning pixel coordinates and the third dimension was the gray level of every pixel of image. This three-dimensional matrix formed the input to the networks, created for experimentation.

Networks were created to compress the image while retaining its key features. Experiments were done with the help of Network/Data manager tool of the MATLAB software. Every network created was uniquely identified by its name. The networks created were Self-Organizing Maps having dimensions as 15x15, 20x20, 25x25, 35x35 and finally 45x45 dimensional map varied from 225 neurons to 2025 neurons. The topology adopted was a grid topology. The distance function selected was 'LINKDIST'. The ordering phase learning rate was fixed at 0.9 and the steps for this phase were kept at 2000. Similarly tuning phase learning rate was kept at 0.02. The neighborhood distance was fixed to unity.

After the creation of the network, a three-dimensional matrix (as described above) was given input into the network. Where the node weights match the input vector, that area of the lattice was

selectively optimized to more closely resemble the data for the classification of the input vector. From an initial distribution of random weights, and over much iteration, the SOM eventually settle into a map of stable zones, where each zone was effectively a feature classifier, so you can think of the graphical output as a type of feature map of the input space. Self-organizing feature maps (SOFM) learn to classify input vectors according to how they are grouped in the input space. They differ from competitive layers in that neighboring neurons in the self-organizing map learn to recognize neighboring sections of the input space. As a result, self-organizing maps learn both the distribution (as do competitive layers) and topology of the input vectors they are trained. After the completion of training, weights were extracted from the network object, obtained as a result of training.

# 5. RESULTS

Based on these weights, reconstruction of the image was performed and the results were found to be satisfactory. We noticed that as we increase the dimensions of the SOM, the images begin to resemble more closely the original image. Also, more feature extraction took place as we increased the dimensions of the map. Since SOM is computationally intensive a substantial amount of time is expended in mere training of any SOM network.

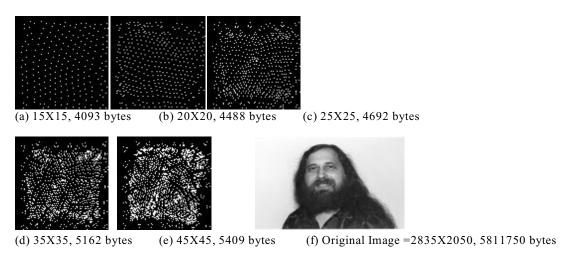


Figure 2:Reconstruction of Images

# 6. CONCLUSION

In this study, we used SOM for segmenting images. The unsupervised learning paradigm implemented using SOM has been one of the major methods for image segmentation research. Image compression addresses the problem of reducing the amount of data required to represent a digital image. Digital Image Processing encompasses processes whose inputs and outputs are images and encompasses processes that extract attributes from images, up to, and including the recognition of individual objects. A global processing technique was used for the image compression and the image taken was in jpeg format. As we increased the dimensions, the picture was reduced by the number of bytes and started to closely resemble the actual picture through the feature extraction property of SOM thereby making the images very convenient for storage and transmission.

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- (A complete list of references is available upon request from Dinesh Sharma at dksharma@umes.edu)

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