Color Image Compression Using Self-Organizing Feature Map

Banu Diri, Songül Albayrak
Yıldız Technical University, Department of Computer Engineering
Yıldız, Istanbul, Turkey
{banu,songul}@ce.yildiz.edu.tr

Abstract. This paper presents a compression scheme for color images, by using Self-Organizing Feature Map algorithm which is a neural network structure. In this application 1-dimensional SOFM is used to map 256-color to 64-, 32- and 16-color. After the quantization process, relative coding and entropy coding are performed without any loss in the information.

Keywords: Image Compression, Color quantization, 1-D Self-Organizing Feature Map, Entropy Coding

1 Introduction

Image compression is very important in terms of reducing the required storage space and decreasing the transmission bandwidth while maintaining a good level of visual quality. A common characteristic of most images is that the neighboring pixels are correlated and therefore contain redundant information. Two fundamental components of compression are redundancy and irrelevancy reduction. Redundancy reduction aims at removing duplication from the signal source. Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver.

In order to achieve high compression ratios with complex images, lossy compression methods are required. Lossy compression provides tradeoffs between image quality and degree of compression, which allows the compression algorithm to be customized to the application. In this work, one of the lossy compression methods, vector quantization by 1-D self-organizing feature-map, is used.

After the quantization process, also relative coding and Huffman coding which are lossless compression methods are used. Lossless coding techniques allow exact recovery of the original data from its compressed version. Lossless compression methods are necessary in some medical imaging applications [1].
To show the efficiency of compression schemes, we use quantization from 256-color to 64-, 32- and 16-color with 1-D Self-Organizing Feature Map algorithm which is a neural network method. In the SOFM, the neurons are placed at the nodes of a one-dimensional lattice. The neurons become selectively tuned to various input patterns in the course of a competitive learning process. The location of the neurons so tuned that they tend to become ordered with respect to each other. Taking the advantage of topological property of SOFM, we use differential entropic scheme to improve the compression ratio.

2 The Global Compression Scheme

The global compression scheme for lossy compression is shown in Fig.1. It consists of three closely connected components namely vector quantizer, relative coding and Huffman coding. After the quantization process, done by using 1-D Self-Organizing Feature Map, relative coding is performed. Finally, the results are compressed by using Huffman coder which is an entropic coder. This method allows the quantized values to be compressed further with no loss to give better overall compression. It uses a model to accurately determine the probabilities for each quantized value and produces an appropriate code base on these probabilities so that the resultant output code stream will be smaller than the input stream. The last two parts do not introduce any loss in the information.

![Fig.1. Global compression scheme for lossy compression](image)

The next part includes the subsections of the SOFM, measure of the quality of the image, relative coding and Huffman coding. Section 3 deals with experimental results. Finally conclusion is presented.
2.1 SOFM

Self-Organizing Feature Mapping is a kind of neural network method based on competitive learning. The output neurons of the network compete among themselves to be activated, with the result that only one output neuron or one neuron per group wins the competition. The output neurons that win the competition are called winner-take-all neurons. One way of inducing winner-take-all competition among the output neurons is to use lateral inhibitory connections between them [2] [3] [4].

In this work, we use a one dimensional self-organizing neural network. In the competitive learning process, the weight vectors for each neuron are produced to represent each cluster and each color in the image is placed in the closest cluster [5]. Our application supports mapping from 256-color to 64-, 32- and 16-color image to show the quantization results. To demonstrate the results of color image quantization algorithm we have chosen a set of 8-bit RGB images. We quantize the color image from 256-color to 64-, 32 and 16-color by one-dimensional SOFM clustering. Fig.2 shows us the quantization result of image Peppers for 64-color.

![Fig.2. The quantization results of 1-D SOFM algorithm for the original image(a) The reconstructed image for 64-color is shown in (b)](image)

SOFM algorithm has tuned the location of the neurons with respect to each other after 3000 iteration. Fig.3 shows an ordered one-dimensional lattice of neuron after learning phase.

![Fig.3 1-D lattice of 64-neuron after learning phase for the image Peppers](image)
2.2 Measure of the Quality of Image

Removal of psycho visually redundant data results in a loss of real or quantitative visual information. The presence of distortion in the reconstituted image will be unavoidable, in view of that a process was carried out that it causes loss of constituent elements of the original image [6]. Two general classes of criteria are used as the basis for any process of compression involving quantization: objective fidelity criteria is a quantitative measure and subjective fidelity criteria is based on qualitative analysis [7]. The peak signal/noise relation (PSNR) and the root of the mean square error (Erms), are respectively defined as:

\[
PSNR = 10 \log_{10} \left( \frac{255^2}{\text{MSE}} \right)
\]

\[
E_{\text{rms}} = \left[ \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left( \hat{I}(x,y) - I(x,y) \right)^2 \right]^{1/2}
\]

Where MSE=(Erms)^2, I(x,y) represents the original image and \( \hat{I}(x,y) \) the restored image. These parameters usually are used as objective criterion of fidelity.

2.3 Relative Coding

Relative encoding is used in cases where the data to be compressed consists of a string of numbers that don’t differ by much, or in cases where it consists of strings that are similar to each other. If we assume that most parts of the image are smooth, a relative encoding applied to the codeword after vector quantization will lead to “small” codes in average. The use of a relative encoding, which encodes these differences into variable length words will thus lead to further compression [8].

2.4 Huffman Coding

The Huffman code is a minimum length code. This means that given the statistical distribution of the histogram, the Huffman algorithm will generate a code that is as close as possible to the minimum bound, the entropy [9][10]. This method results in a variable length code, where the code words are of unequal length. For complex images, Huffman coding alone will typically reduce the file by 10 to 50%, but this ratio
can be improved to 2:1 or 3:1 by preprocessing for irrelevant information removal [1]. The Huffman algorithm can be described in five steps:

1. Find the histogram probabilities for the image.
2. Order the input probabilities from smallest to largest.
3. Combine the smallest two by addition.
4. Go to step 2, until only two probabilities are left.
5. By working backward along the tree, generate by alternating assignment of 0 and 1.

3 Experimental Results

To illustrate the results of color image quantization and compression, we have chosen a set of 8-bit RGB images like Golden Gate (640x480), Peppers (513x513) and Lena (512x480). We quantize the color image from 256-color to 64-, 32- and 16-color by one-dimensional SOFM clustering. Fig.4 gives the peak signal-to-noise ratio evolution with the number of color and Fig.5 gives the root of the mean square error ($E_{rms}$) evolution with the number of color for a set of image. It is noticed from figure 4 and 5, as expected, 1-dimensional SOFM with 64-color gives a higher PSNR than 32- and 16-color. Lena image which is quantized to 64-color gives the PSNR=31dB and $E_{rms}=14.5$ and is quantized to 16-color gives PSNR=28.2dB and $E_{rms}=20$.

![Fig.4. Peak signal-to-noise ratio evolution with the number of color](image)
The Fig.6 shows the compression percentage and the number of color for a set of image with proposed lossy compression scheme. This figure shows that the compression percentage is higher for 16-color (80%) than 64-color (67%) for the image Golden Gate.

**Fig.5.** Root of the mean square error ($E_{rms}$) evolution with the number of color

**Fig.6.** Compression percentage and the number of color for a set of image with proposed lossy compression scheme

### 4 Conclusion

In this work, we proposed a compression method having as base the algorithm SOFM and Huffman coding. SOFM structure is based on the fact that consecutive blocks in
an image are often similar, and coded by similar codewords with a vector quantization algorithm. By using entropy coding lossless compression has been achieved after the quantization process. The global compression scheme is applied to a set of image and average compression percentage of 78% and average PSNR=27dB have been obtained for 16-color. Meanwhile average compression percentage of 61% and average PSNR=30dB have been obtained for 64-color. If the number of neurons is increased in 1-D SOFM algorithm which is used for quantization, the quality of image is also increased. On the other hand, compression rate decreases. The results encourage the use of SOFM for image compression.

References