Compression of Monochromatic and Multicolored Image with Neural Network

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Authors’ contributions

This work was carried out in collaboration among all authors. The first draft of the manuscript was written by author BA, he also wrote the protocol. Author RM designed the study and performed the statistical analysis. Authors RM and KM managed the analyses of the study. Author BA managed the literature searches. All authors read and approved the final manuscript.

ABSTRACT

Nowadays we have so much images provided by different types of machines, while we need to store them or transfer to other devices or via internet, we need to compress them because the images usually have large amount of size. Compressing them reduces time for transferring files. The compression can be done with different methods and software in order to reduce their capacity expressed in megabytes as much as tens of hundreds of gigabytes for more files. It is well known that the speed of information transmission depends mainly on its quantity or the capacity of the information package. Image compression is a very important task for data transfer and data storage, especially nowadays because of the development of many image acquisition devices. If there is no compression technique used on these data, they may occupy immense space of memory, or render difficult data transmission. Artificial Neural Networks (ANN) have demonstrated good capacities for lossy image compression. The ANN algorithm we investigate is BEP-SOFM, which uses a Backward Error Propagation algorithm to quickly obtain the initial weights, and then these weights are used to speed up the training time required by the Self-Organizing Feature Map algorithm. In order to obtain these initial weights with the BEP algorithm, we analyze the hierarchical approach, which consists in preparing the image to compress using the quadtree data.
structure by segmenting the image into blocks of different sizes. Small blocks are used to represent image areas with large-scale details, while the larger ones represent the areas that have a small number of observed details. Tests demonstrate that the approach of quadtree segmentation quickly leads to the initial weights using the BEP algorithm.

Keywords: Photo compression; neural network, BEP-SOFM; frame segmentation; vector quantization; color spectrum.

1. INTRODUCTION

There are many advantages of neural models learned through standard techniques “with a teacher” is the skill of associating facts [1]. This enables associations to be made for the input data networks based on patterns learned in the past [2,3]. The optimization of neural radial weights found in these networks is carried out through a “non-model” technique. One frequently used method uses the SOFM (Self-Organizing Feature Map) models proposed by Tuevo Kohonena [4]. An interesting feature of autoassociation neural models of the SOFM type is their ability to classify objects even though the previously classified models were not known [5-7].

2. MONOCHROMATIC IMAGE [8]

Monochromatic image in Fig. 1 usually has the meaning of black and white or grayscale image. In computers, monochromatic has two meanings:

In a monochromatic bitMap image each pixel is stored as a single bit (0 or 1). In this regard a monochromatic image with a resolution of 640 x 480 pixels requires not less than 37.5 [kB] of memory. A monochromatic image looks like the following Fig. 1.

In 24-color images in Fig. 2, the graphic image is displayed and stored (especially in computer processing) in a very large number of colors and shades with very high quality photographic images or complex graphics. By definition, these images are colored with at least 256 shades of red, green and blue, so in total with 16 777 216 color variations. This 24-bit color image definition is important for computer graphics, where colors are represented by numbers, and each number is equivalent to the color to be represented. An example of 24-bit color photography is shown in Fig. 2.

Fig. 1. Monochromatic image 24-bit color photos [8]

Fig. 2. Example of 24-bit color image

Data compression is a very important task for data transfer and storage. It is the modification process of the information recording method in order to reduce redundancy (and hence the information volume) without changing the transmitted or stored information [9]. Nowadays the transmission of information through images plays an important role because of the development of many image acquisition devices [10]. A large number of image compression techniques have been developed, in order to make the process of image storage and transmission more economical [11]. Artificial Neural Networks (ANN) have demonstrated good capacities for problems that deal with noisy or incomplete data [12]. In the literature different approaches of image compression have been presented. One of these is BEP-SOFM algorithm [13] which uses a Backward Error Propagation algorithm to obtain quickly the initial weights, and then these weights are used to speed up the training time required by Self-Organizing Feature
Maps algorithm. The image is divided into same-
size blocks. The pixel gray level values within the
block are reshaped into a column vector and
inputted to the neural network through the input
nodes.

The purpose of this work is to present an
analysis of the BEP-SOFM algorithm for network
learning, but instead of dividing the image into
same-
size blocks, we use the quadtree
segmentation. This procedure is based on
segmenting the image into variable blocks size,
depending on its level of activity [14, 15]. We
developed a software application for building the
SOFM and BEP-SOFM algorithms (with same-
size blocks and quadtree segmentation), for
compressing and decompressing the images,
and displaying the compression ratio statistics.
Simulation results are presented, together with
algorithms comparisons.

3. IMAGE PRE-PROCESSING

We used the gray scale images. The pixel can
take values from 0 to 255. In order to change the
colour image into gray scale image, we
summarize 30% of the red component, 59% of
the green and 11% of the blue component. The
image is subject to this process before
compression.

3.1 Image Fragmentation Into Blocks

The easiest technique of preparing the image for
compression is its same-sized blocks
fragmentation [16, 17, 8]. Fig. 3 presents the
image of size 64 x 64 divided into blocks of 8 x 8.

3.2 Quadtree Segmentation

In most images, we can distinguish regions
containing more or less details [10]. In this
technique, the image is divided into blocks of
different sizes that contain similar levels of gray
colour [5]. The small blocks represent the parts
of the image with many details, while the bigger
ones represent the regions with less detail. The
image is divided into smaller blocks, if the
contrast of gray level on the block is larger than a
specified threshold. Here the contrast is the
difference of the pixels in the examined block
with the average pixels value in this block. The
block size is $2^n$ pixels ($n$ – natural number) [18].
By using these techniques a tree structure is
formed as shown in Fig. 4. First the image is
divided into blocks and for each of them the
difference of the contrast is checked. If this
contrast is less than the predetermined
threshold, then it means that the block has no
detail (or just a few). Otherwise the block is
divided into 4 smaller blocks of size 2 times
smaller (L1). This procedure is repeated for each
of the newly formed blocks (creation of the L2,
L3, ...). This operation of dividing the image into
smaller blocks continues until reaching the
minimum block size. An example of this
procedure is shown in the Fig. 5.

The average pixel value in the block is calculated
and then for each pixel the inequality is checked by:

$$\left| x_{ij} - x_m \right| \leq R$$  \hspace{1cm} (1)

Where $x_m$ is the average pixel value for block $m$;
$R$ is a constant that helps to determine the
number $L$ of pixels that do not meet the condition
(1). If this condition is true for all pixels in the
block, then the block is not divided further.
Otherwise the decision for further division
depends on the value of parameter $L$. This
procedure continues until the minimum block size
is reached and the pixel block values are set to
the average pixels value [18,14].

Fig. 3. Image fragmentation into blocks
All the actions realized during the quadtree segmentation are stored in the segmentation map in order to achieve the process of reconstruction of the compressed image. This requires the use of a bilinear interpolation.

4. BEP-SOFM ALGORITHM FOR NEURAL NETWORK

Kohonen proposed an unsupervised learning algorithm SOFM for the vector quantization [16], where the main disadvantage is the long time required to calculate the code book. This delay is due to the use of random initial values for the SOFM algorithm. Panchanathan [13] proposed a new schema of image compression, which was a combination of BEP and SOFM algorithms. Linking BEP-SOFM accelerates the execution of vector quantization. The initial values of weights for the SOFM algorithm are quickly obtained from the BEP algorithm.

Before compression, the image is divided into frames using quadtree segmentation. Each frame represents an input vector. The network architecture (Fig. 6) is a three-layer network with N input nodes, N output neurons, and M hidden neurons. N and M are respectively the input vector size and the codebook length. $W_{k,j}^{(1)}$ is the weight connection between the $k$-th input node and the $j$-th hidden neuron, where $1 \leq k \leq N$ and $1 \leq j \leq M$. Similarly, $W_{j,k}^{(2)}$ is the weight connection between the $j$-th hidden neuron and the $k$-th output neuron. In the SOFM algorithm weights $W_{k,j}^{(1)}$ are randomly initialized. To accelerate the generation of code books, it is important that the SOFM algorithm begins the calculation with the appropriate initial weight values.

BEP-type learning algorithm [17, 19] can be used for effective network learning, in order to generate the required weights when the image pattern is presented in the network input.
It is expected that the required output (response) during the learning process should be identical to the input vector. Then the hidden neurons will decode the input vector. That's why the neuron in the hidden layer may be sensitive only for a certain group of similar vectors and can be used as a representative of the input signal characteristics. Therefore, the weights at the end of the BEP learning algorithm are well calculated as initial weights for the SOFM algorithm.

5. THE EXPERIMENTAL RESULTS AND DISCUSSION

We analysed the impact of image size on the compression process for BEP-SOFM algorithm and compared the results obtained from the SOFM algorithm, the BEP-SOFM with same-size segmentation and the BEP-SOFM with quadtree segmentation. These results are presented in terms of mean square error (MSE) and peak signal to noise ratio (PSNR).

5.1 Image Size

Image compression with the BEP-SOFM algorithm is tested on different image sizes. The network architecture is as follow: input nodes 64; hidden neurons (equal to the code book length) 256; output neurons 64; frame size 8 x 8; The Fig. 7. represents the results for an image of 512 x 512.

Image 512 x 512  
MSE = .002947 PSNR = 4989918

For other images

| Image Size   | MSE          | PSNR       |
|--------------|--------------|------------|
| 256 x 256    | .0038510     | 48.73810   |
| 128 x 128    | .0053690     | 47.29497   |

For the 512 x 512 image, we have the highest PSNR ratio value. This is because the 8 x 8 frame size in a small image contains more details, a fact that is significant in an image of these sizes. Meanwhile in a bigger image, the frame contains just a few details and that is why the PSNR ratio has higher values.

5.2 Comparison of Algorithms

We compared the BEP-SOFM algorithm with SOFM algorithm, and the influence of the quadtree segmentation on the image compression process. The graphic (Fig. 8) shows the error values for these scenarios.

The use of BEP algorithm to obtain quickly the initial weights value for the SOFM algorithm provides clearly better results. On the other hand, the use of quadtree segmentation for the BEP-SOFM algorithm also provides better error results, but from the test we noted that the image quality for small images is not or is slightly improved. The difference is noted for bigger images. (Fig. 9)
Fig. 8. Error results graphic for SOFM, BEP-SOFM and BEP-SOFM with quadtree segmentation

Fig. 9. BEP-SOFM algorithm image

6. CONCLUSIONS
The presented work is about the issue of image compression using neural network. We analyzed the BEP-SOFM algorithm, which uses Backward Error Propagation algorithm to quickly obtain initial values of the weights for Self-Organizing Feature Maps algorithm. The image to compress was prepared by dividing it into same-size blocks and by using the quadtree segmentation. The tests showed that using quad tree segmentation for the BEP-SOFM algorithm provides better error results than dividing the image into same-size blocks. An important feature for the image compression process is the image size. Quadtree segmentation for small images did not, or slightly improved the image quality comparing with the results obtained from the simple dividing method. But, for bigger images the quality is improved evidently. This is because, dividing the training image into smaller blocks by changing the pixels value to the average value, the input vector components have the same value. This means that on the decompressing process, the blocks will have the same color value. But for a bigger image, these blocks do not have many details in them [10].

COMPETING INTERESTS
Authors have declared that no competing interests exist.

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