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SELF-ORGANIZATION FEATURE MAP BASED ON VQ COMPONENTS TO SOLVE IMAGE CODING PROBLEM

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ABSTRACT

This paper present image coding which is gained many researchers attention in order to improve the quality of image after the compression process. Since this is expended most computing resources and research which is related not only to search for a mathematical transformation, but also to study the characteristics of visual perception of the image features and fail-safe transmission of images via communication channels. There are many methods of image coding with neural networks of 2D SOFM kohonen map have been suggested and investigated. The coding schemes are proposed methods vector quantization as the original image, and the spatial frequency image component derived from the adaptive to the contours of the two-dimensional analysis and synthesis. The calculation of the computational cost in compression based on Kohonen maps. The methods are characterized by a high level of adaptation due to the introduction of educational stage that provides for the increase of multiplication ratio and high quality of image restarting after coding. The modified method of image multiplexing based on characteristic feature of the given method is vector digitizing of image components. This paper considers the coding problem of photo realistic images, presented in a digital form. The characteristic feature of the method is the application of pair exchange, this increases processing speed and sorting of data arrays. However the result of proposed method is shown the image quality after compression processor. Using this approach the differences or lost pixels between the image after and before compression processer are considered. The propose method may useful for image representation and image coding researcher and such related field.

Keywords: image, compression, VQ vector quantization, multiplexing, neural networks, kohonen map, self-organization feature map (SOFM).

INTRODUCTION

There are many image file format standard has been introduced. Such format uses in order to save the storage and transmission via internet. The benefit can be to gain small size of image by using image compression technique. This technique can compressed the image to smaller size with keeping the image originality as itself. However, coefficients of image compression, which were obtained, are not sufficient as compared with necessary volumes of data transmission. Hence, the increase of the image compression ratio which saved high quality is the main direction of research performed of image coding. One of the approaches providing the increase of image compression coefficient, which is given guarantees of high quality of application based on artificial neural network. However, in scientific literature, there is too various approaches which are considered and using neural networks for image compression. Mishra and Zaheeruddin (2010) proposed mutual subset hood based Fuzzy Neural Network for image compression; the inputs to the network are the preprocessed data of original image, while the outputs are reconstructed image data, which are close to the inputs [1], Hebbian required a large training set in order to get accurate result [2], Jilani and Abdul Sattar (2010) proposed fuzzy optimization design method based on neural networks [3]. After all special attention is paid to approaches based on principles of vector quantization of images, since this provides high compression ratio and ensures high quality of restored image [4]. The fraction method provide roughly of same compression ratios and reduced quality of image [5, 6, 7], While Kohonen Map not required to organize neural network due to such these methods are performed self-organization at initial process of learning, it's called Self-organization feature map (SOFM) [8], using kohonen map, image compression are perfect networks to solve this problem, network in the form as 2D Kohonen map. Kohonen map has two important features used for image compression and applying methods of vector quantization. First, this map is very similar to other methods of vector quantization to apply image compression with image lossy of images. Second, near clusters of input vector are corresponded by closely located neurons. This improves the efficiency without losses and is used at the next stage of coding. In this paper the method of image coding with neural networks of 2D Kohonen map type have been proposed and investigated.

The rest of this paper organize as flow: Section2, present the related works, section 3 methodology, section 4 gives the evaluation, the conclusion of this paper describe in section 5.

RELATED WORK

This section present to two approaches is: back-propagation neural network and fractal image. Back-propagation neural network, actually the image is divided into non-overlapping sub-images. For instance, the image will be split into 4 x 4 or 8 x 8 or 16 x 16 pixels. Gaidhane *et al*. (2010) used feed forward back propagation neural network method with PCA technique for image compression [9], Paliwal, Mukta. (2009) used back-propagation neural network with multilayer perceptron's

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[10], Panda, S. S., Prasad, (2012) the compression process using back-propagation required more time due to the need to differentiate and match pixel space between the images in gray scale [11]. On other hand, affine redundancy, which is based fractal image compression techniques. There are sets of affine coefficients describing the rotation, compression, expansion, distortion of the image objects. Mathematically proved that fractal version of the original image can always been recovered with its affine factors [5, 6], Nappi, M.; Riccio, D. 2006 fractal-based on algorithms which are strongly asymmetric and there is many different solutions have proposed such this problem [7], The highest compression coefficients provides a method of fractal image compression, opened in 1988. The process has based on fractal compression assertion that real-world images are affinely redundancy [12, 13]. Odds compression may reach 50-60 times. The main drawback to this method is much computational complexity. However, given the high degree of compression, as well as huge progress in increasing the productivity of microprocessors and other hardware should been expected of the widest application of this method in the coming years.

THE PROPOSED SYSTEMS ARCHITECTURE

In this section, present four main phases to build the propose system namely: description of Kohonen Map, the methods and system architecture of self-organization feature map.

Phase 1: Kohonen map

Scientist T. Kohonen, namely, self-network in the form of two-dimensional maps Kohonen [17, 18].

Figure-1 shows the scheme of the Kohonen Map neural network. The first layer is called an input layer which is used to enter the inputs data. The second layer is called kohonen layer where is each neuron connected to the input layer, each neuron of the Kohonen layer has a weight connection w_{ij}. The Figure-1 shows. Kohonen neural network learning algorithm which is called self-organization feature map (SOFM) is a neural network without training, the SOFM algorithm is to minimize the difference between the given input signals neuron and given weights neuron.

SOFM has two important features, which are used in image compression based on vector quantization techniques. First, it is very similar to other methods of vector quantization, which apply for lossy image compression, and the second, is a family clusters of input vectors which is correspond closely located neurons and then increases the efficiency of compression without loss, which applies to the next stage of coding, the Kohonen map size is determined by the minimum number of digits that represents pixel and provides sufficient image quality, SOFM has a number of input elements, which is responsible dimension of input vectors and set output elements, which serve as prototypes. The basic network architecture SOFM shown in Figure-1.

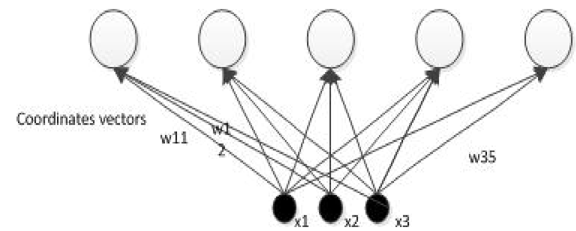

Figure-1. The basic network architecture.

Kohonen Map based on vector quantization methods [4]. The idea of vector quantization is very simple, the image is divided into square blocks, for example, 2 x 2, 4 x 4, 8 x 8. Each block is considered as the vector in 4, 16 or 64 space. A limited number of vectors are chosen from this space, they create a code block to approximate vectors which have the smallest distance from the vectors, being excluded from the input image and code book itself, and are written in communication channel or file. Since, the quantity of vectors in the codebook is smaller than the total quantity of vectors in the input image, and then the numbers of vectors are less than the initial bit.

To choose the optimum options, for solve the basic problem is comparing two approaches which provide same compression ratios approximately and the quality of the reconstructed image: Fractal image compression, Compression using Kohonen maps.

Compare two approaches of computational cost, which is required for implementation, to perform the fractal compression, its need a number of multiplications and divisions:

$$L_f = 8(4n^{k+1}(n^{k-1}-3)+9n^2)*n^{2k-2} \quad (1)$$

Where n - ranking block size and dimensions of the image sides equal N=M=n^k, L_f - number of arithmetic operations needed for fractural compression.

At the expense of this it's obtain the compression. The multiplying the number of operations as shown on formula (1) needed to carry out the compression m x m with the size and amount of the fragment images, which can be vector quantization n x n under the same size image, for one fragment with two passages it needs to multiply the number of operations:

$$m^2 * n^2 * 2 \quad (2)$$

Since the total number of fragments in the image size n x n is m^{2k-2}, multiplying the number of operations as in mathematical formula:

$$L_k = 2 * n^{2k-1} * m^2 \quad (3)$$

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Where m - size of Kohonen map, L_k - number of arithmetic operations needed for suggested compression method which have taken the attribute:

L_f / L_k In order to accomplish such a fractal compression methods. There are several necessary operations such as multiplication and division. These operations are formulated in the following mathematic formula:

$$L_f / L_k \approx n^{2k-1} \quad (4)$$

It follows that performance of image compression of applying Kohonen map requires for less operation of multiplication and distribution, The mentioned mathematical formula (3) used to perform image compression requires far few operations such as multiplication and division. Consolidated data obtained in Table-1 shows that the application Kohonen Map has advantages for the majority of parameters in comparison with the method of fractal. Therefore, the Kohonen method is used in this study due to keep the quality of image in high ration of compression [18]. In addition, the propose method can use to minimize the number of arithmetic operations. By this way the time consuming of compression will be reduced.

Table-1. The comparative characteristics of fractal image compression method and the method of Map Kohonen

Comp-ression	Image Quality	Compression Ratio/ Coefficient	Arithmetic Operations	Scaling Images Possibility	Research Work
Fractal method	High	High	More carry out in n^{2k-2}	Yes	[5, 6, 12]
Kohonen Map	High	High	Less carry out in n^{2k-1}	No	[15-18]

PHASE 2: ARITHMETIC CODING

The basic principles of arithmetic coding have been developed in the end of 70 years [13]. Arithmetic coding, as well as probabilistic methods, uses compression technology as the basis for probability of a symbol in the file, but the arithmetic coding process is fundamentally different. The arithmetic coding sequence of the character (line) is replaced by actual number greater than zero and less than one. The process of arithmetic coding message is that every character assigned interval probability (range), the length calculated on the basis of the probability of occurrence in the message. The first letter word gets the interval from lower bound interval- β^l, and from the top- β^h lower boundary becomes the first significant digit code. Then calculates the boundaries of each sub-interval for the next letter of such expressions:

$$\beta_n^l = \beta_{n-1}^l + (\beta_{n-1}^h - \beta_{n-1}^l) P_n^l$$
$$\beta_n^h = \beta_{n-1}^l + (\beta_{n-1}^h - \beta_{n-1}^l) P_n^h \quad (5)$$

Where β^l, β^h - are lower and upper boundaries of code interval P^l and P^h - lower and upper boundaries of probability interval for the character, Arithmetic coding ensures a high ratio of data compression, especially in cases, where the frequency of occurrence of different characters is very different from one to another. At the same time, the procedure arithmetic coding requires a powerful computing resources, and recently, the method doesn't used for images coding due to slow operation of the algorithm and the large delay for data transmission. Although, should expect high compression ratio when applied to the images coding, this paper uses 2D Kohonen maps to code of photo realistic images with losses. The method of image compression based of vector quantization using neural networks of 2D Kohonen map type.

PHASE 3: REQUIREMENT TO DEVELOP THE ALGORITHM

There are few questions required for algorithm of Kohonen Map:

- What is the size of Kohonen maps to choose?
- What is the dimension of the input vector?
- What is a bit of coefficients weight of Kohonen maps?

A bit of coefficients weights are selected according to the bit input data. Because the images are usually presented in the format of 8x8x8, a composite RGB color represents as one byte, and then chooses the bit of coefficients weights as 8 bits.

Dimension of input vectors are selected and based on the correlation of input data. It's known that the greatest correlation is characterized neighboring samples images, which may have similar values. Therefore, the image is divided into adjacent squares size 2 x 2, each of these is seen as a vector in 4 - dimensional space.

The size of Kohonen Maps is determined by the minimum number of bits, which pixel is represented and provided sufficient image quality. Based on scientific literatures, where is known that less than 2 bits per pixel at any transformations to achieve a problem for given the high requirements for images quality [26], Moreover, to increasing the size of map, it's leading to significant loss of network training performance. The speed of learning is proportional to the square of the size of a Map, that is:

$$T_H = kN^2 \tag{6}$$

Where N - the size of Kohonen Map, k - coefficient of proportionality, depends on the specific implementation.

As given above, the maximum size of Kohonan Map which satisfied these contradicting requirements is 16 x 16. Because the size of input bits equal 4, then the Map by vector quantization provided the following number of bits per pixel.

$$M = \log_2 N^2 / n = 8/4 = 2bit/px \tag{7}$$

N - size of the fragment of initial image, selected for vector quantization,
k= $\log_2 N$, N = M - dimensions of initial image.

Based on above which is acceptable for performance and the quality of reconstructed image is provided.

Vector Quantization using Kohonen maps achieved by two stages of initial image:

- The first stage - learning network;
- The second stage - vector quantization.

Moreover, training vectors are all fragments of images with the size 2x2. Thus, encryption algorithm will be:

- **Learning network**

Step1: Initialize weight coefficients of neurons by random values.

Step2: Select the first fragment 2x2 from the image

Step3: Represent it in the form of learning vector.

Step4: For each cluster element of the map are computed the distance through learning vector:

$$d_j = \sum_{i=0}^{3} (w_{ij} - x_j)^2 \tag{8}$$

Find cluster element j for which d_j is min?

Step5: For given cluster element are updated weighing coefficients according to the formula:

$$w_{ij}(n+1) = w_{ij}(n) + \eta(n)[x_i - w_{ij}(n)] \tag{9}$$

Where η - norm of learning, X_i - coordinate of learning vector.

Step6: Update norm learning and select the next fragment from the image of 2×2 and repeat steps 3 - 6 for the following learning vectors until all the fragments are selected.

- **Vector Quantization**

Step7: Select the first fragment 2x2 from image.
Step8: Submit it to the form of learning vectors.
Step9: For each cluster element of the map, compute the distance to learning vector.

$$d_j = \sum_{i=0}^{3} (w_{ij} - x_j)^2 \tag{10}$$

Step10: Save the number of cluster element with minimal d_j into output file.

Step11: Select from the image the next fragment 2x2 and repeat steps 8 - 11 until all the fragments are selected.

Step12: Save the values of coefficients W_{ij} into output file - the total number is 1024 bytes.

Step13: Save the size of initial file into output file

Step14: Compress received file using the method of arithmetic coding.

Decoding is performed much faster and includes the following steps:

Step1: Decoding the compressed file using arithmetic method.

Step2: Read from the input file and write values of cluster elements to the corresponding arrays, the coefficients W_{ij} and the size of the initial image.

Step3: Choose the number of cluster element from an array for a first fragment of 2x2.

Step4: The coefficients W_{ij} of the cluster element (4 coefficients) are written into the initial image as the value of the corresponding fragment of 2x2 elements.

Step5: Select the next number of cluster element and repeat steps 4-5 until it will not be restored all fragment of the image.

PHASE 4: COMPONENTS CODING

A further increases of computational expenditures can be achieved applying vector quantization of high - frequency image components since their frequency distribution is characterized by the peak, located close to zero, allowing to reduce the size of the network and computational expenditures needed for the learning of the network. This idea considers the application of Kohonen map in combination with 2D analysis adaptive to contours and synthesis (by - component coding).

To obtain the necessary accuracy of analysis and synthesis of the image the application of symmetric filters is suggested, since the sphere of provision of such filters corresponds to non-casual model, and images as it is known, by their nature, are non-casual. Coding process comprises the following steps:

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Step1: Transformation of the image in optimal coloring space (only for color images).

Step2: Sub digitalization of color components by means of averaging of pixel groups (only for color images).

Step3: Formation of 2D low - frequencies components of the image (components of brightness/ color can be processed separately) with limiting frequencies.

$$f_{gm} = \frac{w}{2m} - Y_8, Y_4, Y_2 \tag{11}$$

(W-Width of frequency band of image signal, m = 3, 2, 1).

Order of filters - N - 15, 7, 3. Amplitude - frequency characteristic of filters are: formula (12):

$$H_m(jw) = \left| \frac{1}{2^m} + 2\sum_{k=1}^{k=N} \frac{\sin(\frac{k\pi}{8})}{k\pi} \cos(kwT_a) \right| \tag{12}$$

Step4: Samples Form of image difference components:

$$\begin{aligned} \Delta Y_4 &= \Delta Y_4 - \Delta Y_8; \\ \Delta Y_2 &= \Delta Y_2 - \Delta Y_4; \\ \Delta Y_0 &= \Delta Y_0 - \Delta Y_2; \end{aligned} \tag{13}$$

Where Y_8, Y_4, Y_2, – low-frequency components of the image; Y_0 – initial image.

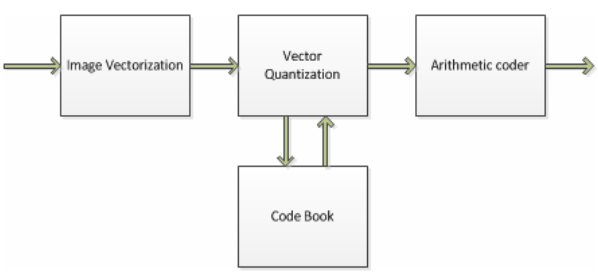

Figure-2. The total coding scheme.

Step5: Discretization and quantization component Y8 components and difference components using 2D Kohonen map.

Step6: Coding samples of high-frequency and low $\Delta Y_4, \Delta Y_2, \Delta Y_0$ frequency, image components using methods of statistical coding (for instance, Huffman coding, arithmetic coding, etc.).

EXPERIMENTAL RESULTS

The Teaching vectors are all the fragments of initial or differential image, that have the size 2×2 the results of investigations showed that vector quantization of a high - frequency component of the image, provides rather high characteristics as compared with direct quantization of initial image. Where the Kohonen map 16×16 is used, dimensions of a Kohonen map can be reduced to 8×8 that enables to increase the speed of the neural network teaching several times. Authors and Affiliations.

Figure-3. Images after coding compression ratio-9.

Figure-4. Images after coding compression ratio - 14, 8.

Figure-3. As shown below is a source image, Figure-4 shows the results obtained in this division of frequency values of pixels brightness for initial image LANA.BMP and its high frequency component.

Table-2. Experimental data on file LENA.BMP for vector quantization of the original image.

Compression	Size of Initial file, byte	Size of comp-ressed file, byte	Comp-ression ratio	Average of square error
JPEG	192 054	13106	14, 7	0, 019
Map Kohonen (16x16)	192054	11740	16, 4	0, 02
Map Kohonen (14x14)	192 054	10979	17, 5	0, 023
Map Kohonen (11x11)	192054	9245	20, 8	0, 026
Map Kohonen (8x8)	192054	6954	27, 6	0, 03

The analysis of these results shows that the vector quantization of high frequency of image components are provide a sufficiently high performance. By comparison with direct quantization of the source image, which uses the size Kohonen map 16x16, as seen from the Table-2, the size of Kohonen maps can be reduced to 8x8, which in turn will increase the speed of network training several times.

CONCLUSIONS

The research paper has proposed an image compression approach based on neural networks of 2D Kohonen map, the method is characterized high degree of adaptation due to introduction of additional stage of teaching that provides increase of compression coefficient and high quality of image, restored after coding. The results obtained in the paper allows to solve important scientific problem - increase of coefficient of compression of images, presented in digital form due to application of neural network of 2D Kohonen map type. Truth of the results obtain is provided by the correctness and accuracy of the task, mathematical conversions, based on main principles of the theory of digital processing of signals, theory of functions of neural logic and by the results of experimental research and computer simulation. The result of the research can be used both for further research of image compression based on neural networks, and for creation of industrial programming and technical means of image compression, since existing coefficients of image compression are 10 - 30 for greater part of images and even exceed such well - known standard of image compression as jpeg.

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