Medical Images Compression by Neural Networks
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Abstract – This paper presents a compression method for still images, based on Kohonen’s neural network. To avoid the edge degradation caused by high compression ratio, the blocks are classified into two classes: blocks with high activity (edge blocks) and blocks with low activity. The image is divided first into blocks of 16 pixels. Each block of high activity are divided again into small blocks of 4 pixels. Blocks of high and low activity are coded separately with different codebooks. We have obtained a noticeable improvement of visual quality of all the rebuilt images while keeping an important compression rate.

Keywords : Compression, Medical images, Neural Networks, Vector Quantization, Classification.

1. Introduction

In many fields, the digitized images replaces the traditional analogical images. In the medical field, the use of radiographies, ultrasonic and IRM images creates a great problem of storage. For example : a hospital of 200 beds, produces on average each year 875 Go of data images. In addition of this problem, if such images must be transmitted through a network, the time of transmission is often too long.

To avoid all these problems, compression of these images becomes an imperative operation. The aim of image compression is to reduce the quantity of bits necessary to describe them while keeping an acceptable visual aspect of the rebuilt images. Vector Quantization (VQ) was successfully used for speech coding [1] and still image compression [2][3][4]. To perform vector quantization, several systems exist [5][6]. These systems use mainly the LBG algorithm [1].

Neural networks approaches used for data processing seem to be very efficient, this is mainly due to their structures which offers parallel processing of data and, the use of training process makes them able to perform various kind of data. New techniques use neural networks to perform compression. The Kohonen Self-Organizing Features Map (SOFM) [7] is a particular network, it can be used for designing a codebook for vector quantization of images. The Kohonen’s SOFM has been successfully used in still image compression[8][9]. We propose an compression method based on SOFM and classification to avoid the edge degradation caused by high compression ratio. The classification was performed by using activity and direction functions.

This article treats medical image compression using Kohonen’s SOFM. This document include four sections. In section 2, the Kohonen network and its use to design codebook for vectors quantization are briefly presented. In section 3, results of compression obtained on medical images are presented. The problem produced by blocks of important size will be underlined. An improvement method of compression will be proposed in section 4. The last section conclude this paper.

2. Kohonen’s neural network & VQ

The Kohonen’s SOFM [10] is an competitive neural network [11]. In SOFM, neurones are organised in a topological map according to a well defined structure [11].

When an input is presented to the network, neurones of the topological map are activated differently and a competition is established between them. The neurone which the synaptic weights vector is most approaching the input is declared winner of the competition.

The SOFM was used in several applications; for example: pattern recognition, acoustic treatment of the speech and classifications [7]. This network is also used in compression [12][9].

Several research showed that Kohonen’s network generate a codebook which gives better representation of the data. Kohonen [7], developed an algorithm in which the synaptic weights \( w_i \) of the network reflect, at the end of training, the component of the codebook. In this algorithm, the input vector is used to update the synaptic weights of the winner neurone and the neurones belonging to its neighbourhood. The weights are adapted according to the following rules [7]:

1) find the neurone \( c \), winner of the competition :

\[
d(X,w_i) \leq d(X,w_c) \quad \forall \; i ;
\]
d is an Euclidean distance.

2) update the weights \( w_i \) of the network :

\[
w_i(t+1)=w_i(t)+h(c,i,t)[X-w_i(t)]
\]

where \( w_i(t) \) is the vector weight of the \( i^{th} \) neurone at time \( t \). \( h \) is a function defined by :

\[
h(c,i,t) = \begin{cases} a(t) & \text{if } i \in N(c,t) \\ 0 & \text{else} \end{cases}
\]

The function \( h \) defines the extent of the update to give to the winner neurone and it’s neighbourhood. The neighbourhood of the winner neurone \( c \) is determined by the function \( N \) which is decreasing with time. \( \alpha(t) \in [0,1] \) is the adaptation gain or the step size which also decreases with time.

Kohonen [10] has demonstrated the efficiency of the SOFM network in recognition and compression of speech signal. In the next section are exposed the results of compression obtained on medical images.

3. Experimental results and discussions
The images used in training process are obtained from medical field. Each image has 256 x 256 pixels, and each pixel is coded on 8 bits. Figure 1 shows one on the images used for training.

Fig.1. An image used in learning.

During the training process, images are partitioned into non overlapping square blocks which constitute the input vectors. Then, the blocs are used for designing the codebook according to the rules (1), (2) and (3). The quality of decoded images is evaluated by the PSNR (Peak Signal Noise Ratio):

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (\hat{n}_i - n_i)^2
\]

(4)

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

(5)

where \( T \) : size of the image, \( n_i \) : \( i \)th pixel of original image, \( \hat{n}_i \) : \( i \)th pixel of decoded image.

The tests images used are presented below:

![Image 1](image1.png) ![Image 2](image2.png) ![Image 3](image3.png)

Fig.2. Images used in the tests.

3.1 Size of the input vectors equal to 4 pixels

In this experiment, a square topological map of 16 x 16 neurones was used. Each image to be compressed is partitioned into blocks of size 2 x 2 pixels. Results of compressions obtained on test images are the following:

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR (dB)</th>
<th>MSE</th>
<th>CR %</th>
<th>BR bits/pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>36.21</td>
<td>15.52</td>
<td>75</td>
<td>2</td>
</tr>
<tr>
<td>Image 2</td>
<td>35.36</td>
<td>18.90</td>
<td>75</td>
<td>2</td>
</tr>
<tr>
<td>Image 3</td>
<td>31.08</td>
<td>50.71</td>
<td>75</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 1. Compression results.

In figure 3, the decoded images and differences images are presented. The quality of decoded images is good and it is almost difficult to notice differences between the original image and decoded ones. Nevertheless, the images difference shows that the coding errors are located mainly at edge of decoded images.

In table 1 is presented the result of evaluation of the PSNR, the MSE, the Compression Ratio (CR) and the Bit Rate (BR):

\[
BR = \frac{\log(\text{size of the topological map})}{\text{size of input vectors}}
\]

(6)

\[
CR = \frac{100 \times (1 - (BR/8))}{\%}
\]

(7)

For a bit rate equal to 2 (compression ratio equal to 75 %), the PSNR is higher than 30 dB for whole of the images.

In the next experiment, size of input vectors is increased, this allows more important compression ratio.

3.2 Size of input vectors equal to 16 pixels

In this experiment, we use a topological map of 256 neurones. The images are divided into blocks of 4 x 4 pixels, this makes the CR increases to 93.75 % (0.5 bits per pixel). This interesting increase in the compression ratio is followed by an important degradation of quality of decoded images (fig.4). In figure 4 is shown image N°3 decoded, where the tiling effect appears clearly. The PSNR obtained is equal to 24.79 dB, this corresponds to a loss of 6.29 dB compared to the first test. The results for the three images are presented in the table which follows:

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR (dB)</th>
<th>MSE</th>
<th>CR %</th>
<th>BR bits/pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>32.03</td>
<td>40.72</td>
<td>93.75</td>
<td>0.5</td>
</tr>
<tr>
<td>Image 2</td>
<td>30.03</td>
<td>64.43</td>
<td>93.75</td>
<td>0.5</td>
</tr>
<tr>
<td>Image 3</td>
<td>24.79</td>
<td>215.74</td>
<td>93.75</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 2. Results of compressions. Case of input vectors of 16 pixels with a topological map of 16 x 16 neurones.
As the block size increases, the tiling effect becomes more pronounced, especially at the edges of the decoded images.

This reduction in quality can be explained by the fact that there are insufficient vectors in the codebook to represent the various edge blocks found in the images. Also, the measurement $d$ used to determine the winner of an input vector does not ensure that an edge block will have a representative edge vector in the codebook. Consequently, the codebook cannot code with good quality the various edge blocks that the images contain.

The quality of edges is very important to ensure good visual quality of decoded images. If the edge blocks are badly coded, visual quality of images is dramatically reduced. Moreover, in the case of medical imagery, decoded images must be excellent to eliminate the risk of incorrect medical diagnosis due to an image of bad quality.

The use of one codebook to represent the homogeneous blocks and edge blocks does not ensure good decoded images. A solution for this problem consists in creating several codebooks, each one being specialized in representing certain types of blocks in an image.

### 4. Compression with classification

#### 4.1 Blocs size equal to 16 pixels

In this series of experiments, the blocks of the images used are classified according to the nature of details contained in each block. Thus, several codebooks will be created by this process. Each codebook will be specialized in coding a well-defined type of blocks.

To carry out the classification of a block, several manners exist; for example: A. GERSHO [4], B. RAMAMURTHI [7] and E. LE LEASE [11] used a classification based on the directions of the gradient. NASRABADI [9] used the value of the variance to distinguish between two classes of blocks. In our experiments, blocks are classified according to their degree of activity. The degree of activity of the block $B$ is measured by the function $A_B$ defined by:

$$A_B(B) = \sum_{m,n} A_P(x_{m,n}) \quad x_{m,n} \in B$$

with $x_{m,n}$: pixel belong to the block $B$;

$A_P$: activity of the pixel $x_{m,n}$:

$$A_P(x_{m,n}) = \sum_{i=1}^{4} \sum_{j=1}^{4} (x_{m,n} - x_{m+i,n+j})^2$$

The use of activity function allows the identification and discrimination between two classes of blocks; blocks of high activities and blocks of low activities. Those which belong to the class of high activities are still subdivided in four classes according to the orientation of details contained in these blocks. In a given block, the orientations of structure of details are: horizontal ($h$), vertical ($v$), and the two diagonal orientations ($d$ and $e$). To define these orientation, direction functions are used:

$$B_{ij} = \frac{1}{M(M-1)} \sum_{m=1}^{M} \sum_{n=1}^{M-1} (x_{m,n} - x_{m,n+1})^2$$

#### Table 3. Results of compressions. Case of input vectors of 16 pixels with a topological map of $16 \times 32$ neurones.

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR (dB)</th>
<th>EQM (%)</th>
<th>CR (%)</th>
<th>BR bits/pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>32.85</td>
<td>33.70</td>
<td>92.96</td>
<td>0.5625</td>
</tr>
<tr>
<td>Image 2</td>
<td>30.67</td>
<td>55.68</td>
<td>92.96</td>
<td>0.5625</td>
</tr>
<tr>
<td>Image 3</td>
<td>24.91</td>
<td>209.87</td>
<td>92.96</td>
<td>0.5625</td>
</tr>
</tbody>
</table>

Fig. 4. Decoded image N°3. PSNR = 24.79 dB with 0.5 bits per pixel.

Fig. 5. Codebook obtained by Kohonen’s network with 256 neurones in the map.

In figure 5 is observed that edge blocks are slightly represented contrary to the homogeneous blocks.
The five codebooks obtained after the training process are visualized in the figure 7:

Each codebook visualized in figure 7 is obtained with blocks of 4 x 4 pixels with a topological map of 256 neurones. The results of compression using classification are presented in the table 4.

If we compare tables 4 and 2, we notice that for the same compression ratio (93.75 % and 0.5 bits / pixel), the quality of the images compressed by classification is rather better. An average profit of 0.58 dB is obtained.

The fact of classifying the blocks in several classes and building for them each codebooks, makes it possible to obtain the following advantages:

1. an edge block will be represented by an edge block of the same type.
2. Each codebook contains the same kind of vectors.
3. For a given type of block, high number of representative is associated for him

These advantages make it possible to guarantee:

1. that an edge block is not represented by a homogeneous block (what could occur without classification);
2. that the various edge blocks of the images are well represented with an sufficient number of vectors in codebook.

Fig. 6. compression by classification.

Fig. 7. Five codebooks obtained after classification. a: horizontal edges; b: vertical edges; C: edges according to
Table 4. Results of compressions by classification.

<table>
<thead>
<tr>
<th></th>
<th>PSNR (dB)</th>
<th>MSE</th>
<th>CR (%)</th>
<th>BR bits/pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>32.41</td>
<td>37.31</td>
<td>93.75</td>
<td>0.5</td>
</tr>
<tr>
<td>Image 2</td>
<td>30.68</td>
<td>55.58</td>
<td>93.75</td>
<td>0.5</td>
</tr>
<tr>
<td>Image 3</td>
<td>25.51</td>
<td>182.52</td>
<td>93.75</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Using this technique, various tests carried out on the images show that the effect of blocks, observed on edges of the images, is somewhat reduced but it is not completely eliminated. This is explained by the fact that classifying blocks in five classes is insufficient. The blocks of size 16 pixels are very varied and require high number of classes. To solve this problem, while keeping a reasonable complexity of compression technique, we propose to add a classification on the edge blocks after having partitioned them in small blocks of size 2 x 2 pixels.

4.2 Classification with reduction of size of the edge blocks

We propose now a technique bases on the observations performed in several series of tests. Indeed, we noted that:

- Vector quantization performed by using blocks of sizes 4 pixels ensures good decoded images. Errors of coding are generally on edge of reconstituted images;
- the compression ratio ensured by the blocks of 16 pixels is very high. However, edge degradations are very visible.
- the classification (in five classes) carried out with blocks of 16 pixels does not increase considerably the quality of decoded images;
- the compression ratio and the quality of the images are much influenced by variation of the size of input blocks than by the size of the codebooks.

To keep high compression ratio and good visual quality of images, we propose the following technique (fig. 8):

1. divide the image in blocks of size 4 x 4 pixels;
2. determine the activity of the block $X$ to compress;
3. If the block $X$ has a high activity function, subdivide it in 4 small sub blocks ($Y_k$) of size 2 x 2 pixels;
4. determine the activity for each sub block $Y_k$;
5. If the sub block $Y_k$ has a high activity function, determine the orientation of edges containing the sub block;
6. determine the codebook to use for coding;
7. determine the index of winner neurone.

![Fig. 8. The proposed method.](image)

Cl : Codebook to quantify blocks of 4 x 4 pixels of law activity function;
Cu: Codebook to quantify the blocks of 2 x 2 pixels of law activity function;
Ch, Cv, Cd, Ce: Codebooks to quantify blocks of 2 x 2 pixels of high activities (edge blocks).

This technique allows to obtain:

- an important compression ratio, because law activity blocks of size 16 pixels are compressed;
- edges has good definitions, because small edge blocks of size 4 pixels are used. Addition to the classification of these types of blocks, error of coding on edges decreases considerably.

The results obtained on the three test images are:
Table 5. Results of compressions by the suggested method

<table>
<thead>
<tr>
<th></th>
<th>PSNR (dB)</th>
<th>MSE</th>
<th>CR (%)</th>
<th>BR bits/pixel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>34.43</td>
<td>23.40</td>
<td>90.14</td>
<td>0.78</td>
</tr>
<tr>
<td>Image 2</td>
<td>33.61</td>
<td>28.29</td>
<td>91.20</td>
<td>0.70</td>
</tr>
<tr>
<td>Image 3</td>
<td>29.64</td>
<td>70.57</td>
<td>91.91</td>
<td>0.64</td>
</tr>
</tbody>
</table>

These results were obtained by using six codebooks. The codebook associated with blocks of 16 pixels has 256 neurones thus ensuring good fidelity of homogeneous blocks (with low activity function). The blocks having small size are not very variable (compared to the larger blocks) so, small codebooks are sufficient to code them. So, we used codebooks of 64 neurones. The decoded image N°3 is presented in what follows:

![Image N°3 decoded](image.jpg)

Fig. 9. Image N° 3 decoded. PSNR = 29.64 dB with BR equal to 0.64 bits per pixel.

The suggested technique allows to increase quality of decoded images while keeping high compression ratio. For example, in image N°3, PSNR equal to 29.64 dB is obtained with 0.64 bits per pixel in bit rate. Making comparison between the results obtained with the same image in table 2, a profit in the PSNR equal to 4.85 dB is obtained, moreover the edge degradation is eliminated (compare figure 9 with figure 4).

6. Conclusion

In this paper, a compression method of still medical images is presented. The use of blocks of 16 pixels performs a coding with 0.5 bits per pixels. This increase in the compression ratio is followed by a visual degradation of decoded images. To avoid this disadvantage, blocks were classified into 6 classes. By refining the compression of edge blocks, with creating smaller blocks which undergo a pre-classification before quantifying them, edges of decoded images are very good. The use of homogeneous blocks of size 16 pixels allows to increase the compression ratio.

The proposed technique is not very complex to realize nevertheless, the time for compression is little increased by the double classification and the decomposition in sub blocks.

The integration of Vector Quantization by Kohonen’s neural network in an existing system of compression (DPCM for example) will make it possible to get advantage from the simplicity and the performances of the network to decrease the noise of quantization and to increase the quality of the decoded.

References:

Figure 3 Original Image
Figure 4 Filtered original Image
Figure 5 Segmented Image by growing regions

Figure 6 Original image with anomalies Detected
With : Performance = 99.31%.

Figure 7 Original image with anomaly Specified
With : Rate Of Recognition = 50%.

Figure 8 Original Image
Figure 9 Filtered Original Image
Figure 10 Segmented image by mathematical morphology, superposed on the Original image

Figure 11 Image with anomalies Detected
With : Performance = 99.44%.

Figure 12 Image with anomaly Specified
With : Rate Of Reconnaissance = 100%.