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Medical Image Compression Using Vector Quantization and Gaussian Mixture Model

Dr. Alaa M. Elsayad,

Computers and Systems Dept.,
Electronics Research Institute
sayad@mcit.gov.eg

ضغط الصور الطبية باستخدام طريقة الضغط بالمتجهات و نموذج الاختلاط الجاوسى

يتناول البحث مشكلة تصميم كتاب الأكواد الخاص بطريقة الضغط بالمتجهات. حيث قد تم توظيف احدى طرق التجميع العنقودي عالية الكفاءة في تصميم كتاب الأكواد، واستخدام النظام المقترح في ضغط الصور الطبية.

وتتسم الطريقة المستخدمة في تجميع المتجهات بتحليل البيانات إلي عدد من توزيعات جاوس وحساب عوامل كل توزيع وتصنيف كل متجه إلى توزيعة محددة ثم حساب المركز ليكون هو احد عناصر كتاب الأكواد.

وقد أثبت النظام المقترح فعالية كبيرة في ضغط الصور الطبية حيث تم تطبيقه في ضغط صور أشعة الرنين المغناطيسي وصور الأشعة المقطعية ومقارنة النتائج مع طريقة كوهنن المعروفة.

Abstract

Codebook design for vector quantization could be performed using clustering technique. The Gaussian Mixture Modeling (GMM) clustering algorithm involves modeling a statistical distribution by a mixture (or weighted sum) of other distributions. GMM has proven superior efficiency in both time and accuracy and has been used with vector quantization in some applications. This paper introduces a medical image compression technique using GMM clustering algorithm and vector quantization. The parameters of each Gaussian component are estimated using the Expectation Maximization iterative method to minimize the error function (maximize the Likelihood). The results for the proposed compression technique are compared with those obtained using the well-known Kohonen SOM neural network compression technique.

Keywords: Clustering, Vector Quantization, and Image Compression

GMM-based Vector Quantization

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. Introduction

The field of medical imaging has experieneed tremendous advances over the last twenty years. These advances, largely in the areas of speed and resolution. have produced over whelming storage requirements for the resulting data. The need for compression schemes to aecommodate this need for image storage within available media is obvious. Image compression techniques can be divided into lossy image compression and lossless ones. Lossless techniques guarantee a perfect reconstruction of every pixel, however their compression rate is limited. On the other side lossy techniques maintain larger compression rates, but introducing some distortion in the reconstructed images. Vector Quantization (VQ) is an efficient image compression approach, which takes advantages of statistical correlation among data samples [3]. The quantization is performed on several samples simultaneously which achieved a performance closer to the rate distortion bound, according to the result of Shannon's rate distortion theory: a better performance can be achieved when the data source has memory, and even if it is memoryless [3]. The VQ system works by mapping the data vector to the reference vectors (codewords). It is assumed that each data vector is mapped to the nearest codeword according to certain similarity measure. The compression ratio and the quality of the reconstructed image depend on the design of these codewords (codebook). The mechanics of data clustering could be described as VQ system where feature vectors are partitioned to clusters such that each cluster subset is formed of data vectors, which share common properties. Different clustering algorithms have been proposed in the statistical domain of data analysis. K-means, fuzzy c-mcans, hierarchical algorithm, deterministic annealing and Gaussian mixture model (GMM) all are examples of clustering methods. Recent overviews of these algorithms can be found in [11]. Due to this analogy between VQ and clustering process. researcher have been used clustering algorithms in the generation of codebook [4-8]. Recently Glenn Fung in [11] compared the GMM clustering algorithm with other unsupervised clustering techniques in both time and accuracy. GMM regards the data vectors as a collection of Gaussian distributions. The system has been used to vector quantization speech coding [1, 2]. In this paper the GMM clustering algorithm is implemented to model the probability density function of data vectors to generate the VQ codebook for medical image compression application. The proposed algorithm uses the Expectation-Maximization (EM) algorithm to fit the data set to a fixed number of Gaussians. The compressibility of the proposed algorithm is measured by several comparisons with the well-known Kohonen's Self Organizing Map (SOM) Neural Network

2. Vector Quantization

Typical VQ image compression system is depicted in Figure 1., where M-dimensional input Vectors are derived from image data $\{X\}=\{x_i: i=1,2,\ldots,N\}$. Data vectors are quantized into a finite set of codewords $\{Y\}=\{y_j: j = 1,2,\ldots, K\}$. It is assumed that each data vector is mapped to the nearest codeword according to similarity measure in order to minimize the overall distortion of the system.

$$d(X_i,Y_j) \le d(X_i,Y_l) \text{ for all j} \tag{1}$$

Where d is the Euclidian distance measured by L_2-metrics:

$$d(X,Y) = \sqrt{\sum_{l=1}^{M}(x_l - y_l)} \tag{2}$$

The index i_n codeword then serves as index for the output reproduction vector. These indices represent the compressed image and off coarse this representation requires fewer bits than the original image does. VQ compression ratio may reach 60:1.

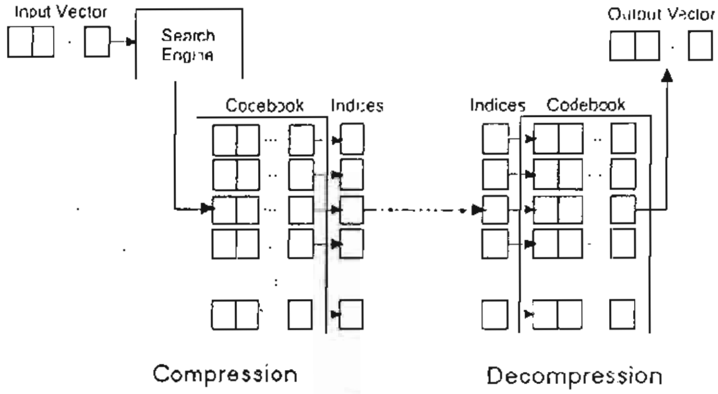


Figure 1. Image compression using vector quantization

However vector quantization, as well as lossy compression techniques, introduces errors in the reconstructed image. The VQ system should compromise between the required compression ratio and the required decoded image fidelity for different applications. Mean Square Error (MSE) is the most common distortion measure for image compression algorithms:

$$MSE = \frac{1}{MN}\sum_{i}^{N} d(X_i, f(X_i))^2 \quad (3)$$

Where $f(X\ )$ is a mapping function from the data vector X to its nearest codeword and M is the number of pixels in each vector X.

3. Kohonen's SOM Neural Network

SOM provides an efficient lossy approach for vector quantization where the codebook is represented by the synaptic weights of each neuron in the map. SOM is a competitive network where for each data vector introduced to the network: the winning neuron (codeword) is activated. The codebook is optimized using an adaptation algorithm to adjust the weights of each neuron [7].

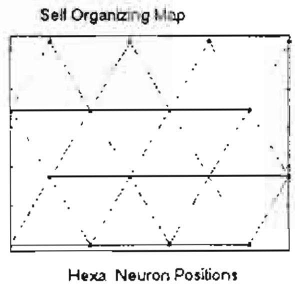


Figure 2. Graphical representation of Self-Organizing Map

The network consists of one competitive layer and the neurons are distributed in 2-dimensional space where they distribute themselves to recognize frequently presented input vectors. The competitive transfer function accepts each input vector for a layer and returns neuron outputs of 0 for all neurons except for the winner one. Let $\{X\}=\{x_i$: i=1, 2,...., N} be input vectors, and the weights of output unit be represented by $\{W\}=\{w_j$: j=1,2,........,$K\}$. When an input **X** is introduced to the network, the winning unit is determined by

$$C(\mathbf{X})= \arg\min \|\mathbf{X}-\mathbf{W}_j\|,\ k=1,2,\ldots,K \quad (4)$$

Where **C(X)** is the index of the winning neuron the input vector and || .|| represent the Euclidean norm [8]. Recall that each neuron competes to respond to an input vector and the neuron whose weight vector is closest to the input vector gets the highest net input and therefore wins the competition and it generates (one) and all other neurons generate (zeros).

4. Gaussian Mixture Model Clustering Algorithm

Let $\{X\}=\{x_i$: i=1,2,........,N} is a set of data points. Clustering algorithm assigns each data item to one of K clusters. Each cluster has to contain data vectors that are sharing common properties. The number of clusters has to be predefined. K-means and Fuzzy c-means clustering algorithms consider the data as a collection of such clusters, while the Gaussian mixture model algorithm considers the data as a collection of Gaussian Distributions [12]. If $\phi(x;\theta_j)$ is the j-th components model parameterized on θ_j then the finite mixture form for the probability density function (pdf) of x is:

$$f_k(x)=\sum_{j=1}^{K} w_j \bullet \phi(x;\theta_j), \quad (5)$$

Where w_j are the mixing weights satisfying $\sum_{j=1}^{K} w_j=1,\ w_j\geq 0$. In GMM $\phi(x;\theta_j)$ components are Gaussian functions and parameterized by a mean vector μ_j, and a covariance matrix $\sum_j$.

$$\begin{aligned} f_k(x) &= \sum_{j=1}^{K} w_j \bullet \phi(x;\theta_j) \\ &= \sum_{j=1}^{K} w_j \bullet p_j(x \mid j;\theta) \\ &= \sum_{j=1}^{K} w_j \bullet \frac{1}{(2\pi)(d/2)\left|\sum_j\right|^{1/2}} \bullet \exp^{-\frac{1}{2}(x-\mu_j)^T\left(\sum_j\right)^{-1}(x-\mu_j)} \end{aligned} \quad (6)$$

w_j, μ_j and $\sum_j$ are adjustable parameters, which are determined to minimize the log-likelihood (the error function):

$$E=-\log L_k=-\sum_{i=1}^{N}\log f_k(x_i) \quad (7)$$

The Expectation Maximization (EM) algorithm is an iterative method used successfully to fit a fixed number of Gaussian components to a data set. Assume that the data set is $X = \{x_1, \ldots, x_N\}$, the EM algorithm determines the adjustable parameters for ach component j, j=1,...,K as follows [11]:

$$P(j \mid x_i) = \frac{w_j \bullet \phi(x_i;\theta_j)}{f_k(x_i)}, \qquad (9)$$

$$w_j = \frac{1}{N}\sum_{i=1}^{N} P(j \mid x_i), \qquad (10)$$

$$\mu_j = \frac{\sum_{i=1}^{N} P(j \mid x_i) \bullet x_i}{\sum_{i=1}^{N} P(j \mid x_i)}, \qquad (11)$$

$$\Sigma_j = \frac{\sum_{i=1}^{N} P(j \mid x_i)(x_i - \mu_j)(x_i - \mu_j)^T}{\sum_{i=1}^{N} P(j \mid x_i)}. \qquad (12)$$

The number of iterations required for the algorithm increases with the number of Gaussian functions in the model, which increase the computational complexity of the proposed compression algorithm.

5. The Proposed Algorithm and Experimental Results

Only CT and MRI images have been used to evaluate the proposed system. These images have been taken from the U.S. National Library of Medicine (NLM)[16]. Our data set consists 30 image slices, all these images are 256x256 pixels, each pixel is 8 bit grayscale. Figure 3 shows the complete block diagram of the proposed compression technique where the outputs of the EM algorithm are the weight, the mean, and the covariance of each Gaussian component for a predefined number of clusters. The cluster centers represent the codewords for VQ compression algorithm. They are used to compress the whole image.

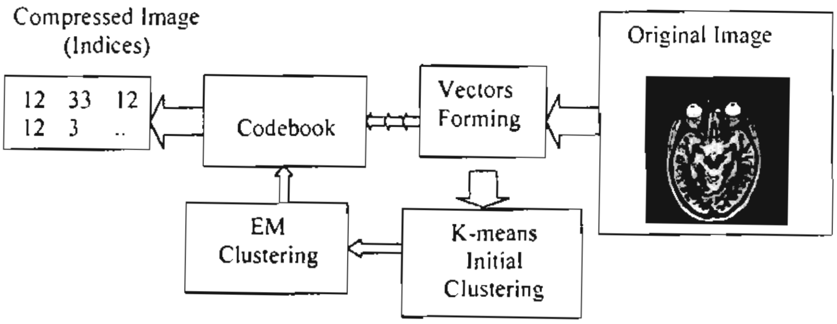


Figure 3. Block diagram of the proposed compression method

The system is implemented using Matlab 6.1 on a Pentium 4 computer. Date set images have been compressed using the proposed system with different codebook sizes. To evaluate the quality of each reconstructed image provided by each system, we use the root-mean-square-error (RMSE) and Peak Signal-to-Noise-Ratio as error metrics. RMSE is the root of the weighted average of the squares of error between the original image and the decompressed one. RMSE represents the standard deviation of the error image. For an input image of size MxN with grayscale $g(i,j)$ and the decompressed image is, RMSE is defined as follows:

$$RMSE = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j}^{N}[g(i,j)-\hat{g}(i,j)]^2} \qquad (13)$$

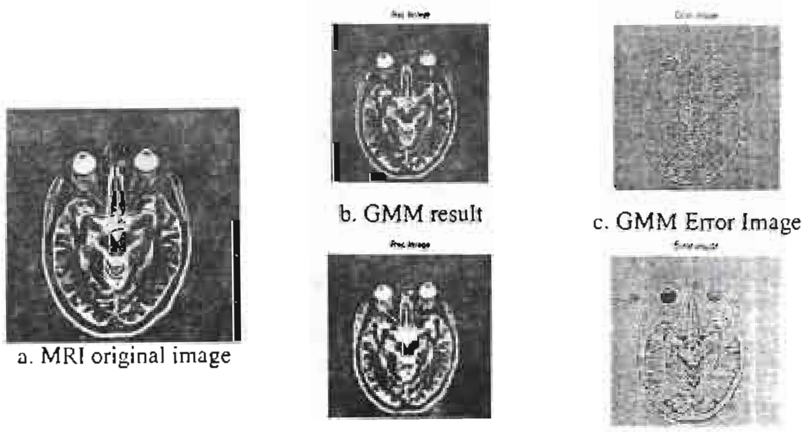
Error image represents the difference between the original image and the decompressed one. To male the errors visible we generate the error image using the following equation [15]:

$$Error(i,j) = 2 \bullet [g(i,j)-\hat{g}(i,j)] + 128 \qquad (14)$$

The related PSNR adopted for evaluating the objective quality, it is measured in dB as follows:

$$PSNR = 20 \bullet \log_{10}(\frac{255}{RMSE}), \qquad (15)$$

for an 8-bit image. However, it is important to mention that both RMSE and PSNR, are objective measures not subjective ones. This means that lower RMSE (or higher PSNR) does not imply a good reconstructed image). Several researchers tries to design techniques for subjective metrics for medical image compression [13],[14]. But regarding their simplicity and common use in compression literature [7,18], we still recommend RMSE and the related PSNR to compare the reconstructed images resulted from the proposed compression technique to those generated from the compression using Kononen SOM technique. Figure 4 shows the comparisons for two images one MRI slice and one CT scan selected from the data set. The reconstructed images as well as the error images computed using equation (14) are computed using 16 codewords, and 4x4 pixel in each codeword.



a. MRI original image

b. GMM result

c. GMM Error Image

d. SOM Result

e. SOM Error Image

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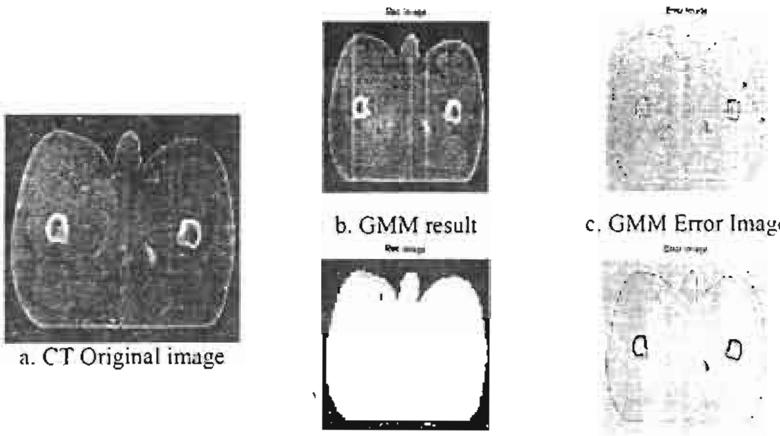
Figure 4. Comparison between GMM-based VQ and SOM-based VQ

i. Compression Results for 256x256x8 MRI medical slice.

ii. Compression results for 256x256x8 CT scan.



a. CT Original image

b. GMM result

c. GMM Error Image

d. SOM Result

e. SOM Error Image

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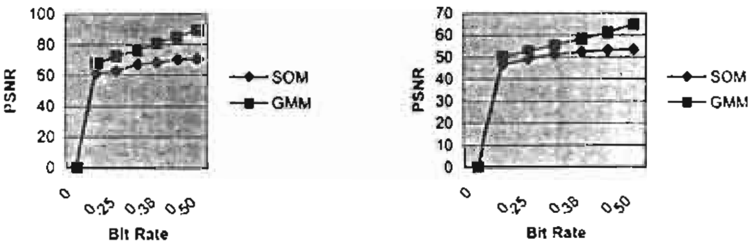
Figure 4. Cont.

The number of iteration in the training steps is 30000 (epoch) for SOM based vector quantization and the number of neurons is the number of codewords that are learned directly with one vector at a time using trainwb1 function in neural network toolbox in Matlab. While in GMM based vector quantization, the termination tolerance is 10^{-6} where the algorithm was iterated until the error value does not exceed this threshold. Figure 5 shows the the resulting rate distortion curves for each image compressed by SOM and GMM techniques. The bit rate means the number of bits required to compress one pixel, it is computed as follows:

$$\text{Bit rate} = \frac{\log_2(N_c)}{N_p} \quad \text{bits/pixel} \qquad (16)$$

Where N_c is the number of codewords in the codebook and N_p is the number of pixels in each codeword.



CT Rate Distortion Curve

MRI Rate Distortion Curve

Figure 5. Rate Distortion Curves for CT and MRI images of GMM and SOM based algorithms

The experimental results have shown that GMM-based VQ is very efficient in terms of root mean square error and the related peak signal-to-noise ratio. The Convergence of GMM algorithm to a global solution does not change with the variations in the starting points [11], that are generated using K-means clustering algorithm.

6. Conclusion

This paper addresses the process of VQ codebook generation as a clustering problem. The Gaussian Mixture Model-clustering algorithm has been used and the resulting VQ system is compared to the Kohonen's SOM neural network. The experimental results showed that the overall distortion is much lower when using small number of codewords in the proposed VQ system. However, in order to maintain the diagnostic accuracy of the decompressed medical images, It will be more efficient to apply VQ system using the quadtree segmentation [8]. In such system, the image is decomposed into small blocks with variable size and the codebook consists of sub-codebooks one for each size.

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