Image Compression using Gaussian White Noise Irregular Segmentation Technique

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***Abstract*—**The aim of this work is to look for a simple technique for the image compression. This method consists in determining the different Gaussian white noise (GWN) segments in each image matrix row. The resulting GWN segments lengths are dependent on the reconstructed image quality. The irregularly compressed image, in this case, is represented by the parameters vector of the corresponding mono-dimensional stochastic model; the variances, means and the corresponding segments lengths. We have, in addition, compared the results obtained with the GWN to those obtained using a uniform distribution model and as a result, we have found that the GWN is more adequate for the irregular image compression. The irregular compression rate obtained in this work is higher than the regular compression rate.

***Keywords*—** irregular compression; image; irregular segmentation; stochastic model.

I. INTRODUCTION

It is well known that image compression is the procedure of reducing the size in terms of bytes of a graphics file without degradation of the image quality to a certain reasonable level. This size file minimization allows more images to be saved or stored in a memory space. It also reduces the time required for transmitting images.

Many successful methods and algorithms in image modeling and compression are performed using statistical models, and it is therefore of interest to improve models in order to obtain a higher compression rate as well as to accurately reconstruct an image that is as close as possible to the corresponding original image. Performing such models is usually a difficult task due mainly to the image data to be processed. To overcome this difficulty, two important assumptions are usually pointed out to simplify model analysis; a) the probability of a pixel is conditioned only on very nearest neighborhood and deemed independent from the remaining pixels of the image. This assumption is called Markovianity. b) The local density is thought of as being independent of its absolute position in the image, in other words the density is homogenous. Any model that is characterized by these two assumptions is called homogenous Markov random field (hMRF). The non-Gaussian statistics of images, in addition, led some authors to develop non-Gaussian MRF models [1, 2]. But so far the most successful, may be, is the fields of experts model which has been recently developed by S. Roth and M. J. Black [3] and has shown a quite good performance. The local statistical properties of images have, also, been modeled using Gaussian scale mixtures (GSMs).

Despite their global consistency and the interesting results provided by such field models, difficulties in their implementation and processing may hamper their performances. We suggest, therefore, in this paper an alternative and simple method based on matrix line segmentation instead of a Gaussian field realization for the image modeling and particularly for the image compression. This mode of representation corresponds to the regular compression and has been applied for the line by line processing of the images, in particular for the coding, the filtering and the storage [4,...,7]. In our case, however, we aimed to obtain a higher compression rate using an approach called irregular compression which will be explained in more detail in the following.

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II. RESULTS AND DISCUSSION

Many authors [8,…,13] have demonstrated that image statistics are not Gaussian realization, and hence they do not follow, particularly, Gaussian distribution. For example, decomposition of images using wavelet transforms provides coefficients that are non-Gaussian as indicated by their histograms. We believe, however, that this case may be slightly different when considering the image matrix line by line treatment and performing segmentation such that any segment may be approximated by a corresponding Gaussian model [14, 15] as formulated in the following:

We started first by selecting a type of model with reasonable results and can be applied to a possible large number of images. After many tests on several types of models, we have decided to choose either the normal distribution model or the uniform distribution model for every resulting segment, mainly because of their simple computing and the good results they provide.

A. *The proposed irregular compression method*

The principle of our proposed method of compression consists mainly of two steps: first, segment each matrix line into even length stationary intervals as shown in the following example corresponding to the first image matrix line (1), and seek the optimal model parameters (variance and mean in the case of a Gaussian model) to represent each of these intervals by an adequate corresponding model. If the reconstructed image is reasonably close to the original one, using this particular model, then this means that all the segments with the same length L are indeed Gaussian White Noises (GWN).

$$X = \begin{bmatrix} \underbrace{x_1(0)\ x_1(1)....x_1(L-1)}_{L\ \text{samples}}\ \underbrace{x_1(L)\ x_1(1)....x_1(2L-1)}_{L\ \text{samples}}......x_1(N_i.L-1) \\ x_2(0)\ x_2(1)..................x_2(N.L-1) \\ .... \\ x_I(0)\ x_I(1)..................x_I(N.L-1) \end{bmatrix} \quad (1)$$

The GWN were obtained by assuming that the pixels are weakly dependent and thus the neighbouring pixel dependency may be neglected. The joint probability of any segment can be, therefore, approximated, using the chain rule, where each sample conditional probability is replaced by its prior probability as shown in the following example in the case of the first segment with the length L ;

$$P(\mathbf{x_1(0)}, \mathbf{x_1(1)}, ...\mathbf{x_1(L-1)}) =$$
$$P(\mathbf{x_1(0)} / \mathbf{x_1(1)}, ...\mathbf{x_1(L-1)}).P(\mathbf{x_1(1)} / \mathbf{x_1}(2), ..\mathbf{x_1(L-1)})...$$
$$\cong P(\mathbf{x_1(0)}).P(\mathbf{x_1}(1))....P(\mathbf{x_1(L-1)})$$

And the corresponding estimated optimal GWN parameters; the mean $\hat{m}$ and the variance $\hat{\sigma}^2$, for each segment, were computed as shown in the case of the first segment using respectively the two following expressions

$$\hat{m} = \frac{1}{L} \sum_{n=0}^{L-1} x_1(n)$$

$$\hat{\sigma}^2 = \frac{1}{L} \sum_{n=0}^{L-1} (x_1(n) - \hat{m})^2$$

Once the reconstruction is reasonably acceptable, we proceed to the second step which consists in grouping as many adjacent stationary segments of the same matrix line with very close variances and means as possible in order to obtain stationary segments with longer lengths as indicated in the image matrix (2) in which it is shown that the first and the second segments are grouped into one segment with length 2L.

$$X = \begin{bmatrix} \underbrace{\underbrace{x_1(0)\ x_1(1)....x_1(L-1)}_{L\ \text{samples}}\ \underbrace{x_1(L)\ x_1(1)....x_1(2L-1)}_{L\ \text{samples}}}_{2L\ \text{samples}}.......x_1(N_i.L-1) \\ x_2(0)\ x_2(1)..................x_2(N.L-1) \\ .... \\ x_I(0)\ x_I(1)..................x_I(N.L-1) \end{bmatrix} \quad (2)$$

Each of these stationary segments is represented by three parameters; the variance, the mean and the segment length. The latter must be specified as the third parameter since the segments are not all of the same length in the case of the irregular segmentation. In order to obtain a higher irregular compression rate than the regular compression rate, the following criterion must be, therefore, satisfied;

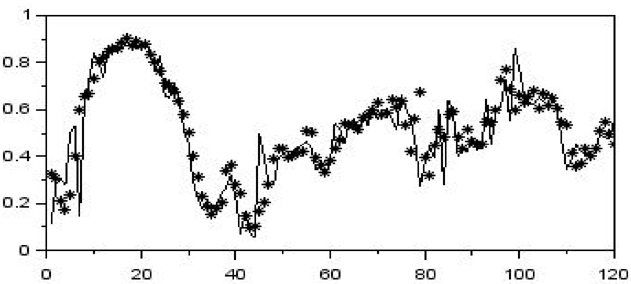
$$N_{ir} \le \frac{2}{3}.N_r \quad (3)$$

Where N_{ir} and N_r are respectively the irregular and the regular segments total numbers

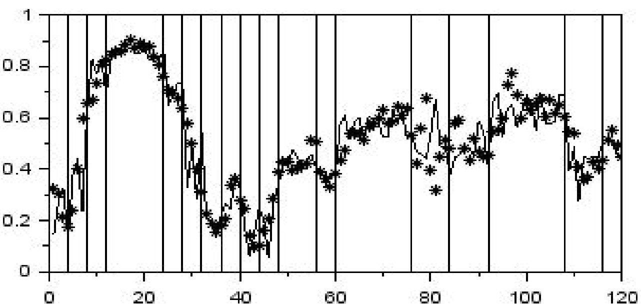
We have represented in figure.(1a) below both the 300th line (column 201 to column 320) of the original image and its reconstruction version using the regular segmentation. It can be seen that this matrix line is well reconstructed indicating that the GWN is the right choice for the regular segmentation. Figure 1b illustrates the irregular segmentation and in which the stationary irregular segments are delimited by the vertical lines. We can notice in this figure that the reconstruction corresponding to the irregular segmentation is, also, almost perfect. So, this procedure is not only an alternative test to Kolmogorov-Smirnov test, but it represents also a simple way of determining the stationary and ergodic segments [16] for any matrix line. Notice that this second step is called an irregular compression since the stationary segments, obtained using our algorithm are not of even lengths, whereas the former is known as the regular compression. The obtained irregular segments are delimited by the breakpoints separating the adjacent segments. We then gather all these optimal parameters and their corresponding segments breakpoints indices in a matrix form with a smaller size than that of the original image matrix. The goal of our method for compression is, therefore, to reduce the size of the parameters matrix as possible as we could without degrading too mach the information in the original image.

B. The suggested algorithm for the irregular compression

The basic idea of the irregular (compression) segmentation is to seek for longer stationary segments by joining as many adjacent smaller regular stationary segments which are determined using statistical models as possible. This method is applied to each image matrix line. The parameters of the resulting adequate statistical model corresponding to the irregular compression are then gathered in the parameters matrix which is supposed to represent the irregular compressed image.



a)



b)

.

Fig.1. Original line (dotted curve) and its reconstructed (continuous curve); a) the regular stationary segmentation, b) the irregular stationary segmentation, where the vertical lines delimit the stationary segments.

Algorithm:

1- Divide each image matrix line into segments with an even given length L.

2- Compute the parameters; the variance and the mean of every segment.

3- Use these parameters to reconstruct segments [17] using the selected model, and hence to reconstruct the image.

4-If the reconstructed image is reasonably perfect as in fig. 4, then go to step 5, else reduce the segment length L and go back to step 1.

5- Gather as many adjacent segments with approximately even variance and mean as possible to obtain longer stationary segments.

6-Groupe the different breakpoints indices (lengths) of the obtained stationary segments as well as their corresponding parameters; variances and means in a matrix form whose size should be not less than that of the original image matrix only but also less than that of the parameters matrix of the regular compression as well. Notice that the latter corresponds to the first step up to the fourth, whereas the irregular compression starts from the fifth to sixth step.

The following scheme below in figure.2 describes briefly the six steps of our suggested algorithm for the irregular compression by the matrix line segmentation.

-The original image matrix size is I*J=348*620=215760, where I and J are the rows and the columns numbers respectively.

-The regularly compressed image parameters matrix size obtained is 2*Nr= 2*155*348= 107880, where Nr is the total number of the regular segments (same length) and finally the irregularly compressed image size obtained using our algorithm is 3* Nir = 3*30605= 91815, where Nir is the total number of all the irregular segments. As results we have obtained the following compression rates: the regular compression rate Tr=215760/107880=2 and the irregular compression rate Tirr=215760/91815=2.35. These results which are summarized in the following table 1 show clearly the improvement of the compression rate corresponding to the irregular compression.

Table.1:

Image nature	Image size	Compression Rate
Original	**215760**	**1**
Regular compression	**107880**	**2**
Irregular compression	**91815**	**2.35**

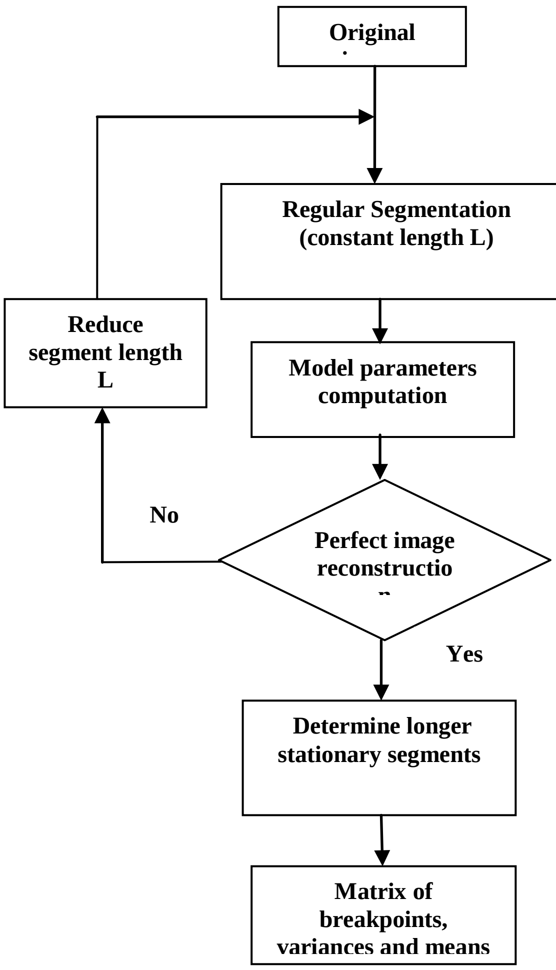


Fig. 2. The image irregular compression algorithm.

The image modelling was performed using the image toolbox of Scilab5.3.3 which is free software. The results of our algorithm for the irregular compression are shown in fig.5 using the normal distribution (fig.5b) and the uniform distribution (fig.5b).

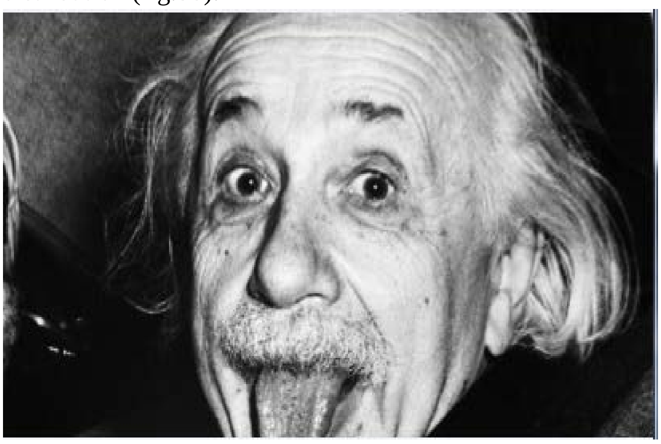
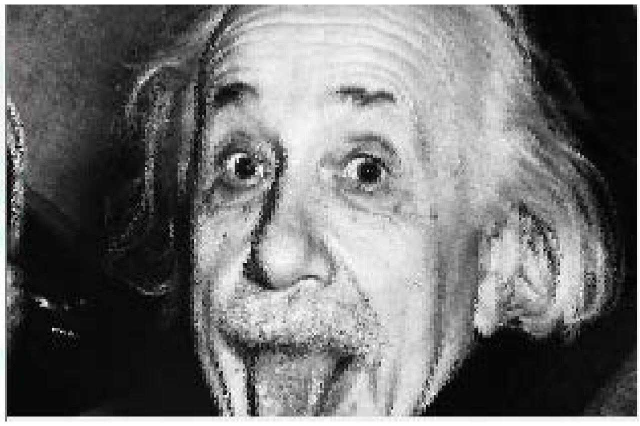
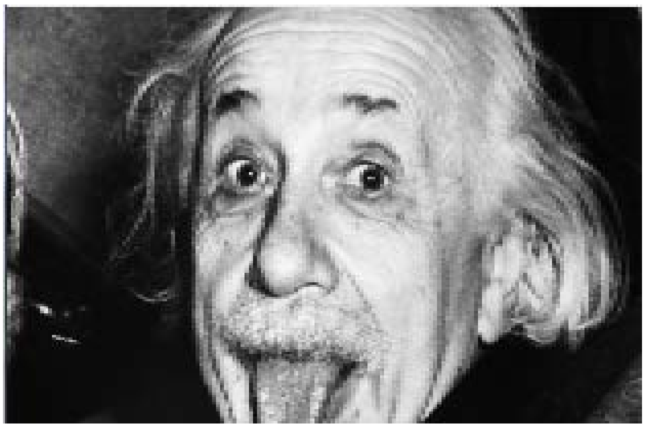


Fig.3. Original image

We can see that the results obtained with the latter distribution are better than those obtained using the former distribution.



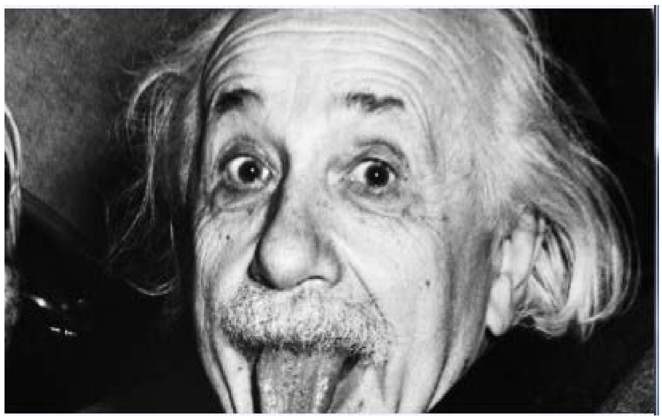
a



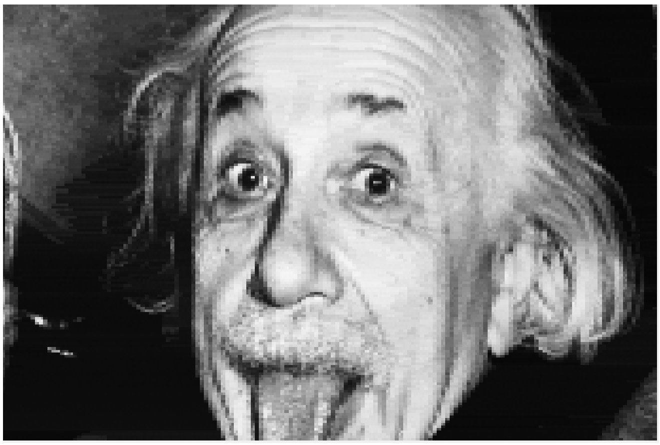
b

Fig.4. Regular compression; a) reconstructed image with normal distribution and b) with uniform distribution

It should be noticed that we cannot perform the irregular compression without obtaining a very good image reconstruction quality corresponding to the regular segmentation as shown in fig.4.



a



b

Fig.5. Irregular compression; a) reconstructed image with normal distribution and b) with uniform distribution

The parameters matrix for the irregular compression, obtained using our algorithm, is 3 rows by a number of columns which is equal to the number of the breakpoint indices. Each breakpoint index represents a stationary interval length. The first, the second and the third row of the parameters matrix represent, respectively, the breakpoint indices, the variances and the means of the corresponding segments.

III. CONCLUSION

The main advantage of our irregular compression technique for the image compression over most non-Gaussian fields based methods, lies in the ease of computing the mono-dimensional Gaussian representation of the stationary segments of each matrix line. The high irregular compression obtained in this work, indicates that our proposed irregular compression method can be very efficient in practice. It should be noted, however, that in our line by line analysis of the image matrix, we have assumed that the pixels are very weakly dependent in order to reconstruct the image using the independent random variables joint probability. The quality of the reconstructed image using GWN model shows, indeed, that this assumption is quite reasonable.

REFERENCES

[1] S. C. Zhu, Y. Wu, and D. Mumford. Filters, random fields and maximum entropy (FRAME): Towards a unified theory for texture modeling. Int'l. J. Comp. Vis., 27(2):107–126, 1998.

[2] P. Gehler and M. Welling. Products of "edge-perts". In Adv. in Neural Info. Proc. Systems (NIPS*05). MIT Press, 2006.

[3]] S. Roth and M. J. Black. Fields of experts: a framework for learning image priors. In IEEE Conf. on Comp. Vis. and Pat. Rec., volume 2, pages 860–867, 2005.

[4] Zhong , J. and Sclaro, S..,. Segmenting foreground objects from a dynamic textured background via a robust Kalman filter. In Proceedings of the International Conference on Computer Vision (ICCV), pp. 44-50, 2003.

[5] B. Yagoubi. Geometric Approach to a Non Stationary Process. 2nd Int. Conf.on Mathematical Models for Engineerign Science(MMES'11), pp179-183, Tenerife, Spain, , Dec.10-12, 2011.

[6] B. Yagoubi. Use of power Spectral density Image to support Early Forest Fire Direct Detection. 13th International Conference on Signal Processing, Computational Geometry and Artificial Vision(ISCGAV '13),pp.20-22,Valencia, Spain, Aug. 6-8, 2013.

[7] B. Yagoubi, S. Benkraouda and A. Bouziane. Belonging probability Inverse Image Technique to Early Detection of Volcanic Eruption. 14th International Conference on Systems(part of CSCC'14), pp326-329,Santarini Island, Greece, July 17-21, 2014.

[8] D. J. Field. Relations between the statistics of natural images and the response properties of cortical cells, J. Opt. Soc. Am. , 4(12):2379–2394, 1987.

[9] D. Ruderman. The statistics of natural images. Network : Comp. in Neural Sys. , 5:598–605, 1994.

[10] M. J. Wainwright and E. P. Simoncelli. Scale mixtures of Gaussians and the statistics of natural images.In Adv. Neural Info. Proc. Sys. (NIPS*99) , volume 12, pages 855–861, May 2000.

[11] E.P. Simoncelli and E.H.Adelson. Noiseremoval via Bayesian wavelet coring.In Int'l Conf on Image Proc, pp379–383, Lausanne, Sep. 1996.

[12] S. G. Mallat, A theory for multi-resolution signal decomp osition: The wavelet representation,"IEEE Pat. Anal. Mach. Intel l.11, pp. 674-693, July 1989.

[13] X. Descombes, R. D. Morris, J. Zerubia, and M. Berthod. Estimation of Markov random field prior parameters using Markov chain Monte Carlo maximum likelihood. IEEE Trans. Image Process., 8(7):954 - 963, July 1999.

[14] Lafarge. F, Descombes. X, Zerubia. J, Mathieu. S., (2007). Forest fire detection by statistical analysis of rare events from thermical infrared images, Traitement du signal, 24(1),1-12

[15] Lafarge F, Descombes. X, Zerubia. J, Mathieu. S.,, (2007). Forest fire detection based on Gaussian field analysis, European Signal Processing Conference (EUSIPCO).

[16] Kay, S.M., 1998. Fundamentals of Statistical Signal Processing, Detection Theory, vol. 2, Prentice–Hall.

[17] Mumford, D. and B. Gidas: 2001, `Stochastic Models for Generic Images'. Quaterly of Applied Mathematics 59(1), 85-111.