A RECURSIVE ALGORITHM FOR THE REDUCTION OF QUANTIZATION EFFECTS OF IMAGE COMPRESSION

Fabrizio Russo

D.E.E.I. – University of Trieste, Trieste I-34127 Italy
Phone +39 040 6767813 Fax +39 040 6763460 e-mail: rusfab@univ.trieste.it

Abstract - *A simple technique for the restoration of color images degraded by lossy compression is presented. The proposed approach deals with the YIQ color space and processes the luminance component by means of a recursive algorithm based on fuzzy models. This design choice combines effectiveness and simplicity. Indeed, the method can satisfactorily reduce quantization errors produced by lossy compression such as the popular JPEG technique. On the other hand, the tuning process is very fast because it requires one parameter only.*

Keywords – Quantization, noise cancellation, nonlinear filters.

1. INTRODUCTION

Quantization errors typically affect digital images after lossy compression [1-2]. In order to reduce the size of the data, commonly adopted methods resort to transform-based approaches that perform quantization of transform coefficients during the encoding process. The decoding procedure, however, cannot exactly reproduce the original data because some information is missing. As a result, the reconstructed image is affected by errors that significantly degrade the quality of the data, especially when high compression ratios are required. As is known, the most annoying effects encompass *blocking* and *ringing* artifacts [3]. In order to reduce these effects, a variety of post-processing techniques have been developed also including soft-computing approaches [4-8]. In this paper a new recursive algorithm for the reduction of quantization errors in compressed color images is presented. The proposed approach aims at reducing the number of necessary parameters in order to speed up the tuning procedure. Unlike our previous technique [8], the method does not process the RGB components of the multichannel image. On the contrary, it adopts the YIQ color space and operates on the luminance component only. This design choice takes advantage from the fact that the human eye is less sensitive to quantization errors affecting the chrominance components of the image. The nonlinear algorithm is based on fuzzy models and is recursively applied to the data in order to increase the smoothing action and then achieve a satisfactory correction of quantization effects. This paper is organized as follows. Sect.2 describes the proposed method, Sect.3 analyzes some experimental results and, finally, Sect.4 reports conclusions.

2. THE PROPOSED ALGORITHM

Let us suppose we deal with digitized multichannel images represented in the YIQ (or YUV) color space [2]. The value at each image pixel is taken to be a 3-D vector whose components are one luminance value and two chrominance values, respectively. The algorithm deals with the luminance component only and operates on a 4×4 pixel window (Fig.1), according to the innovative paradigm of multiple-output recursive processing [9].

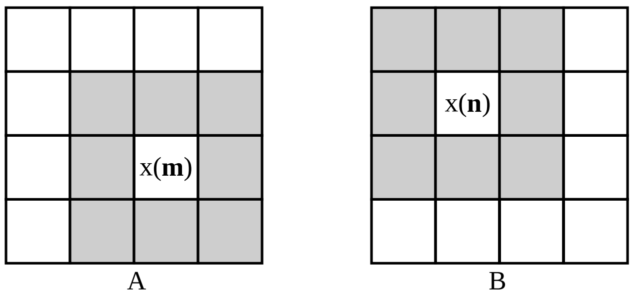

Fig.1 – 4×4 window including the pixel subsets A and B.

The advantage of processing the luminance channel is apparent if we examine the RGB and the YIQ components of a color image. An example of a 24 bit color picture is shown in Fig.2. The corresponding RGB and YIQ channels are depicted in Fig.3. We can easily see that the information is (more or less) equally distributed among the R, G and B components. Conversely, the role played by the Y luminance channel is more relevant with respect to the chrominance I and Q components. Hence, if we choose the YIQ color space, we can reduce the computational burden because the

Fig.2 – 24 bit color image.

Fig.3 – RGB components (a,b,c); YIQ components (d,e,f).

processing can satisfactorily be limited to one channel only.

The proposed method operates as follows. Let $x(\mathbf{m})$ be the pixel luminance at location $\mathbf{m}=[m_1,m_2]$, where $0 \le x \le Q$ (typically Q=255). Let the pixels in the window be grouped into two subsets A and B, as represented in Fig.1. Let $x_1(\mathbf{m})$, $x_2(\mathbf{m}),....,x_8(\mathbf{m})$ denote the luminances of the pixels that belong to subset A. As a first step, the algorithm produces the output $y(\mathbf{m})$:

$$y(\mathbf{m}) = x(\mathbf{m}) + \frac{p}{8}\left\{\sum_{x_i \in A} \mu[x_i(\mathbf{m}), x(\mathbf{m})] - \mu[x(\mathbf{m}), x_i(\mathbf{m})]\right\} \qquad (1)$$

where $\mu(u,v)$ is the membership function of the fuzzy relation: *u is a bit greater than v* [8]:

$$\mu(u,v) = \begin{cases} 1 - \dfrac{u-v-p}{Q-p} & p \le u-v \le Q \\ \dfrac{1}{2} + \dfrac{u-v}{2p} & -p \le u-v < p \\ 0 & -Q \le u-v < -p \end{cases} \qquad (2)$$

The nonlinear behavior of this function is controlled by the parameter p only. The new value $y(\mathbf{m})$ is immediately assigned to $x(\mathbf{m})$ and re-used for further processing.

Now, let us consider the pixel luminance $x(\mathbf{n})$ at location $\mathbf{n}=[n_1,n_2]$, where $n_1=m_1-1$ and $n_2=m_2-1$ (Fig.1). Let $x_1(\mathbf{n})$, $x_2(\mathbf{n}),....,x_8(\mathbf{n})$ denote the luminances of the pixels that belong to subset B.

Since the window scans the input image from left to right and from top to bottom, these luminances represent the results of the previous processing step. In order to increase the ability to remove blocking and ringing artifacts, the fuzzy processing is recursively applied to these data. Thus, the output $y(\mathbf{n})$ is evaluated as follows:

$$y(\mathbf{n}) = x(\mathbf{n}) + \frac{p}{8}\left\{\sum_{x_i \in B} \mu[x_i(\mathbf{n}), x(\mathbf{n})] - \mu[x(\mathbf{n}), x_i(\mathbf{n})]\right\} \qquad (3)$$

As in the previous step, the output value $y(\mathbf{n})$ is immediately assigned to $x(\mathbf{n})$ and re-used for further processing. It should be observed that the overall processing is controlled by parameter p only ($0<p<Q$). This is a key advantage of the proposed method.

(a)

(b)

Fig.4. - Test image compressed at about 35:1 (a), result yielded by the recursive algorithm (b).

3. SOME EXPERIMENTAL RESULTS

In order to show the effectiveness of the proposed approach, we briefly discuss an application example. For this purpose, we have chosen the 24 bit color picture shown in Fig.2 and we have compressed these data at about 35:1 by means of the JPEG technique (Fig.4a). Ringing artifacts are clearly perceivable as sharp oscillations or "ghost shadows" located along the edges of the image. Blocking artifacts are also apparent. They are generated by independent coding of adjacent groups of pixels and are typically represented by abrupt transitions of luminance across block boundaries.

The result yielded by the recursive algorithm is shown in Fig.4b. Quantization effects are significantly smaller. In particular, most blocking artifacts have been cancelled and ringing effects have been significantly reduced.

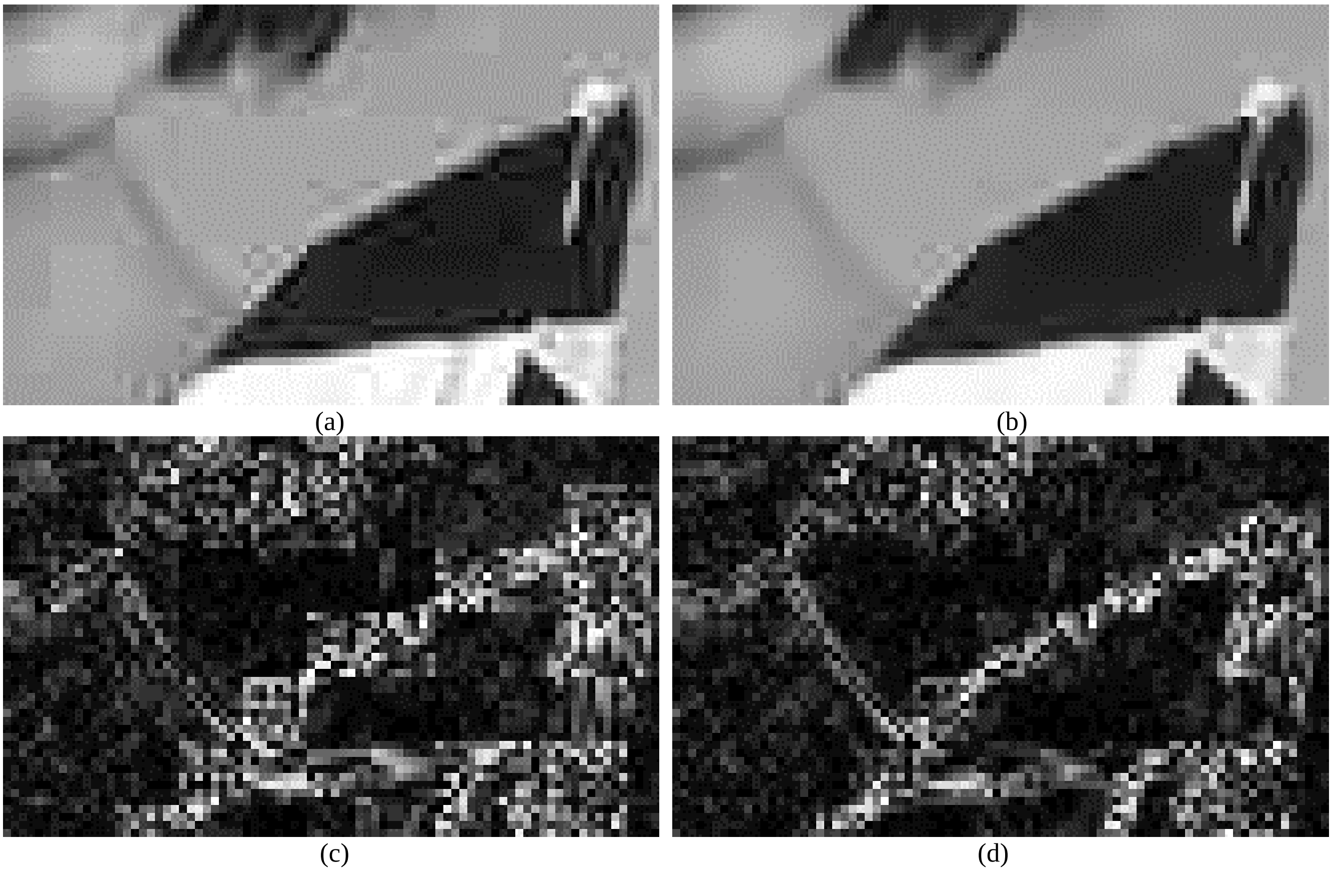

Fig.5 –Detail of the compressed image affected by blocking and ringing artifacts (a), correction performed by the proposed method (b), corresponding error map of the compressed (c) and of the filtered data (d).

In order to analyze the filtering performance of the proposed method, a detail of the test image is shown in Fig.5 for visual inspection. A map of the absolute error with respect to the original data is also reported. Finally, we can observe that a performance index can be obtained by estimating the mean square error (MSE) between the processed and the original luminance component. The MSE values are: 41.9 (compressed) and 34.4 (filtered).

4. CONCLUSIONS

A simple technique for the reduction of quantization errors of compressed color images has been presented. The proposed method deals with the luminance component in the YIQ color space in order to reduce the computational burden. As a result, only one parameter is necessary to adjust the error correction behavior. Experimental results have shown that the recursive algorithm based on fuzzy models can satisfactorily reduce blocking and ringing artifacts produced by lossy compression such as the popular JPEG technique.

ACKNOWLEDGMENTS

This work has been supported by M.U.R.S.T.

REFERENCES

[1] ISO-IEC CD 10918-1, Digital Compression and Coding of Continuous-tone Still Images, Part 1: Requirements and Guidelines, March 15, 1991.

[2] W. B. Pennebaker and J. L. Mitchell, JPEG Still Image Data Compression Standard, Van Nostrand Reinhold, 1993.

[3] Y. Yang and N. P. Galatsanos, "Removal of Compression Artifacts Using Projections onto Convex Sets and Line Process Modeling", IEEE Trans. on Image Processing, vol.6, n.10, October 1997, pp.1345-1357.

[4] K. I. Diamantaras and M. G. Strinzis, "Optimal Transform Coding in the Presence of Quantization Noise", IEEE Trans. on Image Processing, vol.8, n.11, November 1999, pp.1508-1515.

[5] C. Kuo and R. Hsieh, "Adaptive Postprocessor for Block Encoded Images", IEEE Trans. Circuits Syst.Video Technol., vol.5, August 1995, pp.298-304.

[6] J. Luo, C. Chen, K. Parker and T. S. Huang, "Artifact Reduction in Low Bit Rate DCT-Based Image

Compression", IEEE Trans. on Image Processing, vol.5, n.10, September 1996, pp.1363-1368.
[7] R. Castagno and G. Ramponi, "A Rational Filter for the Removal of Blocking Artifacts in Image Sequences Coded at Low Bitrate", in Proc. European Signal Processing Conference, EUSIPCO-96, Trieste, Italy, September 10-13, 1996, pp.567-570.
[8] F. Russo and G. C. Giakos, "Correction of Quantization Errors in Compressed Color Images", in Proc. 5th International Workshop on ADC Modelling and Testing, IWADC'2000 (Parallel event to XVI IMEKO World Congress, Wien, September 25-28, 2000.
[9] F. Russo, "A Multiple-Output Nonlinear Filter for Image Denoising", in Proc. XVI IMEKO World Congress, Wien, September 25-28, 2000.