A PDE-BASED METHOD FOR RINGING ARTIFACT REMOVAL ON GRAYSCALE AND COLOR JPEG2000 IMAGES

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ABSTRACT

As successor to JPEG, JPEG2000 aims to realize a very low bitrate. Although JPEG2000's rate distortion has been improved by approximately 30% against JPEG, as on most images compressed using overlapping transforms-based algorithms, one can notice visible spurious oscillations, or ringing artifacts, around the edges of a JPEG2000-compressed image. In this paper, we propose a Partial Differential Equations, or PDE-based image enhancement technique, in order to remove these ringing artifacts, while keeping the image's edges. Results are provided on grayscale and color images, showing a visible enhancement, confirmed by the PSNR increase.

1. INTRODUCTION

Unlike lossless image compression, in which every single bit of data that was originally in the file remains after the file is uncompressed, lossy image compression consists in making a trade-off between file size and image quality, by introducing loss of information on an image, so that even lower bitrates can be achieved. As bitrate decreases, degradations caused by information loss become more and more visible. As an example, JPEG's most noticeable degradations are blocking artifacts, caused by short and non overlapping transforms. As a successor to JPEG, JPEG2000 uses overlapping transforms, and achieves lower bitrates without causing any blocking artifact. Degradations can still be noticed though : the high frequency wavelet coefficients' heavy quantization produces spurious oscillations, or ringing artifacts, around the edges or discontinuities of the compressed image.

Instead of increasing bitrate in order to avoid such artifacts, we propose a post-processing method, based on Partial Differential Equations (or PDE), to remove them from the decompressed image, while preserving its edges. Such operation should result in a better looking, artifacts-free image, as well as in an improvement in terms of PSNR (Peak Signal to Noise Ratio).

Ringing artifacts removal techniques have already been proposed in literature. In [1], Yang introduces a method based on Maximum Likelihood, but only applies it to grayscale images. Our algorithm is able to deal with grayscale or color images, and shows satisfying results in both cases. It's also able to work as a totally unsupervised process.

In the first part, we introduce the principle of PDEs and isotropic and anisotropic diffusions, before presenting in second part our diffusion function, that appears to be efficient for ringing artifacts removal. Finally, we will show in a third part results on grayscale and color images.

2. PDEs AND NONLINEAR FILTERING

We propose in this part a classical approach of noise reduction in image processing. This will allow us to quickly introduce the principles of isotropic and anisotropic diffusions, before talking about the stability of such a process, and its application to color images. A variational approach, more aesthetical, but longer, is proposed in [2]; Deriche's approach allows to unify most PDE-based methods in image enhancing and multi-scale analysis under the same formalism.

2.1. Isotropic diffusion

We consider our problem as a noise reduction problem : a classical approach consists in considering the image's noise as a high frequency signal. A well-known solution is linear convolution :

$$I(x, y, t) = \int_{\Omega} G(x-\xi, y-\eta, t) I_0(\xi, \eta) d\xi d\eta \quad (1)$$

with : (x, y) : a pixel of the image

$I(x, y, t)$: the restored image (brightness)
(from now we will write I)
$I_0(x, y, t)$: the noisy image
$G(x, y, t)$: a smoothing operator
t : the smoothing strength control parameter

In such type of smoothing process, the Gaussian operator is commonly used. In [3], Koenderink notices that convolving an image with a Gaussian operator can also be understood as a diffusion process, that can be written as follows :

$$\begin{cases} \frac{\partial I}{\partial t} = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \\ I(x, y, 0) = I_0(x, y) \end{cases} \quad (2)$$

That can be interpreted as the diffusion process of pixel (x, y)'s brightness around pixels $(x \pm \partial x, y \pm \partial y)$, during a time t ($t \in [0, T]$). This process, called isotropic diffusion, gives unsatisfying results, since it operates the same way in all directions, and can't distinct edges from noise, leading to a blurry image. However, it allows us to introduce the notion of anisotropic diffusion.

2.2. Anisotropic diffusion

Anisotropic diffusion, as presented by Perona and Malik in [4], allows this edges/noise distinction ; the process is written as follows :

$$\begin{cases} \frac{\partial I}{\partial t} = div(c(|\nabla I|)\nabla I) \\ I(x, y, 0) = I_0(x, y) \end{cases} \quad (3)$$

with : $c(.)$: a decreasing positive function
div : divergence operator
∇ : gradient operator

This time, conditional smoothing is performed. Its behavior is function of the image's gradient norm, thanks to function $c(.)$. In low gradient areas (homogeneous areas), heavy diffusion is performed, while light diffusion is performed in high gradient areas (edges).

2.3. Conditions of stability

Deriche and Faugeras' approach [2] leads to :

$$\frac{\partial I}{\partial t} = div(\Phi'(|\nabla I|)\frac{\nabla I}{|\nabla I|}) \quad (4)$$

$$= \Phi''(|\nabla I|) I_{\xi\xi} + \frac{\Phi'(|\nabla I|)}{|\nabla I|} I_{\eta\eta} \quad (5)$$

with : $\Phi(.)$: a function to be defined
$I_{\xi\xi}$: the second directional derivative of I in the gradient's direction
$I_{\eta\eta}$: the second directional derivative of I in the gradient's orthogonal direction

As we can see, there's an analogy between (3) and (4), with $c(s) = \frac{\Phi'(s)}{s}$. Writing the parabolic PDE (5) allows us to define conditions of stability. These are :

$$\begin{cases} \Phi''(0) > 0 \\ \lim_{|\nabla I| \to 0} \frac{\Phi'(|\nabla I|)}{|\nabla I|} = \lim_{|\nabla I| \to 0} \Phi''(|\nabla I|) = \Phi''(0) \\ \lim_{|\nabla I| \to \infty} \Phi''(|\nabla I|) = 0, \lim_{|\nabla I| \to \infty} \frac{\Phi'(|\nabla I|)}{|\nabla I|} = 0 \\ \lim_{|\nabla I| \to \infty} \frac{\Phi''(|\nabla I|)}{\frac{\Phi'(|\nabla I|)}{|\nabla I|}} = 0 \end{cases} \quad (6)$$

It means that isotropic diffusion is performed in low gradient areas ($|\nabla I| \to 0$), while diffusion is only applied along the gradient's orthogonal direction for high gradient areas ($|\nabla I| \to \infty$).

Many diffusion functions $\Phi(.)$ can be found in literature [4, 5, 6]. Interestingly, Deriche and Faugeras' formulation turns out to prove a great number of these functions do not have sufficient conditions of stability for high gradient areas, since the continuous filter then behaves as a reverse heat equation (backward diffusion is known to be an unstable process). In [7], Weickert proves that discretizations of the Perona-Malik equation are not unstable. Furthermore, such filter happens to both blur small fluctuations and sharpen edges.

2.4. Color images

In the case of color images, we define a vectorial image $\vec{I}(x, y) : \Re^2 \to \Re^3$. (3) can be easily extended from I (scalar, grayscale image) to $\overrightarrow{I}$ (vectorial, color image). However, an efficient representation of the color image's edges still has to be defined (a multispectral gradient). Many approaches have been developed for that purpose. We decided to use Di Zenzo's norm [8], which is based on differential geometry of surfaces. It consists in defining a tensor gradient, associated with a vector field, to look for local variations in the image. The highest eigenvalue of the tensor gradient then corresponds to the gradient norm.

3. RINGING ARTIFACTS REMOVAL

In this part, we propose an anisotropic diffusion function $c(.)$, inspired by Perona-Malik's, that happens to be efficient for ringing artifacts removal. We also introduce a parameters estimation method, based on a Mean Square Error minimization formulation, in order to make our process work a totally unsupervised way.

3.1. Anisotropic diffusion function

Unlike Perona-Malik's equation (3), our diffusion function $c(.)$ isn't directly linked to $|\nabla I|$, but to a normalized version of it, thus allowing us to define a threshold α, which values remain the same no matter what image is being processed. $c(.)$ is defined as :

$$c(s) = (1 + s^2).e^{-s} \quad (7)$$

with : $s = \alpha.\frac{Max(|\nabla I|) - Min(|\nabla I|)}{Var(|\nabla I|)}.|\nabla I|$

Threshold α allows us to introduce an anisotropy level for function $c(.)$. We can easily notice that for $\alpha = 0$, $c(s)$ equals 1, discarding s : in this case, the diffusion process turns into isotropic diffusion, as defined in (2).

3.2. Parameters estimation

Another difference between Perona-Malik's process and the one presented here is the fact that instead of using a constant threshold, we decide to use our function's backward diffusion property, and make α evolve with time, from purely isotropic diffusion (heavy denoising) to highly anisotropic diffusion (denoising and edges enhancing). The algorithmic implementation then requires the determination of two parameters :

- N, the number of iterations (discrete equivalent to T, the time of diffusion)
- α, which value evolves according to iteration n. We rename it α_n, with $n \in [0, N-1]$

We are looking for an image quality criteria, in order to determine optimal parameters α_n and N. Such criteria should be able to judge the restored image quality, by comparing it to the original image. Many quality measures have been proposed for that purpose. Recent works tend to focus on psychovisual studies, and try to emulate the Human Visual System (HVS). Since we're only looking for an image quality criteria to determine the process' parameters, we decide to use the well-known Mean Square Error (MSE), which main advantage is its simplicity. From now we write the parameters' determination as a minimization problem :

$$\widehat{\alpha_n} = \arg\min_{\alpha_n} \left(\frac{\sum_{x=0}^{P} \sum_{y=0}^{Q} (I(x,y,n) - I_0(x,y))^2}{P \times Q} \right) \quad (8)$$

for $n \in [0, N-1]$, with $P \times Q$ the size of the image

α_n values start from 0 (first iteration : isotropic diffusion), and increase as the number of iterations grow, so to minimize the MSE at each iteration. N is then supposed to be the number of iterations above which the MSE tends to be steady (experiments have shown N barely exceeds 20). It should be noticed that we can't really talk about convergence here, since α's variations during iterations turn this algorithm into N one-iteration anisotropic diffusion processes, instead of one N-iterations process, according to Perona and Malik's initial work.

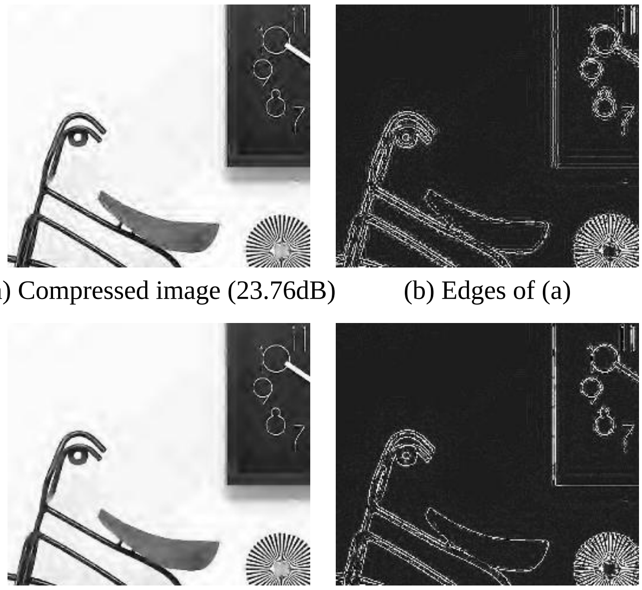
The parameters' determination is a pre-processing, that occurs before the JPEG2000-coded image is transmitted. Once estimated, diffusion parameters are placed in the compressed image file's header.

4. EXPERIMENTAL RESULTS

We are presenting in this part results obtained on grayscale and color images. The JPEG2000 encoder we used is JJ2000 v4.1. Results are given in terms of PSNR. As already mentioned in 3.2, there are better image quality measures than this one, alas none seems to have been proposed as a freely available software application.

4.1. Grayscale images

Fig. 1 shows results obtained for the Bike image (grayscale, 2048 $\times$ 2560) at 0.0625bpp.



(a) Compressed image (23.76dB) (b) Edges of (a)

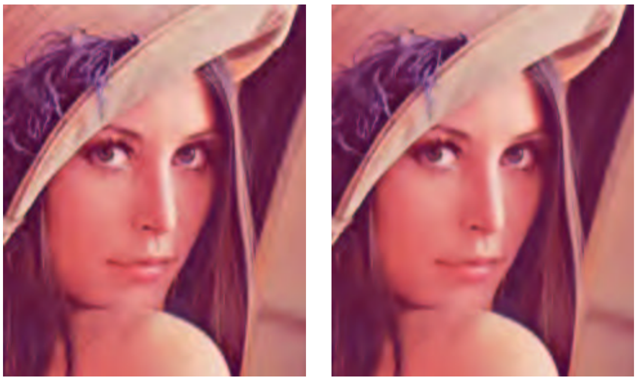
(c) Restored image (24.20dB) (d) Edges of (c)

Fig. 1. Restoration of the Bike image (zoom)

We can notice an 0.44dB increase in terms of PSNR (calculated for the whole 2048 $\times$ 2560 images) between the compressed image Fig. 1.a (23.76dB) and the restored one Fig. 1.c (24.20dB). Fig. 1.d shows oscillations-free edges, as opposed to Fig. 1.b, and proves most ringing artifacts have been successfully removed during restoration.

4.2. Color images

Fig. 2 shows results for the Lena image (color, 512×512) at 0.25bpp.



(a) Compr. image (30.59dB) (b) Rest. image (30.81dB)

Fig. 2. Restoration of the Lena image (zoom)

Again, we can notice the ringing artifacts' removal, giving Fig. 2.b a better quality (from psychovisual point of vue) than Fig. 2.a. This time, PSNR is improved from 30.59dB (compressed image) to 30.81dB (restored image).

Table 1 presents more results on images Bike (2048×2560) and Lena (512×512), in grayscale (GS) and color (C) versions, for various bitrates.

Image	Bitrate	Init PSNR	Final PSNR
Bike (GS)	0.0625 bpp	23.76 dB	24.20 dB
Bike (GS)	0.2500 bpp	29.58 dB	29.92 dB
Bike (GS)	0.5000 bpp	33.47 dB	33.68 dB
Bike (C)	0.0625 bpp	22.94 dB	23.33 dB
Bike (C)	0.2500 bpp	28.18 dB	28.52 dB
Bike (C)	0.5000 bpp	31.32 dB	31.55 dB
Lena (GS)	0.0625 bpp	26.63 dB	26.88 dB
Lena (GS)	0.2500 bpp	32.60 dB	32.75 dB
Lena (GS)	0.5000 bpp	35.77 dB	35.84 dB
Lena (C)	0.0625 bpp	26.07 dB	26.35 dB
Lena (C)	0.2500 bpp	30.59 dB	30.81 dB
Lena (C)	0.5000 bpp	32.84 dB	32.96 dB

Table 1. Results on various images and bitrates

5. CONCLUSION

In this paper, we've presented a Partial Differential Equations-based image restoration method, and used it in order to remove ringing artifacts on low bitrate JPEG2000 images. The main advantages of our method are its simplicity, the fact that it includes a parameters' estimation to work a totally unsupervised way, and a low processing time (about 1 second for 1 iteration on a 512×512 color image[1], knowing the complete restoration process hardly requires more than 20 iterations). We've been able to show promising results on both grayscale and color images. These results may open up new perspectives, especially for moving images, since standard video compression codecs happens to introduce visible degradations similar to those we're now able to remove on still images.

6. REFERENCES

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