CONSIDERING THE WAVELET TYPE AND CONTENTS ON THE COMPRESSION-DECOMPRESSION ASSOCIATED WITH IMPROVEMENT OF BLURRED IMAGES

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Abstract: Uncompressed multimedia data such as high resolution images, audio and video require a considerable storage capacity and transmission bandwidth on telecommunications systems. Despite of the development of the storage technology and the high performance of digital communication systems, the demand for huge files is higher than the available capacity. Moreover, the growth of image data in database applications needs more efficient ways to encode images. So image compression is more important than ever. One of the most used techniques is compression by wavelet, specified in the JPEG 2000 standard and recommended also for medical image DICOM database. This work seeks to investigate the wavelet image compression-denoising technique related to the wavelet family bases used (Haar, Daubechies, Biorthogonal, Coiflets and Symlets), database content and noise level. The target of the work is to define which combination present the best and the worst compression quality, through quality evaluation by quantitative functions: Root Mean Square Error (RMSE), Sign Noise Ratio (SNR) and Peak Sign Noise Ratio (PSNR).

1 INTRODUCTION

Huge images are used in an increased number of applications. They require a considerable storage capacity and transmission bandwidth. Wavelet compression, used in the DICOM standard (Digital Imaging and Communications in Medicine) and JPEG 2000 format is the most used image compression technique (Stahl et al., 2000; Ouled Zaid et al., 2002). Simultaneous compression and denoising is and important aspect of wavelets compression (Bruni and Vitulano, 2007). These, namely comp-denoisers, are mainly based on thresholding the components dominated by noise. We investigate the quality concerning the blur level, the image content and the type of wavelet used. The idea is to modify out the coefficient components dominated by noise. This improves the image quality and the compression rate as well. This work compares results of 36 different wavelet types. For this we implement in the same environment five families of bases: Haar, Daubechies, Biorthogonal, Coiflets and Symlets with many possibilities. They are used to compress a group of natural and synthetic images in different resolutions. We consider three level of degradation by Additive White Gaussian Noise (AWGN). The target of the work is to propose a comp-denoiser adapted to each type of images and technique used. We try to define which aspect present the best and the worst compression quality, through evaluation of the Root Mean Square Error (RMSE), Sign Noise Ratio

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(SNR) and Peak Sign Noise Ratio (PSNR). By analyzing the results is possible to verify that the best choice related to quality is more dependent to the image content than expected initially.

The fidelity with respect to the original is an important aspect of lossy compression methods. However, quality is not an easy issue to measure. Comparisons can be performed considering visual quality of the decompressed image or quantitatively using error evaluators. These are pointwise information associated with the image generated by subtracting the differences between the original image and the decompressed images. Figure 1 shows an example of a compression error for the Lena image (Conci et al., 2008). The pointwise differences were amplified to fit into the interval between 0 and 255 in order to facilitate their visualization. The Haar coefficients in this example are adjusted to get a file 80% reduced. Comparing the performance using error images makes it easier to see where the decompressed image has been slightly changed: some elements with low spatial frequencies have been removed improving the image. If these elements originated from noise the compression process additionally improves the image quality. Moreover, the same idea can be used to improve the details if the noise is responsible of blurring the images.

The following is an outline of this paper: in Section 2 we consider the relation between wavelet based denoising and wavelet coefficients. Section 3 gives a brief review on wavelets types and provides details of the experiments. Finally, conclusions are presented, in section 4.

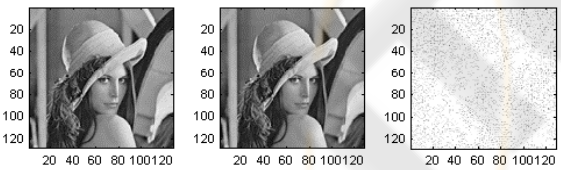

Figure 1: "Lena" (128 x 128), its compressed version by Haar and the rescaled error image.

2 DENOISING BY WAVELET

The low frequency components (smooth variations) constitute the base of a natural image. The high frequency components add upon low frequency components to refine the image, thereby giving a detailed image. Separating the smooth variations and details of the image can be done in many ways. One such way is the decomposition of the image using a Discrete Wavelet Transform (DWT) in the following way: A low pass filter (LPF) and a high pass filter (HPF) are chosen, such that they exactly halve the frequency range between themselves. These are called the Analysis Filter Pair. First, the LPF is applied for each row of data, thereby getting the low frequency components of the row. But since the LPF is a half band filter, the output data contains frequencies only in the first half of the original frequency range. So, they can be sub sampled by two and the output data now contains only half the original number of samples. Now, the HPF is applied for the same row of data, and similarly the high pass components are separated, and placed by the side of the low pass components. This procedure is done for all rows. Next, the filtering is done for each column of the intermediate data. The resulting two-dimensional array of coefficients contains four bands of data, each labeled as LL (low-low), HL (high-low), LH (low-high) and HH (high-high). The LL band can be decomposed once again in the same manner producing even more sub bands. This can be done up to any level, thereby resulting in a pyramidal decomposition as shown in figure 2.

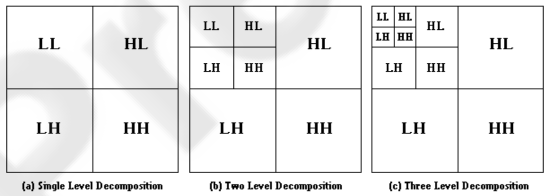

Figure 2: Pyramidal decomposition.

The wavelet transform calculates inner products of a signal with a set of basis functions to find coefficients that represent the signal:

$$f(t) = \sum_{j,k} a_{j,k} 2^{j/2} \Psi(2^j t - k) = \sum_{j,k} a_{j,k} \Psi_{j,k}(t) \qquad (1)$$

where the two-dimensional set of coefficients $a_{j,k}$ is the DWT of *f(t)*. When the index *k* changes, the location and scaling of the wavelet moves along the time axis. When the index *j* changes, the shape of the wavelet changes in scale. As the scale becomes finer (*j* larger), the time steps become smaller. Both the narrower wavelet and the smaller steps allow a representation of greater detail or resolution. In order to use the idea of multi resolution, a scaling function *j(t)* is used to define the wavelet (Kubrusly. and Levan, 2006). Since this is a linear system, the signal can be reconstructed by a weighted sum of the basis functions (Levan, and Kubrusly, 2007). A signal's energy, therefore, is usually well represented by just a few wavelet expansion coefficients. Wavelet analysis produces several important benefits, particularly for image compression. First, an unconditional basis causes the size of the expansion coefficients to drop off with *j* and *k* for many signals. Since wavelet expansion also allows a more accurate local description and separation of signal characteristics, the DWT is very efficient for compression. Secondly, a great variety of different wavelet types provides flexibility to design wavelets to fit individual applications. The LL band at the highest level can be classified as most important, and the other 'detail' bands can be classified as of lesser importance, with the degree of importance decreasing from the top of the pyramid to the bands at the bottom (figure 2) (Conci et al., 2008).

The wavelets denoising main aspect is to distinguish between low and high energy regions, and modify the coefficients using an adaptive thresholding strategy. When noise is added to the image, it tends to increase the magnitude of the wavelet coefficients on average. Specifically, in the regions where one expects the coefficients to be dominated by noise, consequently most of these coefficients should be removed since the noise is highly noticeable here. In regions of sharp variations, the coefficients have a lot of energy due to the signal, and some due to noise (which is not as visible in these regions), thus they should be kept to ensure that signal details are retained.

The wavelet thresholding approach removes noise from wavelet coefficients of the detail, while keeping the lowest resolution coefficients unaltered. It filters each noisy wavelet coefficient, from the detail sub-band, with a non linear thresholding function. The problem is to estimate correctly the threshold value in order to obtain good performance. Statistical approaches have been addressed for wavelet-based denoising (or thresholding). Wavelet hard threshold has been proposed (Donoho and Johnstone, 1994). As an alternative, a denoising algorithm via soft-thresholding has been developed to remove noise from wavelet coefficients (Donoho, 1995). Many variants and improvements of these works have appeared in the literature. It has been shown that optimal thresholding can be carried out based on the ratio between noise and original signal variance at each decomposition sub-band. The T value can then be well approximated by: $T = \sigma_n{}^2 / \sigma$ (Ruggeri. and Vidakovic, 1998). This alternative is implemented using the Wavelet Toolbox (Mathworks, 2001) for Matlab and used in our experiments to exploit the relation of the results to the image type and wavelet family.

3 EXPERIMENTAL RESULTS

The JPEG-2000 standard (selected in 2001 for inclusion in the DICOM standards) is based on the discrete wavelet transform using the Daubechies (9,7) biorthogonal wavelet, also named the Cohen-Daubechies-Feauveau 9/7 wavelet (Daubechies, 1992). Moreover, a coding denoising procedure based on a thresholding function has been integrated to JPEG2000 part II standard which is designed to support a variety of applications, including the compression and transmission of medical images (Stahl et al. 2000). But is this the best choice concerning quality at any time? In this work we compared the results from 36 different variations of wavelets compression schemes to explore their differences related to image content and quality. Two grouped images with different levels of complexities and content are used to evaluate the relation among fidelity, image content and noise level. The contents consist of humans, landscape, things, textual information and synthetic objects. The first group is formed by the natural images: Lena, Cameraman, Goldhill, and Peppers. The second group is formed by the synthetic images: Circle, Checkerboard, Sinusoidal Gray Level and Text. These images are used on three resolutions (128x128, 256x256 and 512x512). They are tested without noise and altered by Additive White Gaussian Noise (AWGN) with three noise levels: $\sigma = 5$, $\sigma = 10$, and $\sigma = 20$. They are reconstructed after compression and denoise by thresholding. To choose these images as samples we observed four aspects: the main motive, the number of elements, the richness or simplicity of the background. The performance of each approach is evaluated by fidelity comparing the original versus the same images after compression/denoising and decompression. Figures 3 and 4 show the first and third noise versions of these images, respectively. It should be noted that only two of these images are binary with well defined boundaries (Circle and Checkerboard). Comparing figure 3 and 4 you see that they are extremely sensitive to noise. Performance analysis was done using three objective evaluation criteria: Root Mean Square Error (RMSE), Signal to Noise Ratio (SNR) and Peak Signal to Noise Ratio (PSNR). Small RMSE means better results: the denoised image is close to the original. High values for SNR means lower error and this translates to a high value of PSNR. The main drawback of using RMSE and SNR as a measure of image quality is that in many instances these values do not match the quality perceived by the human visual system (Wang et al., 2004). The PSNR is more representatives.

Figure 3: Tested image with low noise ($\sigma = 5$).

The test results (3456 cases) are presented in 96 tables or 288 graphs (one graph for each evaluation criteria). Eight of these graphs are presented on figures 5 to 7. In this graphs the horizontal axe represent each one of the 36 type of wavelets used.

Figure 5 shows the PSNR results for the Peppers image with low noise ( ) but with at two different resolution. Comparing these it is possible to see that the worst results at both resolutions is related to the use of Biorthogonal 3.1 type, while the best wavelet type is not the same for both cases (for small image

Figure 4: Images with high noise ($\sigma = 20$).

it is the Biorthogonal 1.3 but for the 512x512 version of the same image it moves to the Daubechies 10 type). Figure 6 shows the results for the Cameraman image at same resolution (256x256) but with two different noise levels (5 and 20). Although, in these case the best and worst results are presented by the same wavelet type (that is Haar and Biorthogonal 3.1), all others intermediate position have been changed. More significant yet are the changes associated with the image content as can be seen comparing the completely different pattern of the graphs considering the RMSE for the four synthetic images in the same resolution without noise (figure 7). The results have been analyzed and combined in different manners. The graphs for natural images related to the wavelets type used have been presents similar distribution considering all noise level and denoising approach. They are combined in a group of natural images. The non binary synthetic images (text and sinusoidal) presents more similar behavior for median and high noise level. But the circle and chessboard images present no characteristics that permits adequate conclusion related with what could be pointed as best wavelet type for compression and denoising.

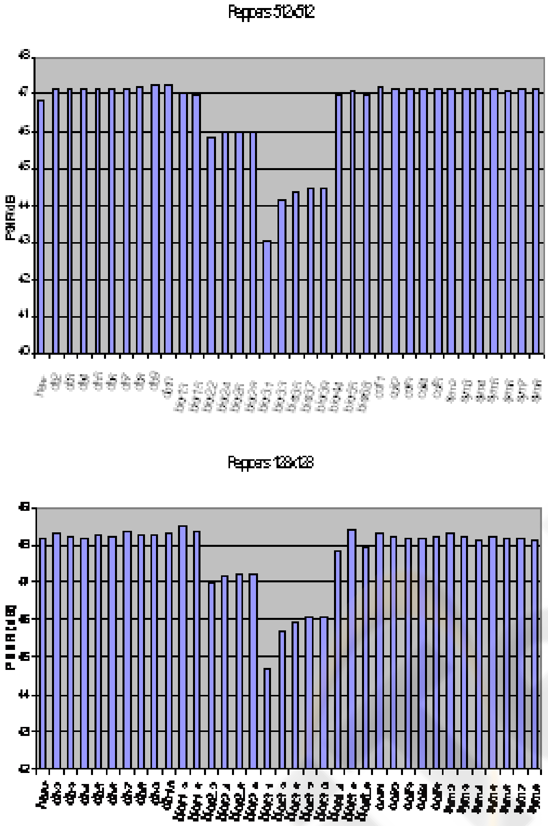

Figure 5: Example of PSNR results variation considering only resolution variation.

4 CONCLUSIONS

In this paper presents a broad analysis for wavelet based compression and denoising of synthetic and photographic or natural images. Our experiments compare a thresholding process to remove additive noise from three noisy versions (low Φ.5, median $\sigma = 10$ and high $\sigma = 20$). Averaging the results, the Haar and Biorthogonal 1.3 types present the first and second best quality. Worst results are obtained with the Biorthogonal 3.1 type. Considering the image content, they show more dependent on the image type and wavelet (Haar, Daubechies, Biorthogonal, Coiflets, or Symlets) used than could be expected.

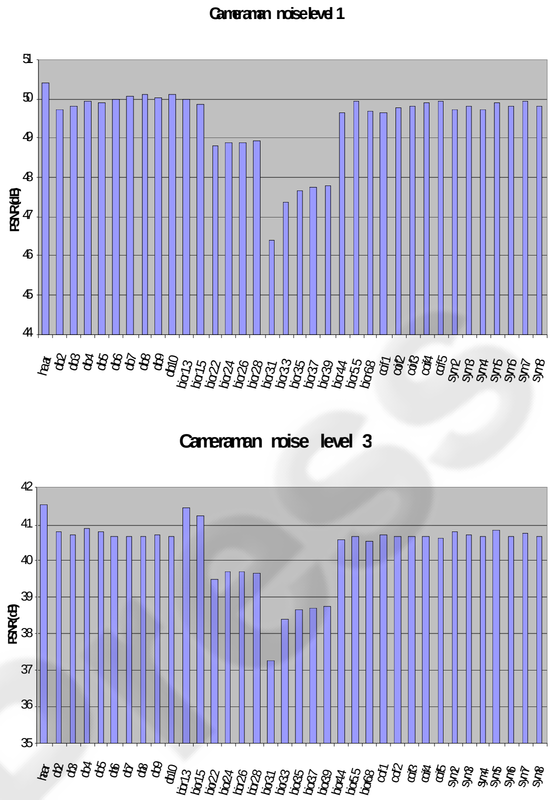

Figure 6: Example of PSNR results variation considering only noise level variation.

The performance assessment of the compression denoising results was performed by RMSE, SNR and PSNR objective measures. Our experiments showed that by incorporating a thresholding in the wavelet based coding chain, we can improve the quality of the compressed natural noisy image, without sacrificing performance and without increasing the computational complexity, but this is not effective on all types of synthetic images. The thresholding process improve the visual quality of natural images on the practically the same amount of the noise added. Based in this comparative study only the binary synthetic images present the denoised process related to the noise level. It is expected that the obtained results can be further improved if the other denoised scheme are exploited. Hence, we are currently investigating context adaptive extensions of the used thresholding process and others compression/denoising process to wavelet based coding.

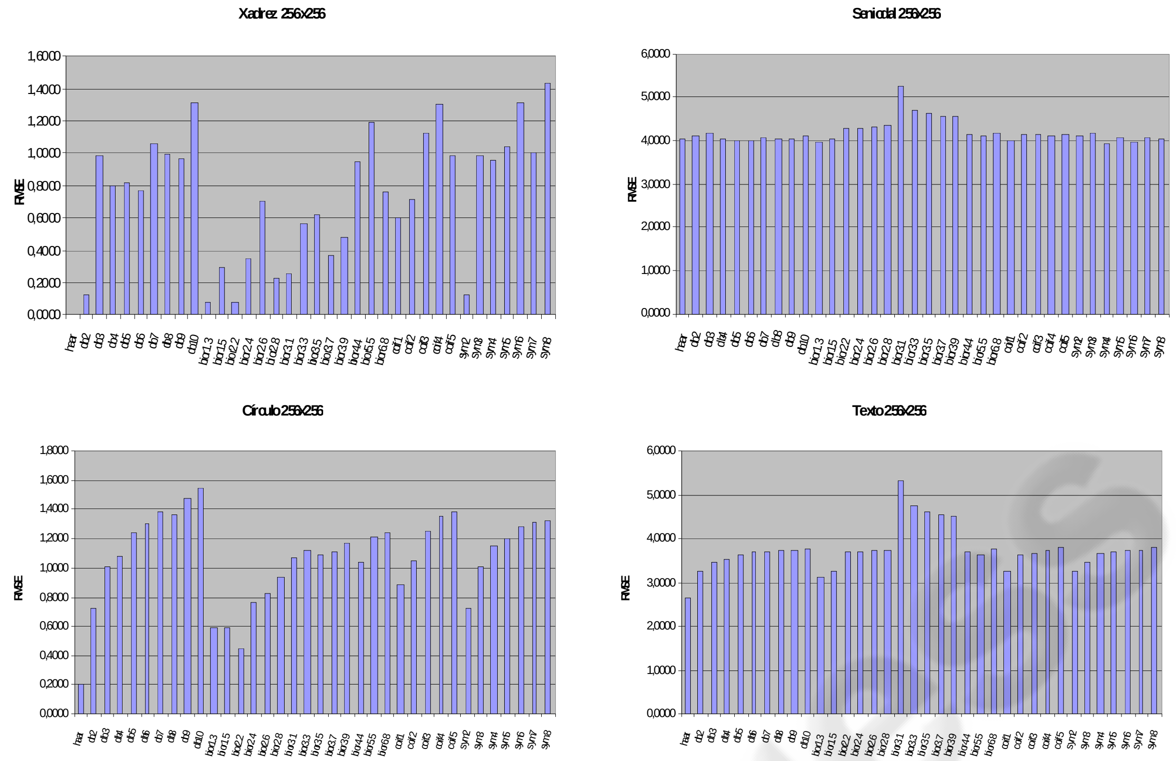

Figure 7: Example of RMSE results variation with the wavelet type for the synthetic image group without noise.

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