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A Comparative Study between Bandelet and Wavelet Transform Coupled by EZW and SPIHT Coder for Image Compression

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Abstract **—** Second generation bandelet transform is a new method based on capturing the complex geometric content in image; we use this transform to study medical and satellite image compressed using the bandelet transform coupled by SPIHT coder. The goal of this paper is to examine the capacity of this transform proposed to offer an optimal representation for image geometric. We are interested in compressed medical image, In order to develop the compressed algorithm we compared our results with those obtained by the bandelet transform application in satellite image field. We concluded that the results obtained are very satisfactory for medical image domain.

Index Terms **—** Bandelet transform, Compression, Optical flow, Quadtree segmentation, SPIHT and EZW coder .

I. INTRODUCTION

Today, distance diagnostic medical system, digital library and Internet are applied popularly. One of the most important problems in such applications is how to store and transmit images [1]. The medical diagnostic field is interested by the researchers. It is well established that the accuracy and precision of diagnostic are initially related to the image quality.

Finding efficient geometric representations of images is a central issue in improving the efficiency of image compression. Many ideas have already been studied to find new bases can capture geometric regularity image. Image representations in separable orthonormal bases such as Fourier, local Cosine or Wavelets can not take advantage of the geometrical regularity of image structures. Standard wavelet bases are optimal to represent functions with piecewise singularities; however, they fail to capture the geometric regularity along the singularities of edges or contours because of their isotropic support. To exploit the anisotropic regularity along edges, the basis must include elongated functions that are nearly parallel to the edges. Multi-scale geometric analysis (MGA) developed recently provides a group of new basis that has anisotropic supports such as Curvelets [2-7], A Curvelet frame is composed of multiscale elongated and related wavelet type functions, for this reason, In this paper, we introduce a new type of transform, called bandelet transform by E Le Pennec and Stéphane Mallat [8], this transform is more recently developed method of compression technique, which decompose the image along multiscale vectors that are elongated in the direction of a geometric flow. This geometric flow indicates directions in which the image gray levels have regular variations; bandelet bases can represent the geometric regular images efficiently.

II. THE BANDELET TRANSFORM

Bandelet transform, introduced by Le Pennec and Mallat [9] built a base adapted to the geometric content of an image. The bandelets are obtained from a local deformation of space to align the direction of regularity with a fixed direction (horizontal or vertical) and is reduced to a separable basis [10], [11].

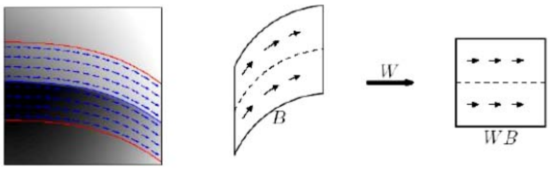


Figure 1. Deformation of horizontal field according to a geometric flow.

A. *Flow-curve relationship*

There is a constant correspondence between the flow along the vertical direction and curves whose tangent is never vertical; the flow associated with this curve is given by flow:

$$\tau(x) = \frac{1}{\sqrt{1+\left|c'(x)\right|^2}} \begin{pmatrix} 1 \\ c'(x) \end{pmatrix} \tag{1}$$

$c^{'}(x)$: Slope of optical flow.

We can generate the basic test bandelet according to the flow and geometric regularity of each sub-block. If there is no flow geometry in the sub-blocks, this means that the sub-block is uniformly regular so that we can use the classical separable wavelet basis for treating this sub-block. If not, the sub-block must be processed by the bandelet.

If the sub-block is not uniformly regular, we can deform it, has variation along geometric flow defined in the sub-block. [12].

For have the sub-block that contains the singularity that is with a calculation of Lagrangian [13].

$$L(f,R,B) = \left\| f - f_R \right\|^2 + \lambda.T^2 \sum_j \left(R_{jG} + R_{jB} \right) \tag{2}$$

λ : Lagrangian.

T : Quantifiction step.

R_{jG} : is the number of bits to code the optical flew in each square.

R_{jB} : is the number of bits to code the quantized bandelet coefficients.

B. *Quadtree segmentatin*

Segmentation operation it is a division successive of image space that allows us to have a set of sub-blocks.

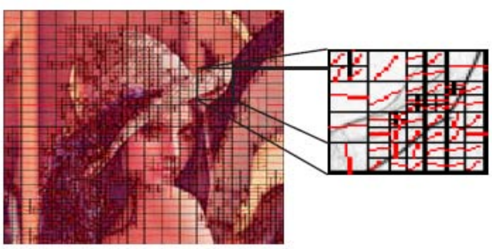


Figure 2. Example of quadtree segmentation

The operating diagram of the quadtree segmentation is the following

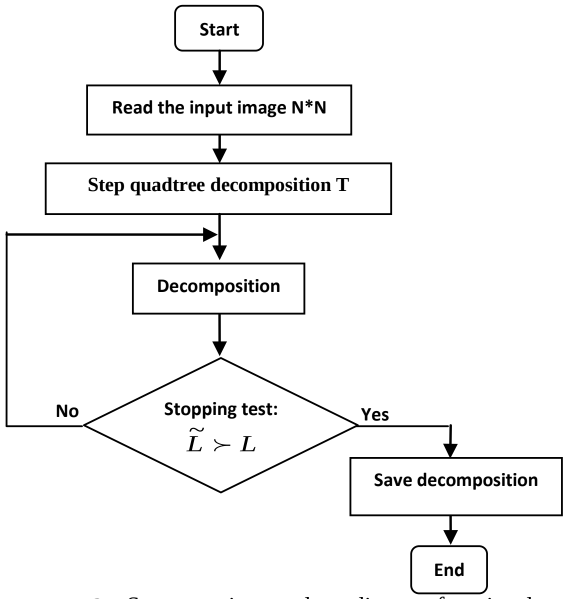


Figure 3. Segmentation quadtree diagram functional

For have the optimal segmentation that is with [14]:

$$L_0(S) = \min\left\{ L_0(S), \tilde{L}(S) \right\} \tag{3}$$

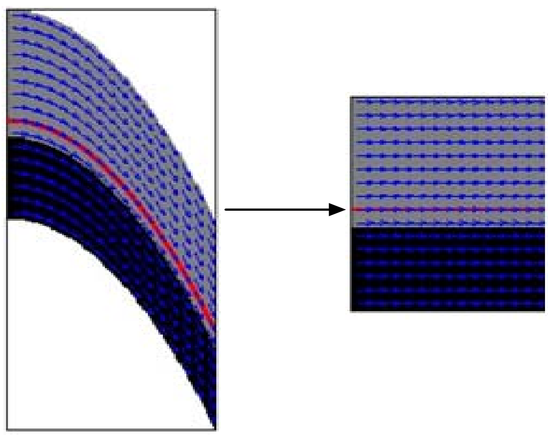
Where

$$\tilde{L}(S) = L_0(S_1) + L_0(S_2) + L_0(S_3) + L_0(S_4) + L_0(S) + \lambda.T^2$$

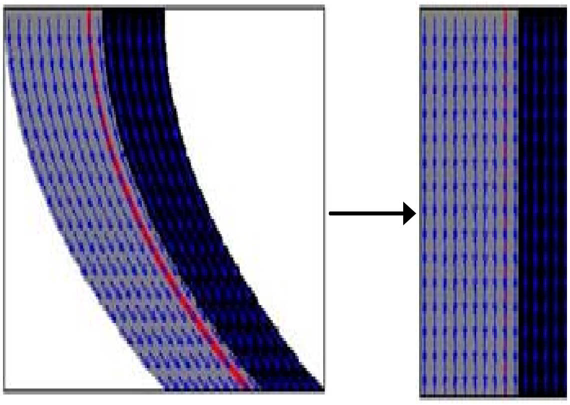
$L_0(S_i)$: Lagrangian of sub-blocks.

C. *The operator of deformation*

The deformation operation is a local operation on a block that contains a curve singularity to align or correct in a direction horizontal and vertical.



(a) (b)



(c) (d)

Figure 4. Example of model horizon and deformation of the field according to a geometric flow. Image distortion: (a) an image having a horizontal flow, (b) its image by the operator W, (c) an image having a vertical flow, (d) the image by the operator W.

Deformation operation gives a wavelet orthonormal basis of $L^2(\Omega)$:

$$\begin{Bmatrix} \phi_{j,n_1}(x_1)\,\psi_{j,n_2}(x_2 - c(x_1)) \\ \psi_{j,n_1}(x_1)\phi_{j,n_2}(x_2 - c(x_1)) \\ \psi_{j,n_1}(x_1)\psi_{j,n_2}(x_2 - c(x_1)) \end{Bmatrix} \quad (4)$$

The horizontal wavelet $\psi^H_{j,n}$ have not vanishing moments along contour, to be replaced by new functions:

$$\psi_{l,n_1}(x_1)\psi_{j,n_2}(x_2 - c(x_1)) \quad (5)$$

This is called bandeletization [15], [16]. The orthonormal basis of bandelet of field warping is defined by:

$$\begin{pmatrix} \psi_{l,n_1}(x_1)\psi_{j,n_2}(x_2 - c(x_1)) \\ \psi_{j,n_1}(x_1)\phi_{j,n_2}(x_2 - c(x_1)) \\ \psi_{j,n_1}(x_1)\psi_{j,n_2}(x_2 - c(x_1)) \end{pmatrix} = \begin{Bmatrix} \psi^H_{l,n} \\ \psi^V_{j,n} \\ \psi^D_{j,n} \end{Bmatrix} j,l \rangle n_1, n_2 \quad (6)$$

III. OPERATIONAL DIAGRAM

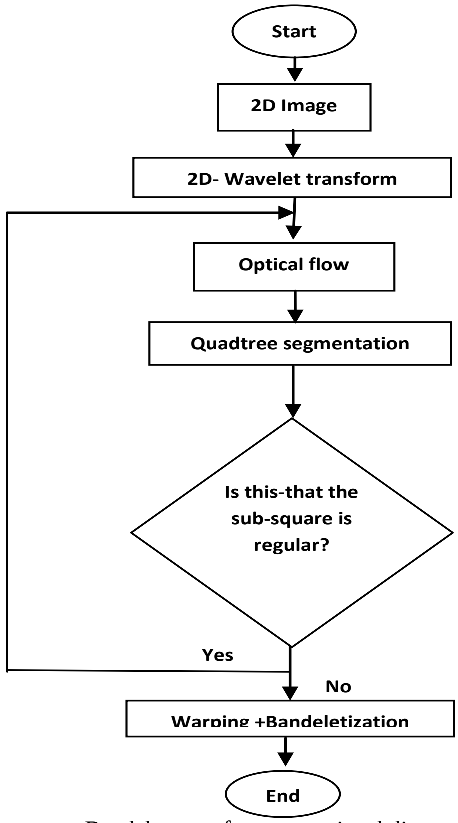


Figure 5. Bandelet transform operational diagram

IV. EZW CODING SCHEME

The algorithm proposed by Shapiro [17], the design of this algorithm is based on two pass with a calculated threshold T, we determine the maximum value of the wavelet coefficients, so in the first dominant pass, if the coefficient absolute value is greater than the threshold, so we obtained a positive code or negative code according to the sign of coefficient, if the absolute value is less, we check the descendants coefficient, if you have a coefficient with absolute value above the threshold, we obtained IZ code, else we have a code ZT.

In the second pass, the comparison is made in the middle of the interval [Tn, 2Tn[, if this coefficient belongs to the first interval, so we are a transmission of the bit 1, if this coefficient belongs to the second interval, so there are a transmission of bit 0.

V. SPIHT CODING SCHEME

The SPIHT algorithm proposed by Said and Pearlman in 1996 [18], ameliorate progressive algorithm is compared to the EZW algorithm, based on the creation of three list SCL, ICL and ISL with a calculated threshold T, each time you make a scan on both lists SCL and ISL and that for the classified the significant coefficient in the list of significant coefficient.

VI. QUALITY EVALUATION PARAMETER

The Peak Signal to Noise Ratio (PSNR) is the most commonly used as a measure of quality of reconstruction in image compression. The PSNR were identified using the following formulate:

$$MSE = \frac{1}{M.N} \cdot \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left[I(i,j) - \hat{I}(i,j) \right]^2 \qquad (7)$$

Mean Square Error (MSE) which requires two MxN gray scale images I and $\hat{I}$ where one of the images is considered as a compression of the other is defined as:

• The PSNR is defined as:

$$PSNR = 10.\log_{10} \frac{\left(2^R - 1\right)^2}{MSE} \left[dB\right] \qquad (8)$$

• The structural similarity index (SSIM):

The PSNR measurement gives a numerical value on the damage, but it does not describe its type. Moreover, as is often noted in [20], [21], it does not quite represent the quality perceived by human observers. For medical imaging applications where images are degraded must eventually be examined by experts, traditional evaluation remains insufficient. For this reason, objective approaches are needed to assess the medical imaging quality. We then evaluate a new paradigm to estimate the quality of medical images, specifically the ones compressed by wavelet transform, based on the assumption that the human visual system (HVS) is highly adapted to extract structural information. The similarity compares the brightness, contrast and structure between each pair of vectors, where the structural similarity index (SSIM) between two signals x and y is given by the following expression:

$$SSIM(x,y) = l(x,y)c(x,y)s(x,y) \qquad (9)$$

Finally the quality measurement can provide a spatial map of the local image quality, which provides more information on the image quality degradation, which is useful in medical imaging applications. For application, we require a single overall measurement of the whole image quality that is given by the following formula:

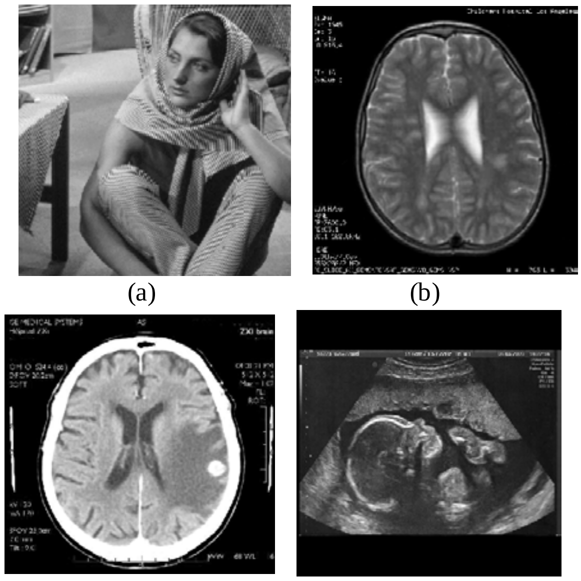
$$MSSIM\left(I,\hat{I}\right) = \frac{1}{M} \sum_{i=1}^{M} SSIM\left(I_i, \hat{I}_i\right) \qquad (10)$$

Where I and $\hat{I}$ are respectively the reference and degraded images, I_i and $\hat{I}_i$ are the contents of images at the i-th local window.

M: the total number of local windows in image. The MSSIM values exhibit greater consistency with the visual quality.

VII. RESULTS AND DISCUSSION

We are interested in this work to the medical images compression, that we applied algorithm (DBT+SPIHT), (DBT+EZW), (DWT+SPIHT) and (DWT+EZW). For this, we chose sets of medical images (MRI, CT and ECHO) images gray level size 512x 512 encoded on 8 bits per pixel. These images are taken from the GE Medical System (database) [21]. The importance of our work lies in the possibility of reducing the rates for which the image quality remains acceptable. Estimates and judgments of the compressed image quality are given by the PSNR evaluation parameters and the MSSIM similarity Index.



(a) (b) (c) (d)

Figure 6. (a). BARBARA, (b). MRI, (c). CT and (d). ECHO original image

From our investigating, we would highlight that the quality of compressed image depends also on the number of decompositions level, for this we have try to determine decomposition levels who permits us to have a high value PSNR for two algorithms (DWT+EZW) and (DWT+SPIHT).

(a). Level-1 (b). Level-2 (c). Level-3

(d) Level-4 (e) Level-5 (f) Level-6

(g) Level-7 (h) Level-8 (i) Level-9

Figure 7. Image compressed resultats by (DWT+EZW) for different valus decomposition levels

(a). Level-1 (b). Level-2 (c). Level -3

(d) Level-4 (e) Level -5 (f) Level -6

(g) Level -7 (h) Level-8 (i) Level-9

Figure 8. Image compressed resultats by (DWT+SPIHT) for different valus decomposition levels

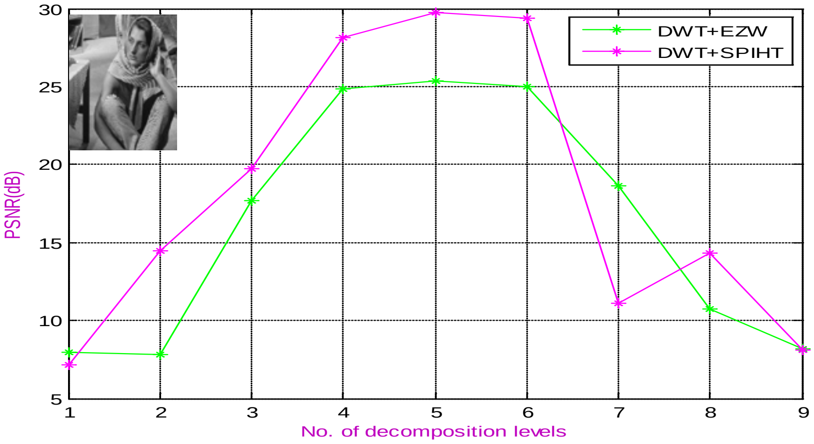


Figure 9. No. of decomposition levels verses PSNR (dB)

It can be seen from figure 9, that we have a high PSNR value for level decomposition equal to five, for this value we presented in the following the results comparison for compressed images by (DBT + SPIHT), (DBT + EZW), (DWT + SPIHT) and (DWT + EZW) algorithms.

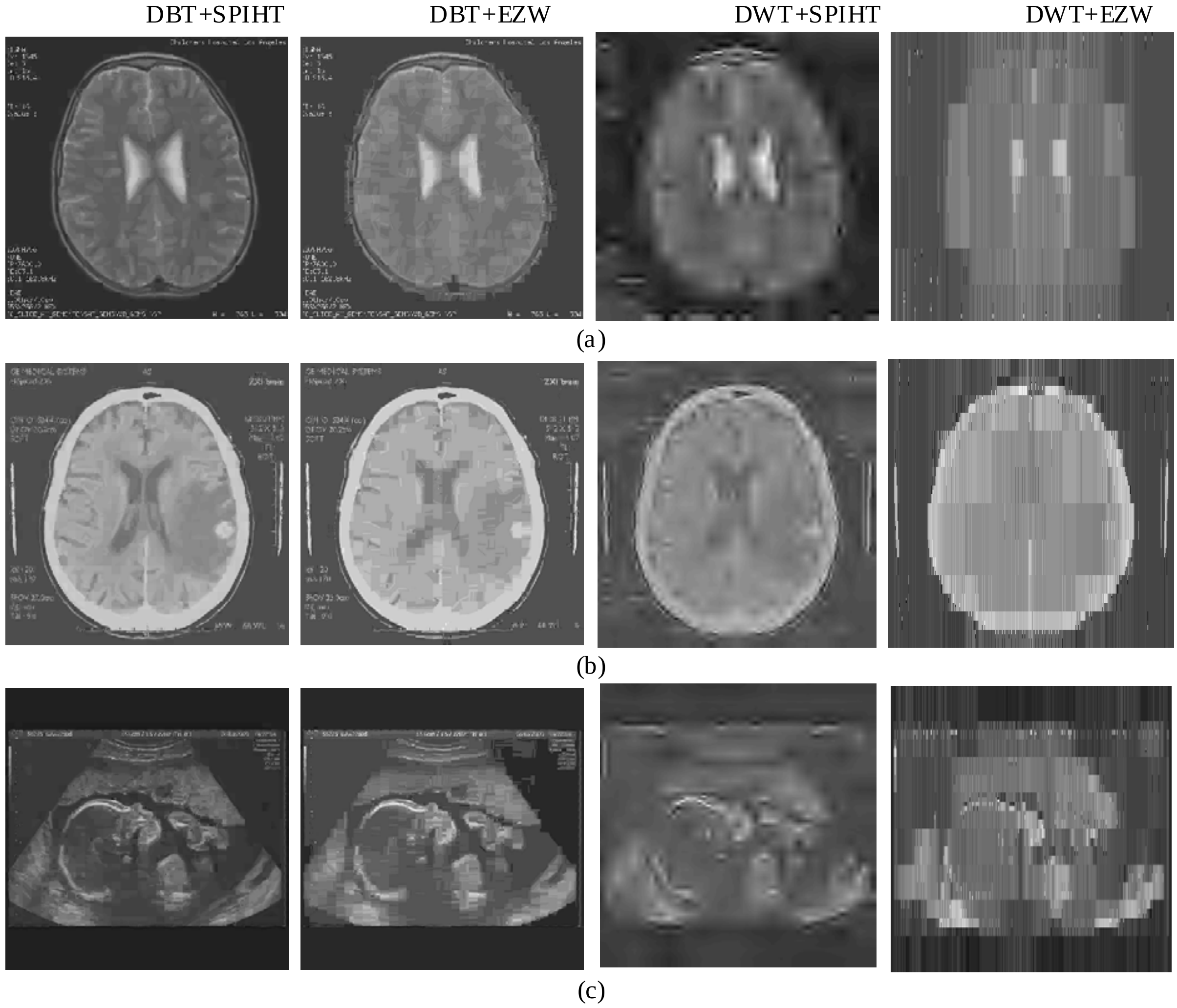
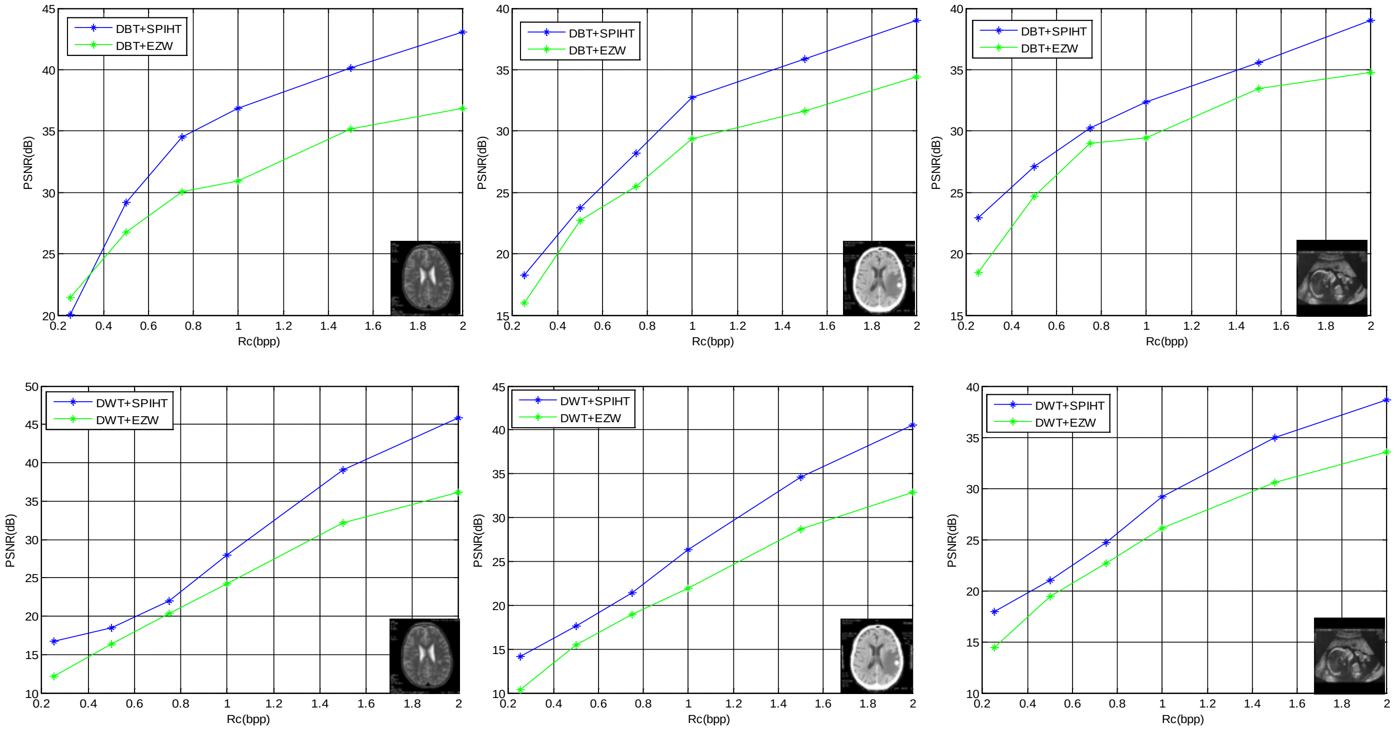
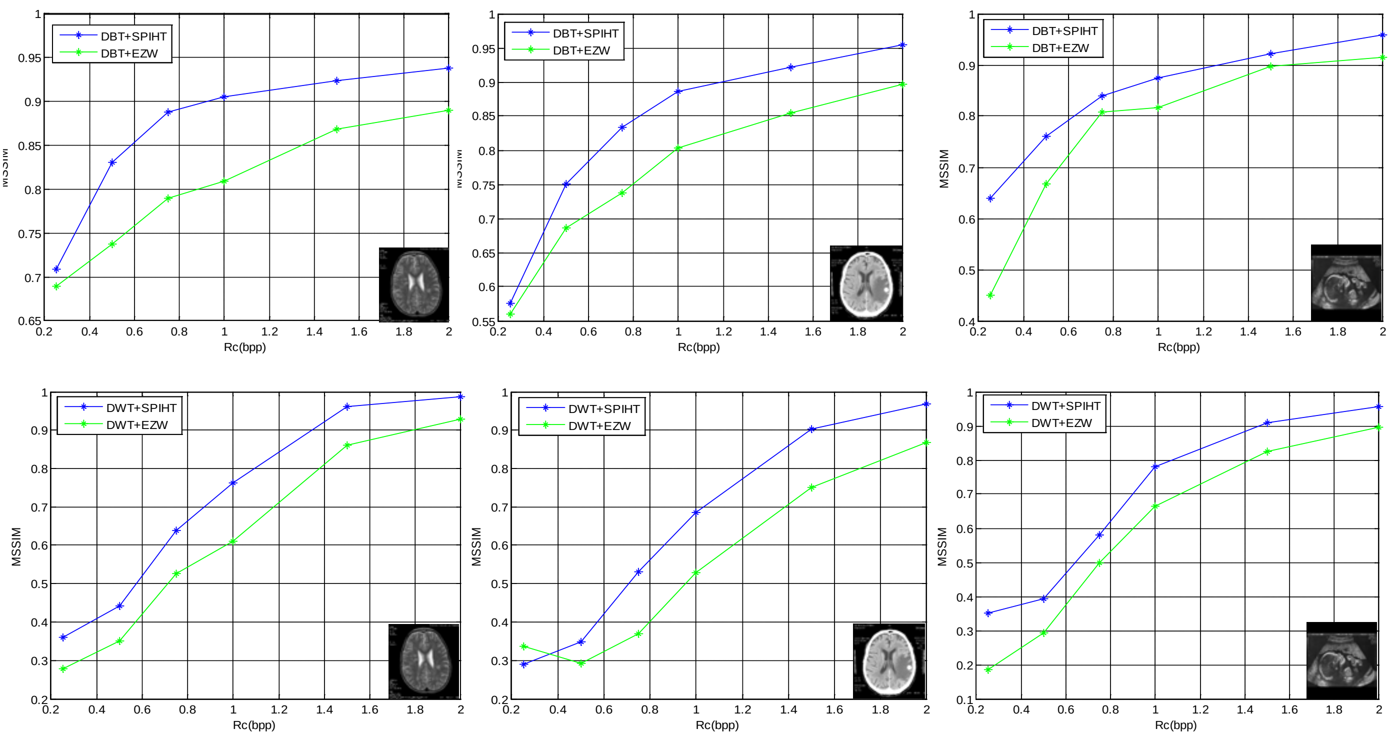


Figure 10. MRI, CT and ECHO compressed images by (DBT + SPIHT), (DBT + EZW), (DWT + SPIHT) and (DWT + EZW) algorithm for $R_c = 0.5\,bpp$: (a) MRI image, (b) CT image, (c) ECHO image



(a) (b) (c)

Figure 11. Numerical results PSNR of compression images by bandelet and wavelet transform coupled with SPIHT and EZW coder: (a) MRI image, (b) CT image, (c) ECHO image



(d) (e) (f)

Figure 12. Numerical results MSSIM of compression images by bandelet and wavelet transform coupled with SPIHT and EZW coder : (d) MRI image, (e) CT image, (f) ECHO image

We see from the figure 11 and 12, that the bandelet transform coupled with SPIHT coder offer PSNR and MSSIM values better than to the other algorithms (DBT+EZW) (DWT+SPIHT), (DWT+EZW).

In order to specify the type of medical image adapted to algorithm (DBT+SPIHT), we recapitulate the results for the three medical images (MRI, CT and ECHO) compressed by (DBT+SPIHT) algorithm in the following figure.

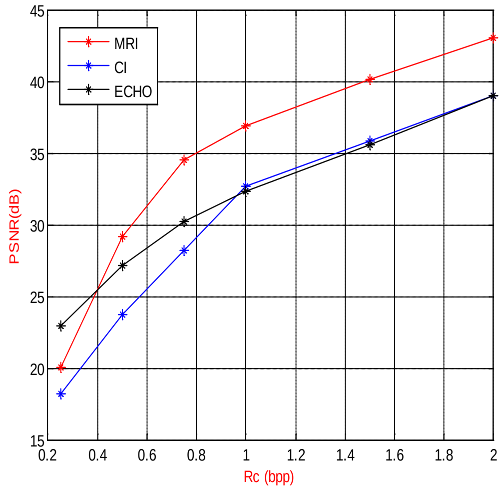


Figure 13. Comparison results between MRI, CT and ECHO image compressed by bandelet transform coupled by SPIHT coder

By comparing the different PSNR values, we can say that our algorithm (DBT+SPIHT) is adapted to the MRI images compression.

After displaying the performance of the compression bandelet to medical images, now we apply our compression algorithm to the satellite image compression. To do so, we opted for a satellite image of size 512x512 (grayscale) encoded on 8bpp.

To investigate the influence of the choice of algorithm, we vary the rate of 0.25 to 2bpp, and calculate the evaluation parameters (PSNR, MSSIM) for both algorithms based on bandelet transform. The results are given in the following figure.

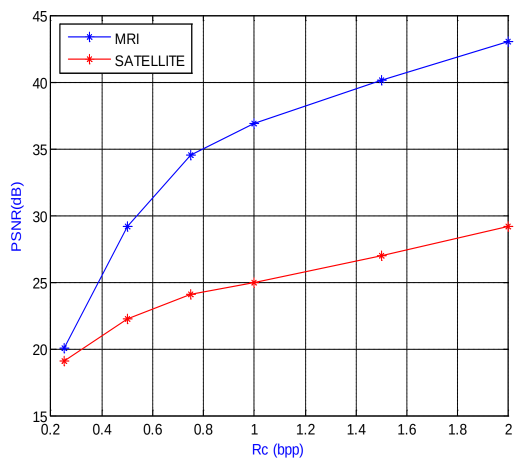


Figure 14. Compression results for MRI and Satellite image compressed by (DBT+SPIHT) algorithm

Visually, from the two curves, it is clearly that the (DBT+SPIHT) algorithm allows us to have a good image reconstruction so a better image visual quality and this is proved by the large values of the parameters evaluation.

VIII. CONCLUSION

Medical image compression using the bandelet transform is still a vast research field. These transform provides a very compact representation of images and can capture more chaotic geometries and a major improvement compared to other transforms. However, research in this domain is still in its beginning and the current obtained results are difficult to evaluate.

In the future we are going to work into defining a strategy to exploit the bandelet transform for color image compression.

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