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Gray Scale and Color Medical Image Compression by Lifting Wavelet; Bandelet and Quincunx Wavelets Transforms: A Comparison Study

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Strictly as per the compliance and regulations of:

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I. Introduction

Today the massive use of numerical methods in medical imaging generates increasingly important volumes of data .One of the most important problems in such applications is how to store and transmit images [1].It is well established that the accuracy and precision of diagnostic are initially related to the image quality.

Over the past ten years, the wavelets (DWT), have had a huge success in the field of image processing such as encoding, weaknesses have been noted in its use in the detection and representation of the objects' contours, and have been used to solve many problems such as image compression and restoration [2].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, contourlet [15-16].

To overcome this problem, In this paper, we introduce tree new type of transform, the first is devoted to representation of the Lifting scheme, and then we present the biorthgonal wavelet CDF 9/7,the second called bandelet transform by Pennec and Stéphane Mallat [17], 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, and the third transform multi resolution decompositions called quincunx wavelets which are better adapted to the image representation. This structure of decomposition allows the construction of a no separable transform. No separable wavelets, by contrast, offer more freedom and can be better tuned to the characteristics of images. Their less attractive side is that they require more computations. The quincunx wavelets are especially interesting because they are nearly isotropic [3].

II. Lifting Scheme Wavelet Transforms

In [4], Calderbank et al.introduced how to use the lifting scheme presented in [5], where sweldens showed that the convolution based biorthogonal WT can be implemented in a lifting-based scheme as shown in figure (1) for reducing the computational complexity. The lifting-based WT consists of splitting, lifting, and scaling modules and the WT is treated as prediction-error decomposition.

It provides a complete spatial interpretation of WT. In figure (1), let X denote the input signal, and XL_1 and $X H_1$ be the decomposed output signals.

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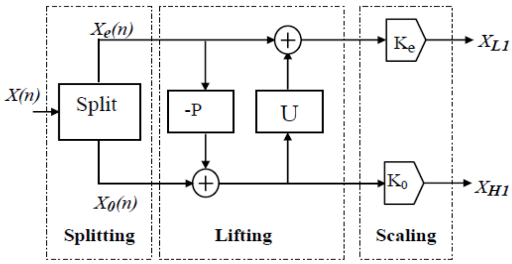


Figure 1 : The Lifting -based wavelet

This article deals with biorthogonal wavelet 9/7. These wavelets are part of the family of symmetric biorthogonal wavelet CDF. The low pass filters associated with wavelet 9/7 have p=9 coefficients in the analysis, p=7 coefficients to synthesize.

The wavelets 9/7 have a great number of null moments for a relatively short support. They are more symmetrical and very close to orthogonality. Antonini and Barlaud were the first **[**7**]** to show the superiority of the biorthogonal wavelet transform 9/7 for the decorrelation of natural images. It has been widely used in image coding [8],[9] ,[25] and is used by the JPEG-2000 codec [10].

III. The Bandelet Transform

Bandelet transform, introduced by Pennec and Mallat [18] built a base adapted to the geometric content of an image.

Bandelet transform is an analysis tool which aims at taking advantage of sharp image transitions in images. A geometric flow, which indicates directions in which the image gray levels have regular variations,is used to form bandelet bases in bandelet transform. The bandelet bases lead to optimal approximation rates for geometrically regular images and are proven to be efficient in still image compression [24], video compression, and noise-removal algorithms[6-10].

Apparently, bandelet transform is appropriate for the analysis of edges and texture of images.

In bandelet transform, a geometric flow of vectors is defined to represent the edges of image. These vectors give the local directions in which the image has regular variations. Orthogonal bandelet bases are constructed by dividing the image support in regions inside which the geometric flow is parallel. Let Ω_i denote the ith region, which composes the image support S = $U_i\Omega_i$. Within each Ω_i the flow is either parallel horizontally or vertically.

Figure 2 shows an example of a vertically parallel geometric flow in a region of the hat of Lena image.

Figure 2 : geometric flow in a region of the hat of Lena image

The image is partitioned small enough into square regions, each region Ω_i includes at most one contour. If a region does not include any contour, the image intensity is uniformly regular and the flow is not defined. In bandelet transform, these regions are approximated in the separable wavelet basis of $L^2(\Omega)$ in:

$$\begin{Bmatrix} \phi_{j,n_1}(x_1)\psi_{j,n_2}(x_2) \\ \psi_{j,n_1}(x_1)\phi_{j,n_2}(x_2) \\ \psi_{j,n_1}(x_1)\phi_{j,n_2}(x_2) \end{Bmatrix}_{(j,n_1,n_2)\in I_\Omega}$$

where I_Ω is an index set that depends upon the geometry of the boundary of Ω , and x_1, x_2 denote the location of pixel in the image, $\phi_{j,n_1}(x_1)\psi_{j,n_2}(x_2)$, $\psi_{j,n_1}(x_1)\phi_{j,n_2}(x_2)$ and $\psi_{j,n_1}(x_1)\phi_{j,n_2}(x_2)$ are the modified wavelets at the boundary. If a geometric flow is calculated in Ω , this wavelet basis is replaced by a bandelet orthonormal basis of $L^2(\Omega)$ in

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

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

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

This is called bandeletization [13], The orthonormal basis of bandelet of field warping is defined by:

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

IV. Quincunx Wavelets

The separable dyadic analysis require three families of wavelets, which is sometimes regarded as a disadvantage, in addition the factor of addition between two successive scales is 4 which may seem high. It is possible to solve these two problems, but at the cost of the loss of filter separability and therefore a slightly higher computational complexity. An analysis has been particularly well studied to find a practical application, known as "quincunx" , [1].Quincunx decomposition results in fewer subbands than most other wavelet decompositions, a feature that may lead to reconstructed images with slightly lower visual quality.

The method is not used much in practice, but [14] presents results that suggest that quincunx decomposition performs extremely well and may be the best performer in many practical situations. Figure (3) illustrates this type of decomposition [3].

We notice that the dilation factor is not more than 2 between two successive resolutions, and that only one wavelet family is necessary [15,16]. It is noticed that the dilatation step is $\sqrt{2}$ on each direction and the geometry of the grid obtained justifies the name given to this multiresolution analysis.

First, we recall some basic results on quincunx sampling and perfect reconstruction filter banks, [17][18]. The quincunx sampling lattice is shown in figure(4). Let $x[\vec{n}]$ denote the discrete signal on the initial grid.

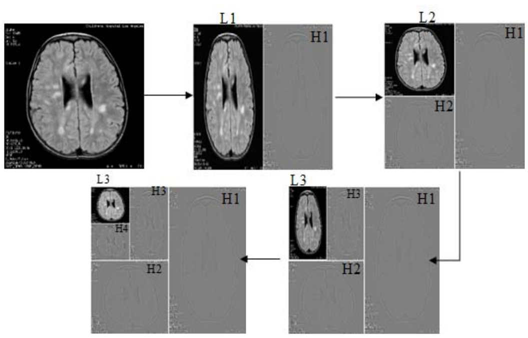
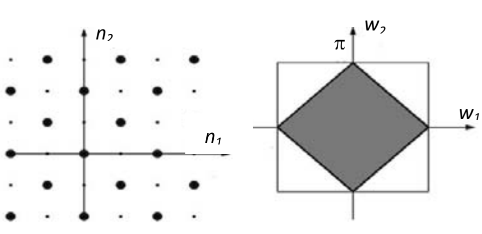


Figure 3 : Quincunx wavelet

Now, we write the quincunx sampled version of $x[\vec{n}]$ as:

$$[x]_{\downarrow M}[\vec{n}] = x[M\vec{n}] \quad where \quad M = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \tag{8}$$



(a) (a)

Figure 4 : (a) Quincunx lattice, (b) the corresponding Nyquist area in the frequency domain

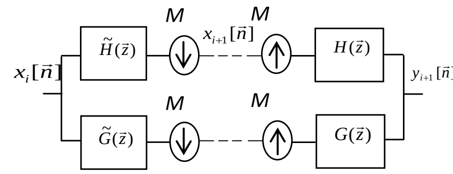


Figure 5 : Perfect reconstruction filter bank in a quincunx lattice

Since quincunx sampling reduces the number of image samples by a factor of two, the corresponding reconstruction filter bank has two channels (Fig.5). The low-pass filter $\tilde{H}$ reduces the resolution by a factor of $\sqrt{2}$; the wavelet coefficients correspond to the output of the high-pass filter $2\tilde{G}$ [15,16,17].

The conditions for a perfect reconstruction is:

$$\begin{cases} \tilde{H}(\vec{z})H(\vec{z}) + \tilde{G}(\vec{z})G(\vec{z}) = 2 \\ \tilde{H}(-\vec{z})H(\vec{z}) + \tilde{G}(-\vec{z})G(\vec{z}) = 0 \end{cases} \tag{14}$$

Where H and G (respectively $\tilde{H}$ and $\tilde{G}$) are the transfer functions of the synthesis (respectively analysis) filters. In the orthogonal case, the analysis and synthesis filters are identical up to a central symmetry; the wavelet filter G is simply a modulated version of the low-pass filter H .

To generate quincunx filters, we will use the standard approach which is to apply the diamond McClellan transform to map a 1D design onto the quincunx structure [19].

Thus, our quincunx refinement filter is given by

$$H_\alpha(e^{j\vec{\omega}}) = \frac{\sqrt{2}\,(2+\cos\omega_1+\cos\omega_2)^{\frac{\alpha}{2}}}{\sqrt{(2+\cos\omega_1+\cos\omega_2)^\alpha + (2-\cos\omega_1-\cos\omega_2)^\alpha}} \tag{17}$$

V. Spiht Coding Scheme

The SPIHT algorithm proposed by Said and Pearlman in 1996 [20,21], ameliorate progressive algorithm is compared to the EZW a lgorithm .The Set Partitioning in Hierarchical Trees (SPIHT) is one of the most advanced schemes available, even out performing the state-of-the-art JPEG 2000 in some situations, 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 andthat for the classified the significant coefficient in the list of significant coefficient.

The adapted for quincunx wavelet transform coupled by SPIHT is done in [26,27],

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 formulae:

$$MSE^{2} = \frac{1}{M\,x\,N} \sum_{1=1}^{i=N} \sum_{j=1}^{j=M} \left(I(i,j) - \hat{I}(i,j) \right)^{2} \qquad (21)$$

Mean Square Error (MSE) which requires two MxN grayscale images I and where one of the images is considered as a compression of the other is defined as:

- *The PSNR is defined as:*

$$PSNR = 10\log_{10}\left(\frac{(Dynamics\quad of\quad image)^{2}}{MSE} \right) \qquad (22)$$

Usually an image is encoded on 8 bits. It is represented by 256 gray levels, which vary between 0 and 255, the extent or dynamics of the image is 255.

- *The structural similarity index (SSIM):*

This parameter compares the similarity 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 , [22].

$$SSIM\,(x,y) = l(x,y).c(x,y).s(x,y) \qquad (23)$$

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:

$$MSSIM\,(I,\hat{I}) = \frac{1}{M}\sum_{i=1}^{M} SSIM\,(I_i,\hat{I}_i) \qquad (24)$$

Where and are respectively the reference and degraded images, and 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 (QWT+SPIHT), (DWT9/7(lifting scheme) +SPIHT) ,(bandelet +SPIHT) , (DWT9/7 banc filter+SPIHT) . For this, we chose sets of medical images (MRI, CT ,ECHO and MAMOG) images gray level size 512x 512 encoded on 8 bits per pixel. These images are taken from the GE Medical System (database) [23].

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.

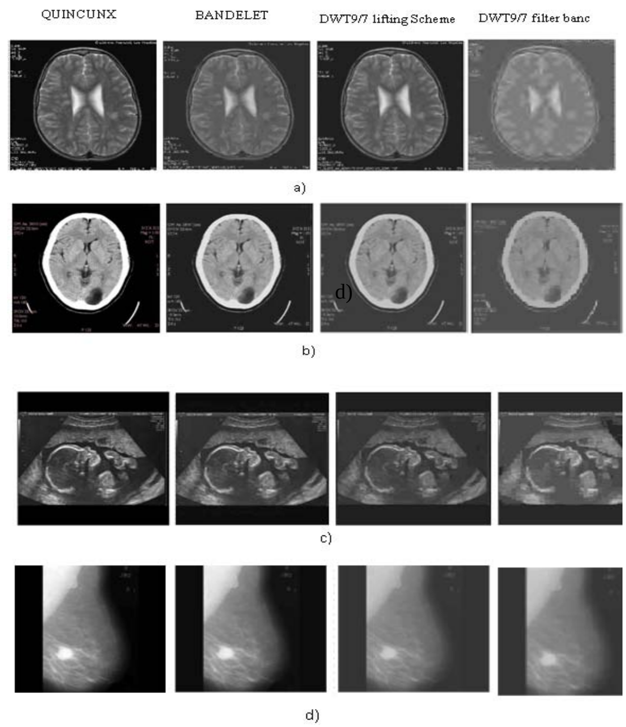
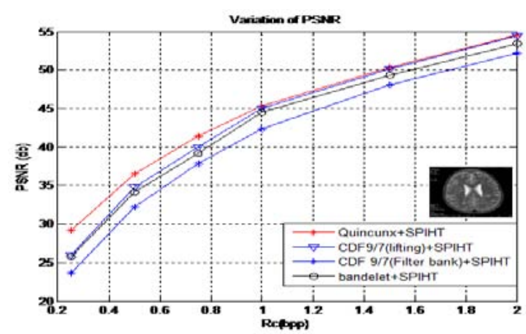
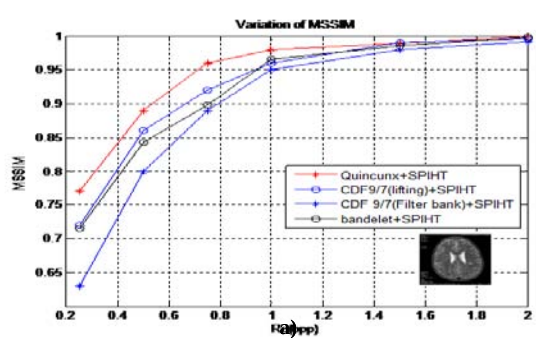


Figure 6 : MRI, CT ,ECHO and MAMOG compressed images by QWT , Bandelet ,DWT 9/7 (filter banc) and (DWT 9/7 (lifting scheme) coupled SPIHT coder for Rc=0.5Bpp (a) MRI image, (b) CT image, (c) ECHO image and (d) MAMOG image





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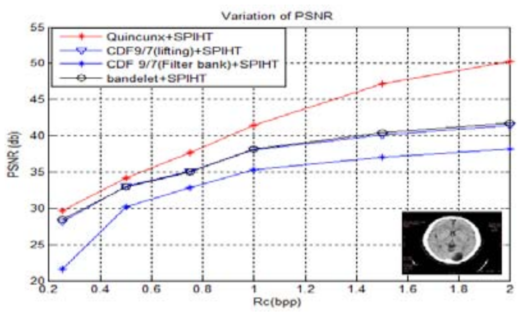
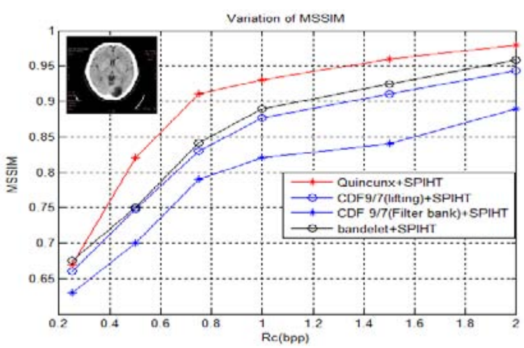
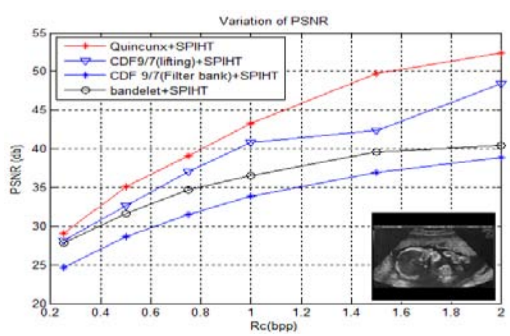
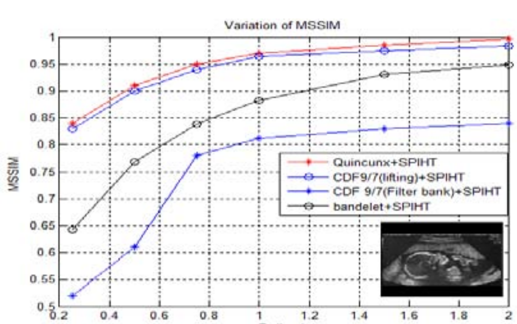




b)





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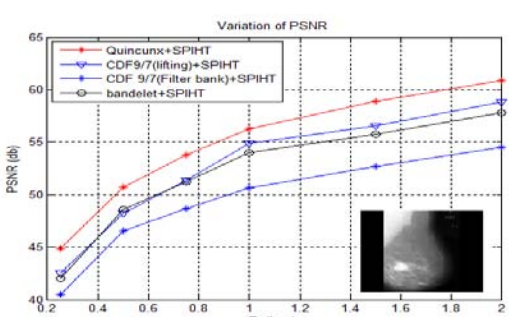
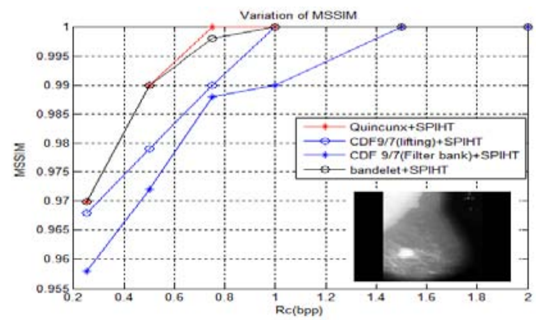
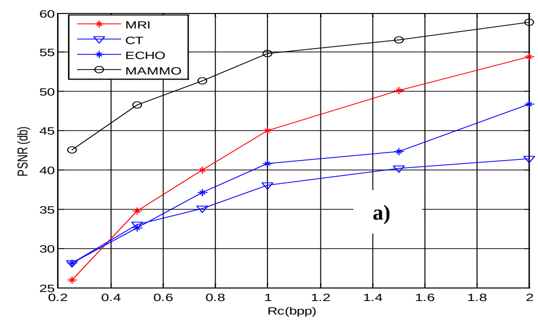
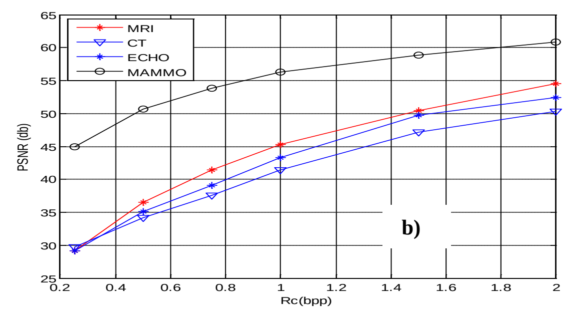




d)

Figure 7 : PSNR and MSSIM variation using different methods for : (a) MRI image, (b) CT image, (c) ECHO image and (d) MAMOG image





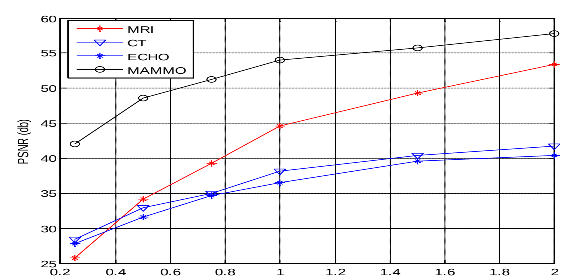


Figure 8 : Comparison results between MRI, CT ,ECHO and MAMMOGRAPHIC image compressed by / a) Quincunx transform ; b) biorthogonal wavelet 9/7 (lifting Scheme); and c)Bandelet transform coupled by SPIHT coder

Figure (6) shown below illustrates the compressed different modality of medical image quality using different transforms. According to the PSNR and MSSIM values, we note that from 0.5bpp, image reconstruction becomes almost perfect. We observe that compression degrades to a lessen extent the image

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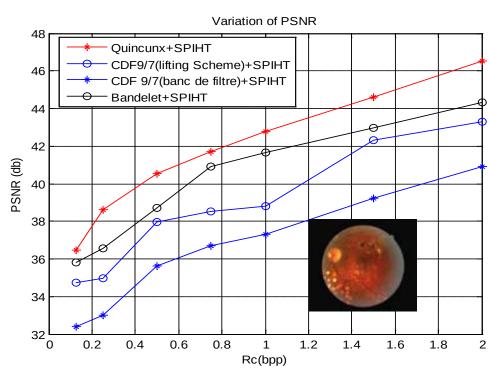
structure for a low compression bit-rate. However, for high compression bitrate, our algorithm better safe guards the various image structures. We note that our algorithm is adapted for the medical image compression.

We see from the figure 7, that the Quincunx transform coupled with SPIHT coder offer PSNR and MSSIM values better than to the other algorithms. In order to specify the type of medical image adapted to algorithm (Quincunx+SPIHT), we recapitulate the results for the four medical images (MRI, CT, ECHO and MAMOG) compressed by (Quincunx+SPIHT), (DWT9/7(lifting scheme) +SPIHT) ,(bandelet +SPIHT) algorithms in the following in figure 8.

Visually, from the two curves, it is clearly that the (QWT+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.

Now we have chosen a retinographic color image of size 512 x 512. In our application, we applied our algorithms for our color image for each layers after converted RGB space to YCrCb layers. We see from the figure 9, that the Quincunx transform coupled with SPIHT coder offer PSNR and MSSIM values better than to the other algorithms.



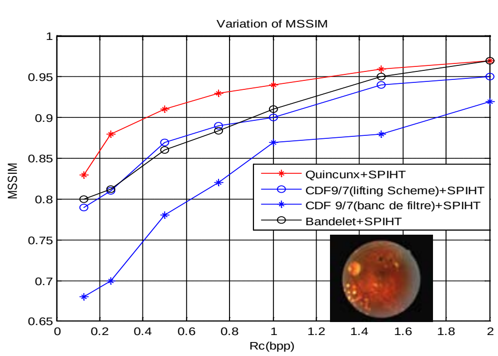


Figure 9 : PSNR and MSSIM variation using different methods for color image

VIII. Conclusion

The objective of this paper is undoubtedly the enhancement of medical images quality after the compression step. The latter is regarded as an essential tool to aid diagnosis (storage or transmission) in medical imaging. We compared the quincunx wavelet transform , bandelet transform and the biorthogonal wavelet 9/7 based on the filter banc and the lifting scheme coupled with the SPIHT coding for the gray scale and color medical image. After several applications for different modality medical images, we found that the algorithm for the quincunx wavelet transform gives better results than the other compression techniques. We have noticed that for 0.5 bpp bit-rate, the algorithm provides very important PSNR and MSSIM values from medical images. In perspective, we aspire to apply our algorithm to compress the medical video sequences.

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