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A based Daubechies Wavelet Transform Approach to enhance the OSEM bone SPECT image reconstruction

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Abstract— **This paper presents a new algorithm for bone Single-photon emission computed tomography (SPECT) image reconstruction based on ordered subset expectation maximization (OSEM) algorithms and can remove the noise from images with the best degree of accuracy. In our proposed method, a de-noising pre-processing wavelet transform is applied on the projections then the OSEM algorithm is used to reconstruct successively 128 axial slices from a 128 enhanced sinograms, and finally we extract the coronal and sagittal slices from the enhanced axial slices volume. Our method is compared with two iterative methods of reconstruction, (OSEM) used only and a Maximum Likelihood Expectation Maximization (MLEM), each method was tested on a bone SPECT database and evaluated qualitatively and quantitatively. The results show that the proposed method has the highest performance on noise reduction with preservation of the singularity in comparison to other methods**

Keywords— Ordered subset expectation maximization, Single-photon emission computed tomography (SPECT), images reconstruction, daubechies wavelet transform, Maximum Likelihood Expectation Maximization

I. INTRODUCTION:

SPECT is a noninvasive imaging technique that is based on the administration into the patients of a single gamma emitter labelled radiopharmaceutical. Where the gamma camera rotates around the patient in order to realize several projections of distribution of the radiopharmaceutical within a region of interest. These projections should be reconstructed to reflect the functional information about the metabolic activity at a region of interest and allow the doctors performing an accurate diagnostic of the radiopharmaceutical distribution in any slice of the body. Therefore, a disadvantage of the reconstructed SPECT image has been its poor spatial resolution and bad contrast, due to the radioactivity disintegration and procedure of acquisition. Then, to obtain a good quality of the reconstructed images we need an excellent algorithm of SPECT image reconstruction.

In the last few years, various reconstruction algorithms have been developed to improve the reconstruction quality which can be divided into two families: analytic reconstruction and iterative reconstruction. The analytic algorithm, such as Simple back-projection and filtered back-projection [1], these methods based on direct inversion of radon transform and needed a sufficient number of acquiring projection [2]. However, because the limited number of projection data, they can generate significant artifact and induce more noise. The iterative algorithm such as the statical iterative Reconstruction (SIR) has been reported to be characterized by improved quality of the reconstructed image. The principle of these methods consists in enchaining a multiple forward and back-projection operation cycles from an initial estimated image. The process is stopped when the reconstructed image gives projections similar to the measured projections. This similarity is assessed using a statically parameter called the likelihood.

MLEM algorithm is one of the iterative reconstruction, which was introduced by Shepp and Vardi in 1982 [3], and then improved in speed by OSEM algorithms [4], [5], [6]. However, by increasing the number of iterations and subsets of the last technique, the convergence of this algorithm is speeded whereas the noise is also increased [7]. To improve the quality of the reconstructed image, several algorithms based on the last standard methods have been published.

In [8], a comparison has been made between several reconstruction techniques based on filtered back-projection and OSEM using a Metz filter and a Butterworth filter applied on a bone SPECT image of the spine with and without scatter correction, the previous work showed that, the contrast enhancing Metz filter or the noise reducing Butterworth filter in combination with OSEM reconstruction improve the bone SPECT image quality, but the scatter correction does not improve image quality.

The Wavelet-based denoising method has been employed in the literature. Junhai Wen et al [9] developed a wavelet-based SPECT image reconstruction algorithm using the inversion formula for the nonuniformly attenuated radon transform and they have demonstrated that the wavelet–based SPECT denoising is accurate and effective in SPECT reconstruction. S Skiadopoulos [10] have demonstrate that the a multi-scale Platelet applied either on projection data or reconstructed images, provide a more efficient noise reduction, while preserving image quality, compared to the Butterworth filter. In 2015, Shailendra Tiwari and al [11] suggested a new hybrid-cascaded algorithm composed on an algebraic iterative reconstruction algorithm (SART) in a cascaded way with OSEM algorithm and a regularization term Anisotropic Diffusion (AD) which reduce the number of iterations, improve the quality of reconstructed images and reduce the computational time.

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In this work , and based on the prior results, we suggested a new de-noising approach based on an efficient OSEM reconstruction combined with a pre-processing daubechies wavelet applied on the acquired projection for improving the quality of bone SPECT images. The novel method is compared with two iterative reconstruction methods used alone for enhancing the bone SPECT image quality.
The remainder of the paper is organized as follows. The proposed method is discusses in section II, the obtained results are presented and analysed in Section III, and Section IV illustrates the conclusion and future directions.

II. MATERIALS AND METHODS

The proposed method is based on using a two dimensional pre-processing Daubechies wavelet transform for removal of Poison noise in the acquired projections, and the Ordered subset expectation maximization (OSEM) algorithm for a tomographic bone SPECT image reconstruction. Fig.1 represents an overview of this method.

A. Pre-processing Daubechies wavelet transform:

1)Methods based on wavelet representation:

Wavelet transform is a time-scale representation which gives an account of the evolution over the time of the frequency content of the signal, which provides an efficient multi-resolution analysis tool of the non stationary signal. The original Discrete Wavelet Transform (DWT) function named as "mother wavelet" generated several wavelet families like Haar, symlets, daubechies [12].

A DWT equation of a signal f[n] is given by:

$$F[s,\tau] = \sum_{-\infty}^{+\infty} f[n]\Omega_{s,\tau}(n)$$

The choice of wavelet families and their order depends on the shape of the analysed wavelet families $\Omega_{s,\tau}[n]$ generated from

a mother wavelet $\psi[n]$, defined by the following mathematical formula:

$$\Omega_{s,\tau}[n] = (\frac{1}{\sqrt{s}}) \times \psi\left[\frac{n-\tau}{s}\right]$$

Where 'τ' is the translation and 's' is the dilatation or compression parameters of the mother wavelet.

The DWT decomposes the SPECT originaux projections into a set of frequency band images by filter banks that describe the signal frequencies content at given time, using a low pass filters and high pass filters to extract respectively the significant wavelet coefficients called approximation AA and removed the non-significant wavelet coefficients called details.

At the level 1, the image is smoothed and reduced to a 1/4 size of the original image. Each level of decomposition repeats the differencing and averaging process on the level 1 sub image.

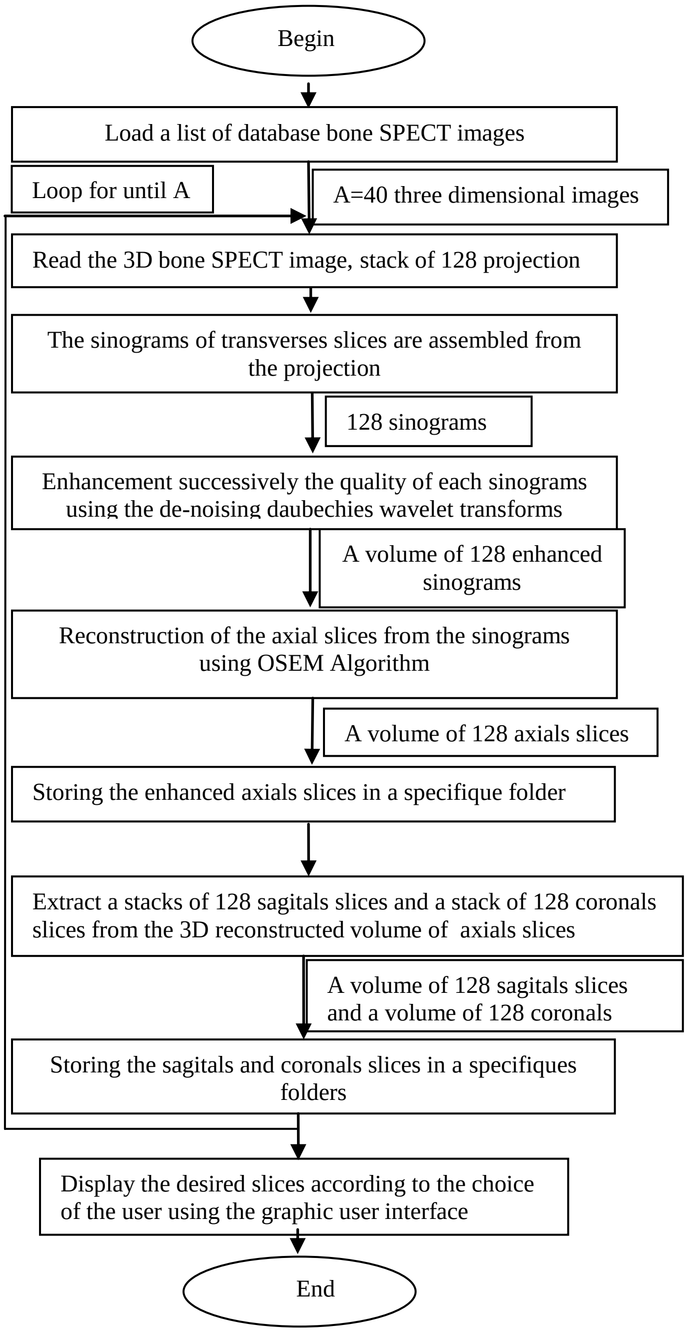

Fig.1. Proposed method

The wavelet algorithm is achieved by the recomposition of the denoised signal using the inverse wavelet transform 'IDWT'. Fig.2 illustrates the steps of wavelet based algorithm of the SPECT image. In this paper we focuses on the Daubechies wavelet transform because by set learning we found that this algorithms provide the best performance of bone SPECT denoising by minimizing the noise and expanding the desired signal.

2)Daubechies Wavelet Transform:

This family of wavelet transform is given by the scaling and wavelet functions that are described respectively in terms of a and b coefficients.

Scaling function H is expressed as follow:

The coefficients of high pass and low pass filters are defined as:

$$a_1 = \frac{1+\sqrt{3}}{4\sqrt{2}}, a_2 = \frac{3+\sqrt{3}}{4\sqrt{2}}, a_3 = \frac{3-\sqrt{3}}{4\sqrt{2}}, a_4 = \frac{1-\sqrt{3}}{4\sqrt{2}}$$

$$H\begin{matrix}1\\1\end{matrix} = (a_1, a_2, a_3, a_4, 0,0,0, \dots)$$

$$H\begin{matrix}1\\2\end{matrix} = (0,0, a_1, a_2, a_3, a_4, 0,0,, \dots)$$

$$H\begin{matrix}1\\N/2\end{matrix} = (a_3, a_4, 0,0,0, \dots 0, a_1, a_2)$$

$$H^{1}_{i} = a_1 H^{0}_{2i-1} + a_2 H^{0}_{2i} + a_3 H^{0}_{2i+1} + a_4 H^{1}_{2i+2} \quad (1)$$

$$H^{2}_{i} = a_1 H^{1}_{2i-1} + a_2 H^{1}_{2i} + a_3 H^{1}_{2i+1} + a_4 H^{1}_{2i+2} \quad (2)$$

Wavelet function G and coefficients b are defined as:

$$b_1 = a_4, b_2 = -a_3, b_3 = a_2, b_4 = -a_1$$

$$G\begin{matrix}1\\1\end{matrix} = (b_1, b_2, b_3, b_4, 0,0,0, \dots)$$

$$G\begin{matrix}1\\2\end{matrix} = (0,0, b_1, b_2, b_3, b_4, 0,0,0, \dots)$$

$$G\begin{matrix}1\\N/2\end{matrix} = (b_3, b_4, 0,0,0, \dots b_1, b_2)$$

$$G\begin{matrix}1\\i\end{matrix} = b_1 G\begin{matrix}0\\2i-1\end{matrix} + b_2 G\begin{matrix}0\\2i\end{matrix} + b_3 G\begin{matrix}0\\2i+1\end{matrix} + b_4 G\begin{matrix}0\\2i+2\end{matrix} \quad (3)$$

$$G^{2}_{i} = b_1 G^{1}_{2i-1} + b_2 G^{1}_{2i} + b_3 G^{1}_{2i+1} + b_4 G^{1}_{2i+2} \quad (4)$$

Where i is the order of wavelet transform.

Signal f(t) is calculated, in terms of A(low frequency signal components) an D (high frequency signal components), using[2] :

$$F = A^i + D^i + D^{i-1} + \dots\dots + D^3 + D^2 + D^1 \quad (5)$$

$$A^i = \left(FH^{i}_{1}\right)H^{i}_{1} + \cdots + \left(FH^{i}_{\frac{N}{i}}\right)H^{i}_{\frac{N^i}{2}} \quad (6)$$

$$D^i = \left(FG^{i}_{1}\right)G^{i}_{1} + \cdots + (FG^{i}_{N/i})G^{i}_{N/2^i} \quad (7)$$

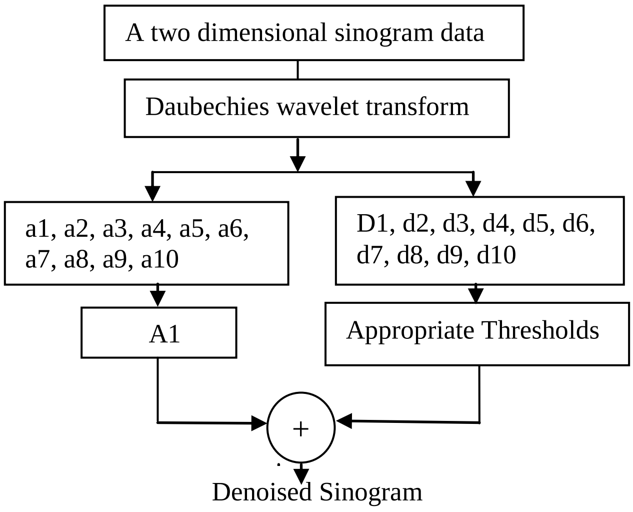

Fig2: Stages of Daubechies wavelet transform

B. Ordered Subset Expectation Maximization(OSEM) algorithm:

The iterative algorithm improves the image quality and reduces efficiently the generated streaking artefacts in low radiation dose datasets [13].

The maximum likelihood expectation-maximization (ML-EM) technique remains the basis of the most iterative method which consists of two alternating steps: An E-step, which computes the expectation of the log-likelihood that assessed the similarity between simulated and measured sinograms, and an M-step, which finds the next estimate through maximizing the expected log-likelihood, while taking into account that the initial estimate image is positive and the measured projections are attained by a noisy Poisson, This point confers on this algorithm so that it is adapted to the reconstruction of the region emitting low photon.

Mathematically, the MLEM algorithm can be computed using the following equation:

$$f_i^{k+1} = f_i^{k} \sum_{j=1}^{N} \frac{p_{ij} C_j}{\sum_{i=1}^{M} p_{ij} f_i^{k}} \quad (8)$$

Where:

f_i^k and f_i^{k+1} are the value of pixel i respectively in the iteration k and k+1 with 1<i<M, M is the total number of pixels along ray j.

C_j is the measured projection data at the detector j with 1<j<N, N is the total number of detectors in all projection angles.

p_{ij} : is the transfer matrix from image pixel i to projection bin j

$\sum_{j=1}^{N} \frac{p_{ij} C_j}{\sum^{M} p_{ij} f_i^k}$ is the back projection of this ratio for pixel i.

The ordered subset was ported to this algorithm forming the OS-EM-based algorithms [3] which allow a significantly faster convergence compared to the original convex algorithm and allows for easy parallelization. The principle of this algorithm is based on the division of the acquired projections into ordered subsets. Subsequently, the MLEM algorithm is applied to each subset in turn. The update of the estimated images with the OSEM method is done with the corresponding subset. More clearly, at the first iteration, the first subset is used to compute the image. This previous image will be used to correct the second projection sub-set at the second iteration to estimate the next image. The operation repeated until the last subset. The OSEM resulted image is computed using equation 9:

$$f_j^{(k+1)}(S_t) = \frac{f_j^{(k)}}{\sum_{i \in S_t} a_{ij}} \sum_{i \in S_t} a_{ij} \frac{p_i}{\sum_{b=1}^{N} a_{ib} f_b^{(k)}} \quad (9)$$

Where S_t presents the t^{th} subset

- $P_i = \sum_{b=1}^{N} a_{ib}\ f_b^{\text{k}}$ This term corresponds to the projection of the current estimate f following a line projection
- pi :measured projection
- $R_j = \sum_{i \in S_t} a_{ij} \frac{p_i}{P_i}$ is the back projection of the rapport $\frac{p_i}{P_i}$ in the image space
- a_{ij} : is the term sensitivity obtained by back projected the value 1 in the image space.

Two back-projections are reported to determine a correction Multiplicative factor, in order to update the estimate f_b^{k} in the iteration k.

To obtain the best enhanced slice image, we compared the different resulted axial slices image quality by varying the number of subset and the number of iterations of the OSEM algorithm, and the value of the order of the daubechies wavelet transform.

By applied learning on the bone SPECT axial slices, the best result is obtained using OSEM algorithm with 8subsets and 4 iterations combined with a threshold value of the daubechies wavelet transform equal to 3 and an order equal to 4.

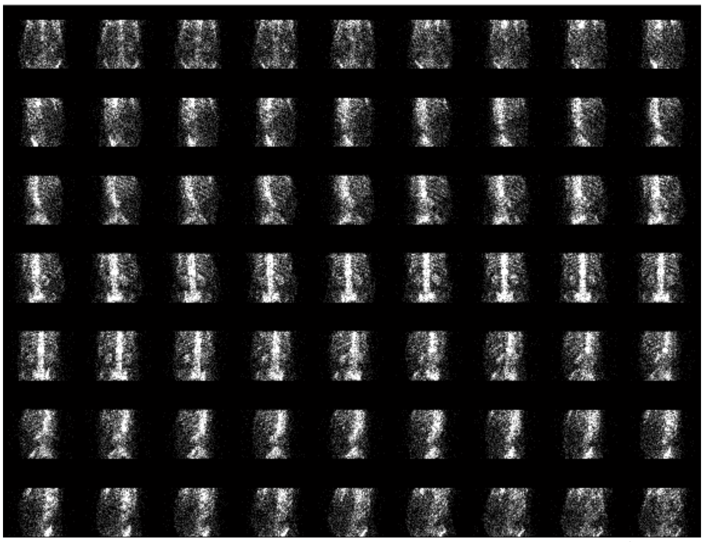

Fig.3. Original bone SPECT 3D image contain 128 projection displayed from right (projection1), to left (projection63).

Figure 4, 5 and 6 shows the slices of transverse, coronal and sagittal views of lumbar vertebrae lesion reconstructed using the proposed technique.

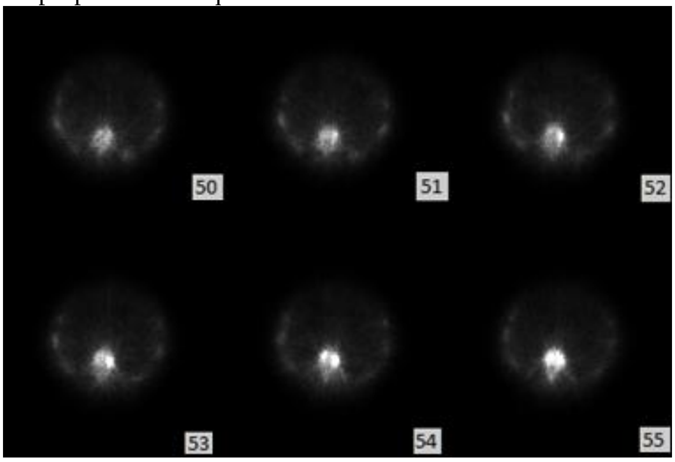

Fig.4. Transaxial slice reconstruction with 1-pixel thick slices, Displayed from cranial (slice50) to caudal (slice55).

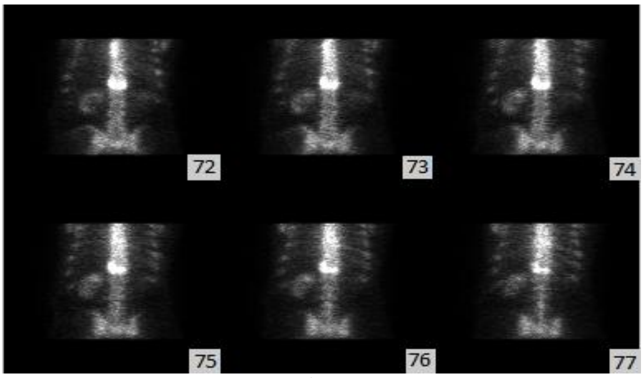

Fig.5. Coronal slices reconstructed from transaxial slices data with 1-pixel thick slices. Displayed from posterior (slice72) to anterior (slice77).

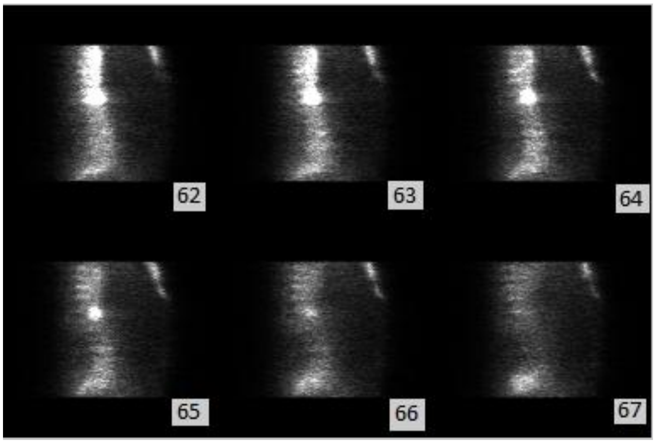

Fig.6. Sagittal slices reconstructed from transaxial slices data that were 1 pixel thick. Displayed from right (slice62), to left (slice67).

III. EXPERIMENTS AND DISCUSSIONS:

On Intel Core with 2.00 GHz CPU utilizing MATLAB software, the execution time of the suggested method to Elapsed time is 203.943174 seconds. We tested the proposed method on a bone SPECT images database, which contains 40 bone SPECT examinations. Each volume projection is a DICOM image with a 128 projections (720°) as shown in fig4 and a 128×128 matrix with a pixel spacing equal to 4.795 mm. this dataset is taken from the radiology department of National Oncology Institute"Salah AZAIZE" of TUNIS generated by a double-head gamma camera equipped with a low dose CT scan was used characterized by a low energy and ultra-high-resolution characteristics.

In order to evaluate the result, we compared qualitatively and quantitatively the capability of our denoising method to OSEM and MLEM techniques. First, a comparison is made between different parameters from the same technique to choose the best one, by applied learning on the bone SPECT axial slices, the best results are obtained using 4 iterations and 8 subset for OSEM and 6 iteration for MLEM.

As original slices we used the direct inversion of the radon transform of projection data which generated a total of 128 undenoised slices for each images. An axial slice contains the lesion is chosen for a qualitative comparison of the reconstruction results shown in figure 7.

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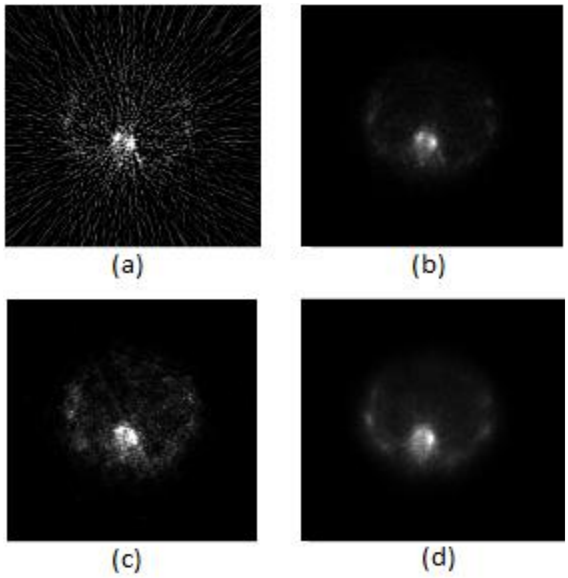

Fig7: Axial slice reconstructed by (a) simple back-projection. (b) ML-EM (6 iteration). (c)OS-EM (8iteration, 4 subsets) and (d) the proposed method

For a quantitative comparison, we computed for each patient the means CNR, means PSNR, means SSIM metrics and the means execution time of slices that contain the lesion.

- Mean square error(MSE)

$$MSE = \frac{1}{KM}\sum_{i=1}^{K}\sum_{j=1}^{M}(X-Y)^2 \quad (10)$$

Where X is the original slice and Y is the reconstructed slice, K and M are the dimensions of these images

- Peak Signal to Noise Ratio(PSNR) is defined as:

$$\mathrm{PSNR} = 10\log\left(\frac{255^2}{MSE}\right) \quad (11)$$

- universal image quality index （UQI) : measured the degree of similarity between the reconstructed and original slices, defined as

$$\mathrm{UQI} = \frac{2 * \sigma_{X,Y}}{\sigma_Y + \sigma_X} \times \frac{(2 * m_Y * m_X)}{(m_X^2 + m_Y^2)} \quad (12)$$

Where X and Y presents respectively the original and the denoised slice; m_X, m_Y, σ_X and σ_Y denote the mean and the variance of the image and their estimation; $\sigma_{X,Y}$ is the covariance of image X and Y

- Structural Similarity (MSSIM) defined as:

$$\mathrm{MSSIM} = \frac{1}{M} \times \sum_{i=1}^{M} \frac{(2m_X m_Y + c_1)(2\sigma_{X,Y} + c_2)}{(m_X^2 + m_Y^2 + c_1)(\sigma_X^2 + \sigma_Y^2 + c_2)} \quad (13)$$

Where X and Y presents respectively the original and the denoised slice; m_X, m_Y, σ_X^2 and σ_Y^2 denote the mean and the variance of the image and their estimation; $\sigma_{X,Y}$ is the covariance of image X and Y; c_1 and c_2 are small constants to have usually a denominator different to zero and M is the total number of the local windows of the image

TABLE 1: DIFFERENT PERFORMANCE MEASURED FOR THE RECONSTRUCTED IMAGED IN FIGURE 1

Performance measures	MLEM	OSEM	Daubechies +OSEM(proposed method)
MSE means	0,0056	0,00577	1,27E-03
PSNR means	70,798	70,696	77,46533
MSSIM means	$2,1.10^{-5}$	$2,1.10^{-5}$	4,03E-05
UQI means	0,2785	0,2787	0,292529092
Execution time(sec)	244,0199	68,96	299.83426

Qualitatively, this study confirmed that the iterative reconstruction using ML-EM or OS-EM algorithms ensures good poison noise suppression and reducing the streaking artifacts that appeared with the analytic reconstruction witch mask other regions and reducing the lesion detection[15],[16],[17].
The qualitative assessment of the various directional feature region of the bone SPECT image illustrated in fig4, fig5 and fig6 shows that the proposed methods provide more accurate detection of lesion and better preservation of the singularity and the limit of region with effective ability of denoising, whereas the iterative method used alone attenuate the detail by giving a blur effect on the edges of the region and making delicate the extraction and the location of the contours therefore the image shape seemed slightly smoothen and appears much noisy
Quantitatively, the optimum method has the highest value of PSNR, MSSIM and UQI and the lowest value of MSE. From Table1 and Figs.8,9,10,11, the value of these metrics favoured the proposed method based on the applied the pre-processing daubechies wavelet transform denoising method as compared to the MLEM and OSEM methods, in fact, it is clear that the proposed method provide the highest value of PSNR , MSSIM and UQI metrics and the lowest value of MSE metrics compared to the other methods for all the patient group which demonstrates the efficiency of our proposed algorithm in reduction of noisy artefacts while preserving resolution and image quality.
From Table 1, we note that the processing time of our proposed approach requires a longer than MLEM and OSEM technique.
To conclude, we can confirm that the proposed reconstruction method using the pre-processing daubechies wavelet transform denoising method outperform the other MLE-EM and OSEM iterative reconstruction method using alone in the improvement of the bone SPECT image reconstruction quality.

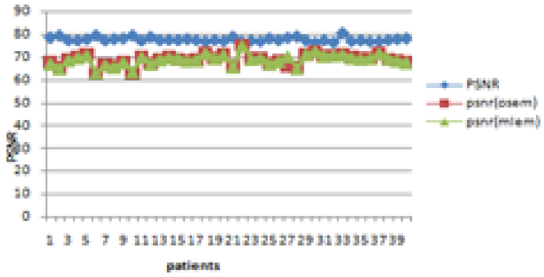

Fig8. Comparison of the PSNR measurement for all patients obtained using different reconstruction method

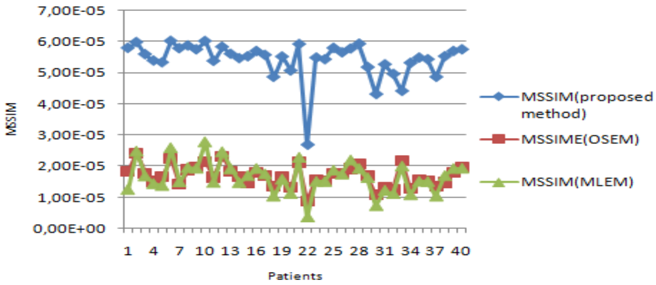

Fig9. Comparaison of the MSSIM measurement for all patients obtained by using different reconstruction method

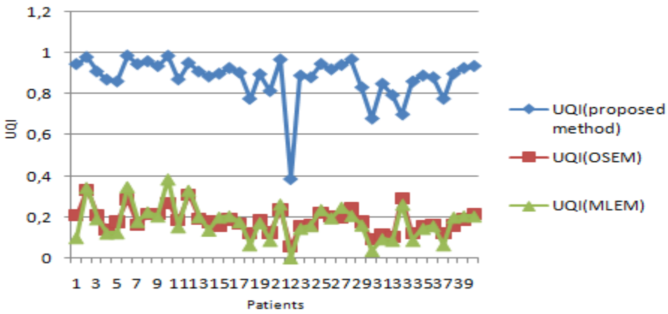

Fig10. Comparison of the UQI measurement for all patients obtained using different reconstruction method

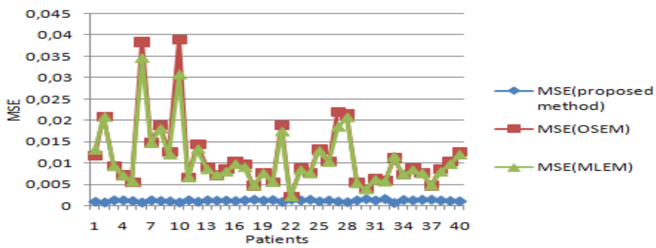

Fig11. Comparison of the MSSIM measurement for all patients obtained using different reconstruction method

IV. CONCLUSIONS

The objective of this paper is to enhance the bone SPECT image reconstruction. Firstly, we applied the pre-processing daubechies wavelet transform denoising successively on 128 sinograms assembled from 128 projection data. Then, we reconstructed 128 axials slices from the resulted sinograms based on the OSEM iterative reconstruction. Summing up the results, it can be concluded that the proposed algorithm can be provided an efficient noise reduction, whereas preserving image quality in bone SPECT imaging.

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