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Improvement of bone SPECT image reconstruction using a combined OSEM algorithm and a Curvelet transform

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***Abstract*— The ordered subset expectation maximization OSEM is the most widely used reconstruction algorithm for Single-photon emission computed tomography SPECT images reconstruction because of their efficiency in providing a better image quality. However, by increasing the number of subsets of this method, the convergence of this algorithm is speeded whereas the noise is also increased. This paper presents a new algorithm for bone SPECT image reconstruction based on OSEM algorithms. In our proposed method, OSEM algorithm is firstly used to reconstruct successively 128 axial slices from 128 projections, then the Curvelet transform is used to improve the quality of axial slices, 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 MLEM and OSEM. The results show that the proposed method has the highest performance on noise reduction in comparison to other methods.**

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

I. INTRODUCTION:

Nuclear medicine is a medical speciality that is based on the intravenous injection into the patients of radiopharmaceuticals. Single-photon emission computed tomography is one of the modalities of this imaging 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 [9]. Therefore, a drawback of the reconstructed SPECT image has been its poor spatial resolution and bad contrast, due to the radioactivity disintegration and procedure of acquisition. Which has made it difficult to detect bone lesions and the diagnosis became inaccurate. Then, to obtain a good quality of the reconstructed images we need an excellent algorithm of SPECT image reconstruction.

In the last decades, many reconstruction algorithms have been developed 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) plays a vital role in the quality of the reconstructed image. These methods consist in linking 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.

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, the quality of the produced image with the last technique becomes noisier by increasing the number of iterations and subsets [7]. To improve the quality of the reconstructed image, several algorithms based on the last standard methods have been published. In [8] Leonid A Kunyansky proposed a new reconstruction algorithm based on the Novikov explicit inversion formula for the non-uniform attenuated Radon transform which improve the quality of bone SPECT image reconstruction in term of accuracy even in the case of strongly non-uniform attenuation coefficient such as the human thorax using a Tretiak-Metz filter.

In [9], 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 noise reducing Butterworth filter or a contrast enhancing Metz 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. In [10], Junhai Wen et al presented 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. In [11] S Skiadopoulos applied a multi-scale platelet and a Butterworth filter as a pre- and post-processing step on cardiac phantom images, reconstructed with and/or without attenuation correction and they found that

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the 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 [12] proposed a new hybrid-cascaded framework includes an algebraic iterative reconstruction algorithm (SART) in a cascaded manner with OSEM algorithm and a regularization term Anisotropic Diffusion (AD) which reduce the number of iterations as well as increase the noise, improve the quality of reconstructed images and reduce the computational time.

In this work , and based on the prior results, we proposed a new hybrid based on an efficient OSEM reconstruction with the use of a multi-scale curvelet denoising method applied as a post-processing step on the reconstructed axial slices for improving the quality of bone SPECT images. The novel approach 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. Section II discusses the proposed method, the obtained results are presented and analyzed in Section III, and Section IV illustrates the conclusion and future directions.

II. MATERIALS AND METHODS

The suggested method is based on using the Ordered subset expectation maximization (OSEM) algorithm for a tomographic bone SPECT image reconstruction with a two dimensional post-processing multiscale curvelet transform to enhance the quality of the reconstructed slices. Fig.1 represents an overview of this method.

A. 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 is the standard methods of the 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.

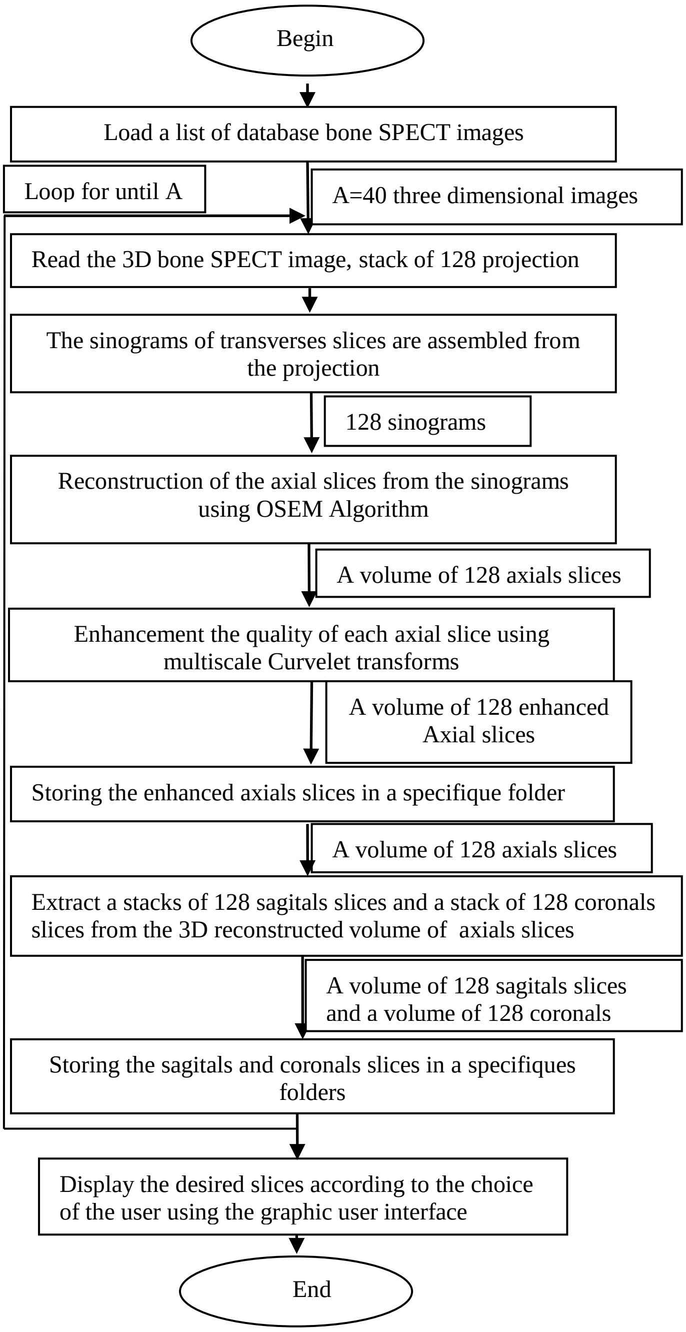

Fig.1. Proposed method

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

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

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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

$\sum_{j=1}^{N} \frac{p_{ij} C_j}{\sum_{i=1}^{M} p_{ij} f_i^k}$ 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 2:

$$f_j^{(k+1)}(S_t) = \frac{f_j^{(k)}}{\sum_{i \in S_t} a_{ij}} \sum_{i \in S_t} a_{ij} \frac{p_i}{\sum_{b=1}^{N} a_{ib} f_b^{(k)}} \qquad (2)$$

Where S_t presents the t^{th} subset

- $P_i = \sum_{b=1}^{N} a_{ib} f_b^{\,k}$ 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.

B. Post-processing multiscale Curvelet transform:

By increasing the number of subsets, the convergence of OSEM algorithm is accelerated, but the noise is also increased. To reduce the Poisson noise and greatly improve the detection accuracy of lesion in vertebrae. We employ the curvelet transform [14]. It is a multi-scale transformation with frame elements indexed by the scale, location and directional parameters. Moreover, it is based on certain anisotropic scaling principle [15]. This transform introduces a multi-scale analysis by applying a ridgelet transform[16] after sub-band decomposition

This transform includes two stapes:

In the first step, the image is decomposed into subband of variable sizes with overlap to avoid the edge effects. Each sub-band is smoothly windowed in the "squares" of a suitable scale. In the second step, each obtained square is renormalized to unit scale. Within these subzones of each block, a discrete Ridgelet transform is applied with an expansion of the wave function of size $2^s \times 2^{s/2}$.Where s ∈ N represents the scale. These waves follow a parabolic law of change of scale in order to adapt to the detected contours. The edge which not detected by the separable wavelet analysis are found in the detail sub bands.

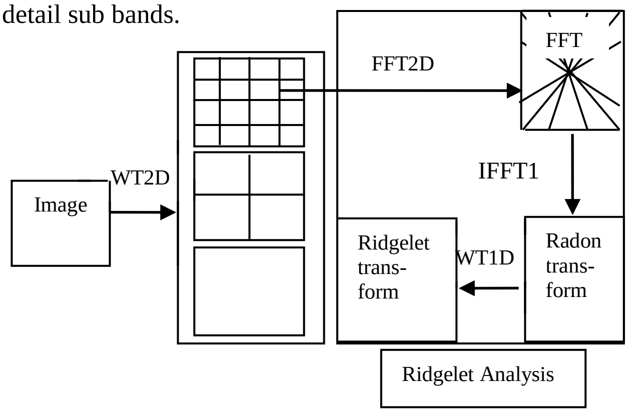

Fig2: Structure of the curvelet transform of an image

Curve let coefficients C_s for each angle θ and scale n is defined in the Fourier domain as:

$$C_s(n, \theta) = 2^{-\frac{3s}{2}} D(2^{-2s} n) R(2^s/2.\tau.\theta) \qquad (3)$$

Where C_s is the polar wave supported by the radial (D) and angular (R) windows. Fig 2 shows the different steps of the curvelet transform applied in our work

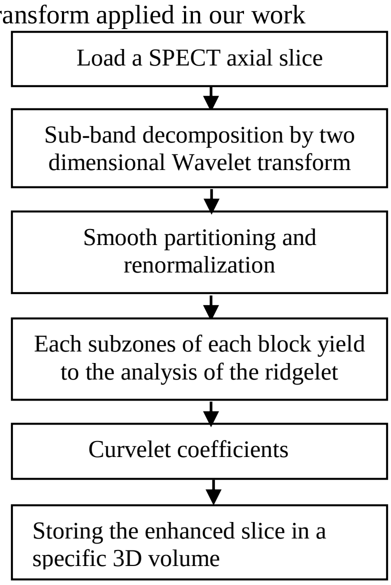

Fig3: Stages of Curvelet transform

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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 threshold of the curve let 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 curvelet transform equal to 0.01.

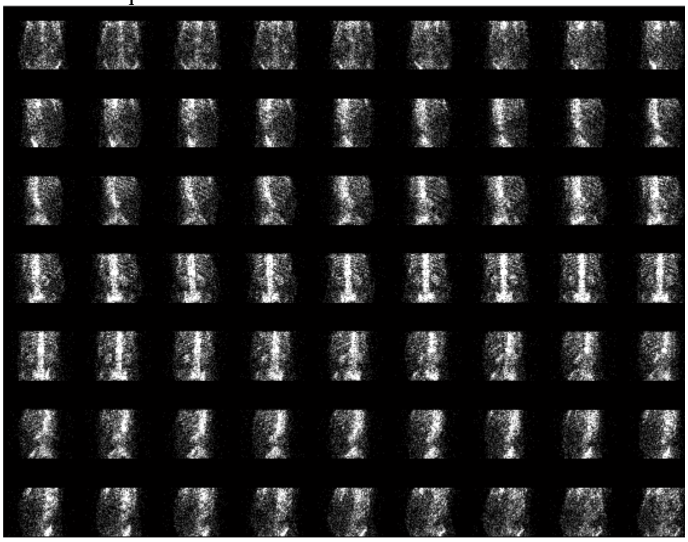

Fig.4. Original bone SPECT 3D image contain 128 projection displayed from right (projection1), to left (projection63).

Figure 5, 6 and 7 shows the slices of transverse, coronal and sagittal views of lumbar vertebrae lesion reconstructed using the proposed technique.

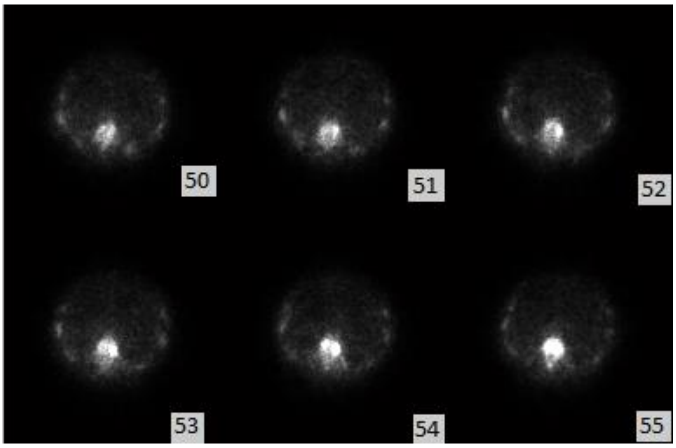

Fig.5. Transaxial slice reconstruction with 1-pixel thick slices, Displayed from cranial (slice50) to caudal (slice55).

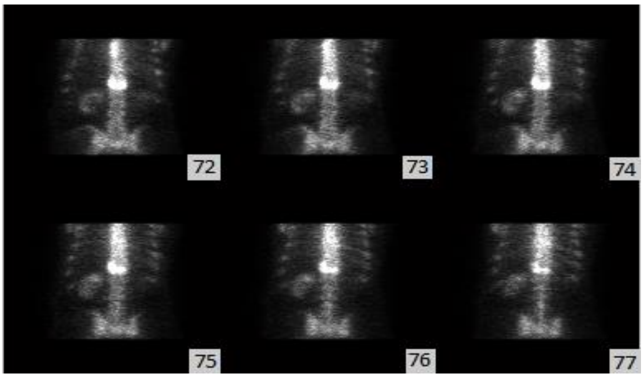

Fig.6. Coronal slices reconstructed from transaxial slices data with 1-pixel thick slices. Displayed from posterior (slice72) to anterior (slice77).

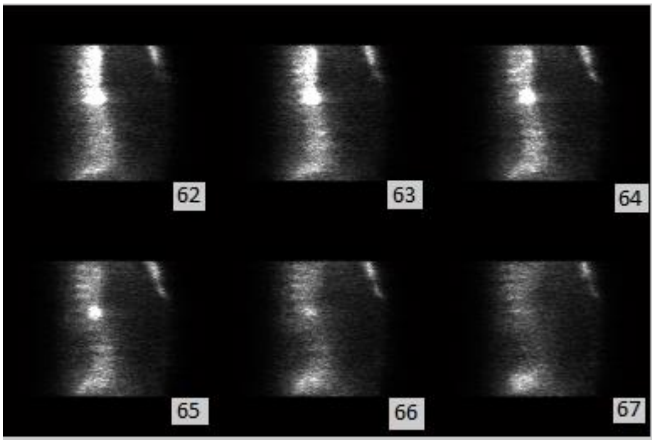

Fig.7. Sagittal slices reconstructed from transaxial slices data that were 1 pixel thick. Displayed from right (slice62), to left (slice67).

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 8.

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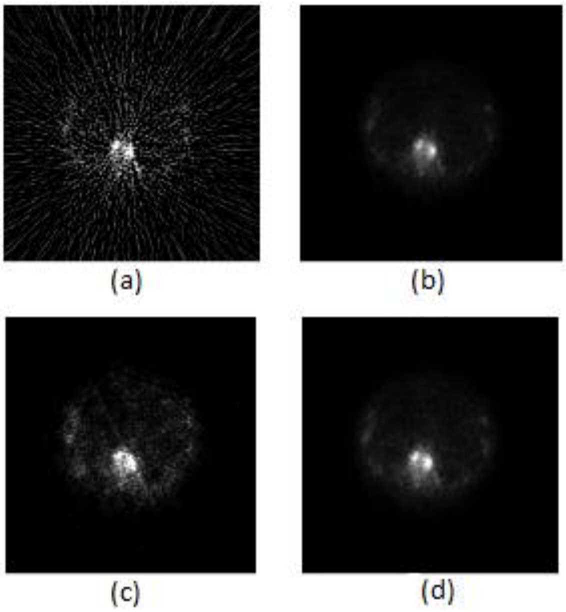

Fig8: Axial slice reconstructed by (a) simple back-projection. (b) ML-EM (6 iteration). (c)OS-EM (8iteration, 4 subsets) and (d) the proposed method

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)

$$MSE = \frac{1}{KM}\sum_{i=1}^{K}\sum_{j=1}^{M}(X-Y)^2 \quad (4)$$

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:

$$\text{PSNR} = 10\log\left(\frac{255^2}{MSE}\right) \quad (5)$$

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

$$\text{UQI} = \frac{2*\sigma_{X,Y}}{\sigma_Y+\sigma_X}\times\frac{(2*m_Y*m_X)}{(m_X^2+m_Y^2)} \quad (6)$$

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:

$$\text{MSSIM} = \frac{1}{M}\times\sum_{i=1}^{M}\frac{(2m_Xm_Y+c_1)(2\sigma_{X,Y}+c_2)}{(m_X^2+m_Y^2+c_1)(\sigma_X^2+\sigma_Y^2+c_2)} \quad (7)$$

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	OSEM+ Curvelet (proposed method)
MSE means	0,0056	0,00577	1,19E-03
PSNR means	70,798	70,696	78,646533
MSSIM means	$2{,}1.10^{-5}$	$2{,}1.10^{-5}$	4,22E-05
UQI means	0,2785	0,2787	0,32529092
Execution time(sec)	244,01995	68,96	123.570688.

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[17],[18],[19].

The qualitative assessment of the various directional texture region of the bone SPECT image illustrated in fig5, fig6 and fig7 shows that the proposed methods provide more accurate detection of lesion and better preservation of the limit of region, 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.10,11,12,13, the value of these metrics favoured the proposed method based on the curvelet 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 7, we note that the processing time of our proposed approach requires a shorter than the MLEM method but longer than OSEM technique.

To conclude, we can confirm that the proposed reconstruction method using the multi-scale Curve let denoising method applied on the reconstructed images outperform the other MLE-EM and OSEM iterative reconstruction method using alone in the enhancement of the quality bone SPECT image reconstruction.

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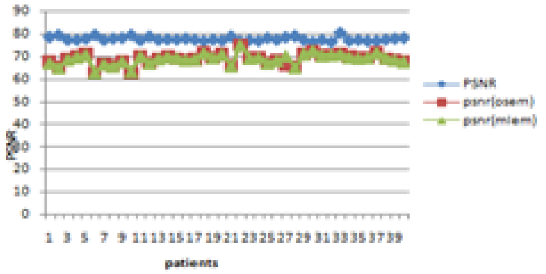

Fig.10. Comparison of the PSNR measurement for all patients obtained using different reconstruction method

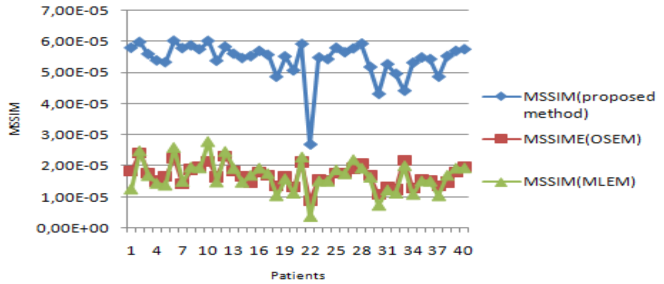

Fig11. Comparaison of the MSSIM measurement for all patients obtained by using different reconstruction method

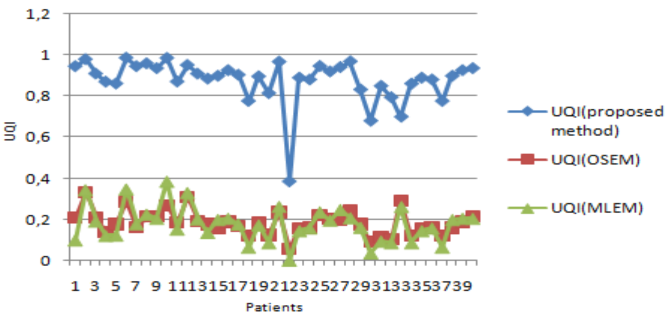

Fig12. Comparison of the UQI measurement for all patients obtained using different reconstruction method

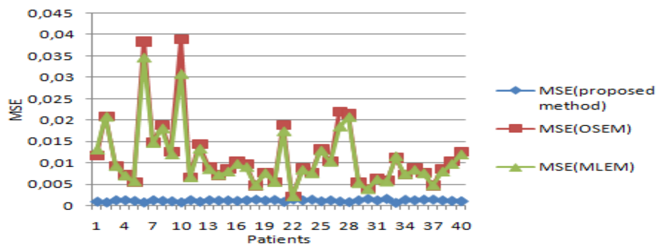

Fig13. Comparison of the MSSIM measurement for all patients obtained using different reconstruction method

IV. CONCLUSIONS

The objective of this paper is to enhance the bone SPECT image reconstruction. Firstly, we reconstructed 128 axial slices from 128 projection data based on the OSEM iterative reconstruction .then, we applied the multi-scale curve let denoising method to enhance the quality of the axial SPECT slices, 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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