Scintigraphic Image Denoising using Fisz Transformation and Redundant Wavelet Packets

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Résumé — *Le débruitage d'images par seuillage des coefficients d'ondelettes est une approche en pleine évolution vu le nombre croissant des publications qui s'intéressent à cette méthode de filtrage. Dans ce papier, nous proposons une nouvelle méthode de débruitage des images scintigraphiques basée sur la décomposition en ondelettes redondantes (utilisant une version modifiée du seuil de Bayes) et la transformation de Fisz pour changer la nature de la distribution du bruit d'une poissonienne à une gaussienne. En collaboration avec des spécialistes en médicine nucléaire, les résultats sont jugés importants.*

Abstract — *Image denoising by wavelet coefficients thresholding is an approach in full evolution considering the growing number of publications, which are interested in this methodology of filtering. In this paper, we propose a new method of denoising scintigraphic images based on redundant wavelet packet decomposition (using a modified version of Bayes's threshold) and Fisz transformation to transform the poissonnian noise in a Gaussian one. In collaboration with physicians of nuclear medicine, results are considered important.*

1. Introduction:

In medical imaging, noise suppression is a difficult task. A compromise between the preservation of useful diagnostic information and noise suppression must be respected. Generally, we rely on the intervention of an expert to control the quality of processed images. For example, in certain cases, such as the ultrasonic images, the noise can contain information which is useful for the physician. Medical images is thus, very variable, it is necessary to operate case by case.

In this paper, will present a new method to denoising scintigraphic images, using the Fisz transformation and the redundant wavelet packet. The originality of this method is his ability to suppress poison noise while preserving the useful details.

2. Denoising by wavelet coefficients thresholding:

Actually, denoising using wavelets proves his ability to satisfy the compromise between smoothing and conserving important features.

The first attempt of medical images denoising using wavelet was that of Weaver et al [5]. Results were encouraging except that the method eliminates small structures which were confused with the noise.

In 1994, Johnston and Donoho [6][7][8][9] formalized the principle of denoising by thresholding wavelet coefficients and since several work were published. [10,11,12,13,14,15,16]

At the beginning, the noise was supposed as Gaussien noise, white and additive. More recently, much of other work were interested in other models of noise. Thus the multiresolution denoising became, par excellence, a robust method of filtering.

In this paper, we propose a new method to denoise scintigraphic images, using the Fisz transformation and the redundant wavelet packet.

3. Denoisng scintigraphic images using Packet wavelet decomposition:

Wavelet packet decomposition gives better exploration of image details, so denoising using wavelet packet decomposition gives better results than classic wavelet decomposition. In the case of scintigraphic image, this decomposition will be associated with the Fisz Transformation.

In fact, in scintigraphic image, the noise distribution is Poissonnian [1]. We then propose the use of a transformation to change the nature of this noise into Gaussian.

In literature, several transformations were proposed such as that of Kolaczyk [2] and Anscombe.

In 2002, P.Fryzlewicz proposed a transformation known as the Fisz one for the monodimensional case [3]. More recently, in December 2003, an extension to 2D was proposed by Fadili which showed the considerable contribution of this transformation compared to other transformations [4].

Our denoising method is composed of the following steps:

- Apply the Fisz transformation.
- Apply our denoising method by thresholding the stationary wavelet packet coefficients:
- Apply the inverse Fisz transformation.

4. The Fisz transformation:[4]

If M indicates the original image of size N^2, m indicates the level of decomposition and I and J indicate the indices of the pixels in each image, the Fisz transformation is resumed in the following steps:

- Apply a level of decomposition by using the Haar wavelet with non normalised filters.

- we note D^m_{ij} the coefficients of details on each level of decomposition and A^m_{ij} the coefficients of approximation. The coefficients of details will then be modified as follows:

$$Z^m_{ij} = \begin{cases} 0 & \text{if} \quad A^m_{ij} = 0 \\ \dfrac{D^m_{ij}}{\sqrt{A^m_{ij}}} & \text{else} \end{cases}$$

- Repeat the first two stages on each level of decomposition (until $j=log_2(N)$) by keeping intact coefficients of approximation.

It results from this that the coefficients of details in all the scales and orientations, thus modified, are a Gaussien version of original coefficients.

- Reconstruct the new image N (by using the Haar wavelet with non normalised filters)

We can then write: $N = F(M)$ where F is the operator of the Fisz transformation.

5. Wavelet packet transform and best bases selection:

In the wavelet transform, one step calculates a low pass result and a high pass result. The low pass result is a smoother version of the original signal. The low pass result recursively becomes the input to the next wavelet step, which calculates another low and high pass result. For more details on the wavelet transform see .

As indicated below, the wavelet transform applies the wavelet transform step to the low pass result. The wavelet packet transform applies the transform step to both the low pass and the high pass result.

The wavelet packet transform can be viewed as a tree. The root of the tree is the original image. The next level of the tree is the result of one step of the wavelet transform. Subsequent levels in the tree are constructed by recursively applying the wavelet transform step to the low and high pass filter results of the previous wavelet transform step.

The best basis algorithm finds a set of wavelet bases that provide the most desirable representation of the data relative to a particular cost function. One cost function that has been proposed in the literature is the Shannon entropy function.

The best basis set can be obtained by traversing the tree, top down, from left to right. The traversal on a branch stops when a best basis node is encountered and this node is added to the best basis list

6. Modified version of Bayes's threshold:

It is an adaptive threshold which depends on the data in each sub-band in each level. Indeed, a threshold T is applied to each sub-band:

$$T = \frac{\beta \hat{\sigma}^2}{\sigma_y}$$

Where β is a parameter calculated for each level of decomposition:

$$\beta = \sqrt{\frac{L_k}{J}}$$

with L K: the length of sub-band in K 2nd scale (equal to the length of the original image), and J the number of the level. $\hat{\sigma}^2$: noise variance estimated by the formula of Donoho and Johstone. σ_y: Standard deviation of sub-band.

7. Proposed method of thresholding:

In literature, soft threshloding is applied to just the last level of wavelet packet decomposition. So the noise variation is estimated just one time. And it is applied to all sub-bands (except that of approximation).

As shown in figure 2, in our method, we apply a one level redundant wavelet packet decomposition, the threshold is calculated, a soft thresholding is applied to different sub-bands (except that of approximation).

The noise variation is then re-estimated for each image to calculate the new value of the threshold witch will be applied to the next redundant wavelet packet decomposition.

8. Results:

The described method was applied to a variety of cardiac scintigrahpic images; results show the suppression of noise and the preservation of ventricles edges (figure 1). In collaboration with physician of nuclear medicine, results are considered important. We mention that wavelets were used in another work to desoining scintigraphic images [17] but the method doesn't respect the particularity of this type of images (bad spatial resolution, poissonnian noise…), it's use the universal thresholding witch known of its incapability to preserve small details.

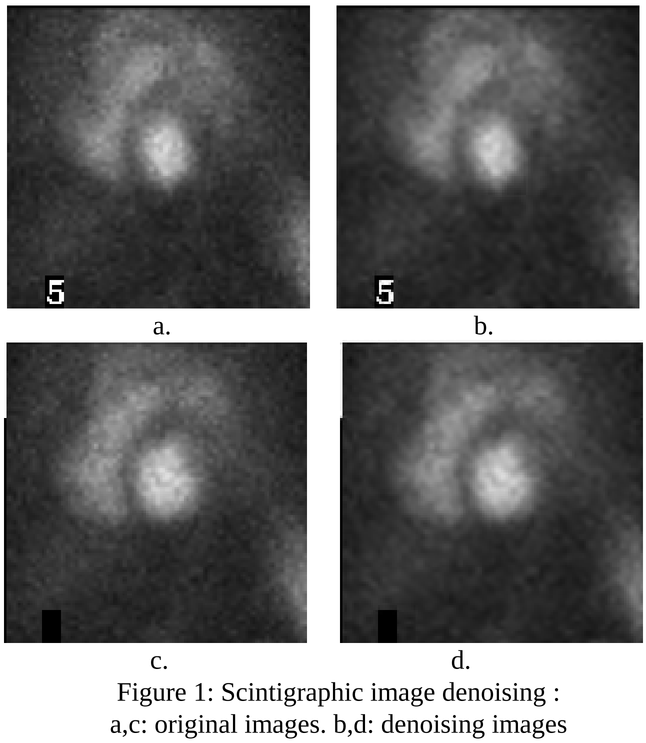

Figure 1: Scintigraphic image denoising :
a,c: original images. b,d: denoising images

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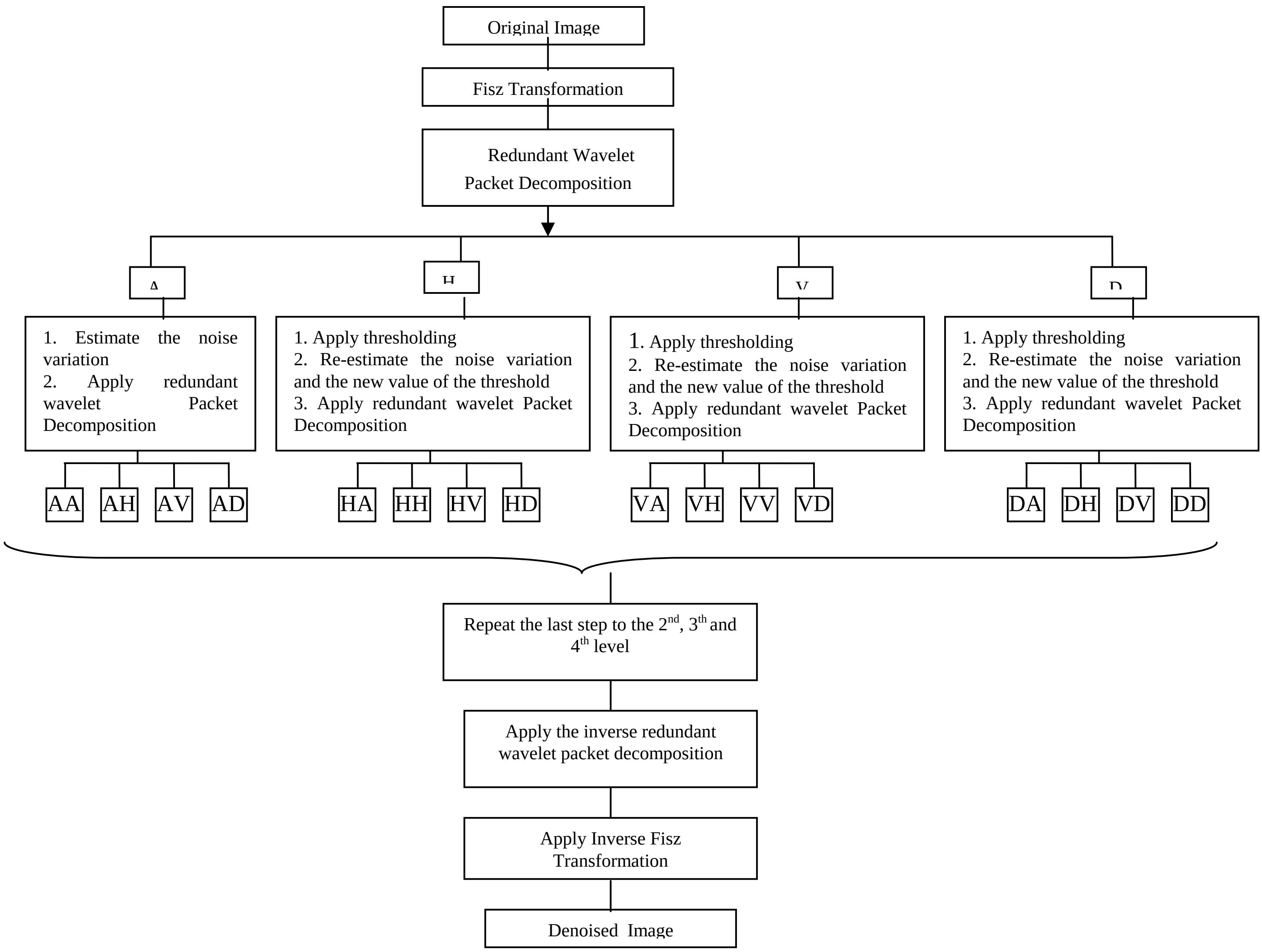

Figure 2: Architecture of the proposed method