ON THE DENOISING OF NUCLEAR MEDICINE CHEST REGION IMAGES

Mitko B. Kostov, Cvetko D. Mitrovski

University St. Kliment Ohridski, Faculty of Technical Sciences, Bitola - Macedonia

In the paper we present our approach on pre-processing of chest-region NM images. The proposed method combines Discrete Wavelet Transform realized via QMF filters with a specific strategy for selecting an appropriate threshold. Due to the signal-dependence of the Poisson noise, the Anscombe variance-stabilizing transformation is applied. As a result, the transformed coefficients are characterized with a white Gaussian noise model for which appropriate threshold selecting is easier. The performance of the proposed method is demonstrated on real NM images.

1. INTRODUCTION

Nuclear Medicine (NM) images are diagnostic digital images, which provide both anatomical and functional information. The raw NM images are created by accumulating the emitted gamma rays from a patient over a fixed observation period. They are very noisy due to the nature of the gamma ray emission process and the operational characteristics of the gamma cameras (low count levels, scatter, attenuation, and electronic noises in the detector/camera) [1]. The noise obeys a Poisson law and is highly dependent on the space distribution of the image signal intensity. Therefore, a suitable image pre-processing must precede the NM images analysis in order to provide an accurate recognition of the anatomical data of the patient (the boundaries of the various objects – organs). This process of separating signal from noise is a rather difficult and much diversified task that should be adjusted to the organs and tissues, which physiology is to be investigated.

This paper presents an approach on pre-processing of chest-region NM images. The images are processed in the discrete wavelet transform domain with linear phase QMF filters designed to achieve both good image decomposition and near perfect reconstruction. Due to the signal-dependence of the Poisson noise, the Anscombe variance-stabilizing transformation is applied. As a result, the transformed coefficients are characterized with a white Gaussian noise model and Donoho's level dependent threshold is used.

The paper is organized as follows. After reviewing the wavelet theory and wavelet-domain filtering in Section II, a suitable chest-region NM images filtration technique is presented in Section III. The performance of the proposed method is demonstrated on real NM images in Section IV, while the conclusion is given in Section V.

2. AN OVERVIEW OF THE DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform (DWT) decomposes a signal into a set of orthogonal components describing the signal variation across the scale [3]. The orthogonal components are generated by dilations and translations of a prototype function ψ called *mother wavelet.*

$$\psi_{i,k}(t) = 2^{-i/2}\psi(t/2^{i} - k), \quad k,i \in Z \tag{1}$$

The above equation shows that the mother function is dilated by the integer i and translated by the integer k. In analogy with other function expansions, a function f may be written for each discrete coordinate t as sum of a wavelet expansion up to certain scale J plus a residual term, that is:

$$f(t) = \sum_{j=1}^{J} \sum_{k=1}^{2^{-j}M} d_{jk}\psi_{jk}(t) + \sum_{k=1}^{2^{-J}M} c_{Jk}\phi_{Jk}(t) \tag{2}$$

The estimation of d_{jk} and c_{Jk} is carried out through an iterative decomposition algorithm, which uses two complementary filters h_0 (low-pass) and h_1 (high-pass). Since the wavelet base is orthogonal, h_0 and h_1 satisfies the quadrature mirror filter conditions (QMF) [5]. Filter bank theory is closely related to wavelet decompositions and multiresolution concepts. For this reason, it is helpful at this point to view the scaling function ϕ as a low pass filter h_0 and wavelet function ψ as a high pass filter h_1. The mother and scaling functions are defined as follows [3]:

$$\psi(t) = \sum_{n} 2^{1/2} h_1 \psi(2t - n) \tag{3}$$

$$\phi(t) = \sum_{n} 2^{1/2} h_0 \phi(2t - n) \tag{4}$$

For computation of wavelet transform, the following pyramidal algorithm is used: The QMF bank decomposes the signal into low and high frequency components respectively. Convolving the signal with h_1 gives a set of wavelet coefficients $c_{J,k}$, while the convolution with h_0 gives the approximation coefficients $d_{j,\mathrm{k}}$. Because of the redundancy of information, these filters are down-sampled, throwing away every other sample at each operation, thus halving the data each time. The approximation coefficients $d_{j,k}$ are then convolved again with the filters h_0 and h_1 to form the next level of decomposition. The backward algorithm simply inverts the process. It

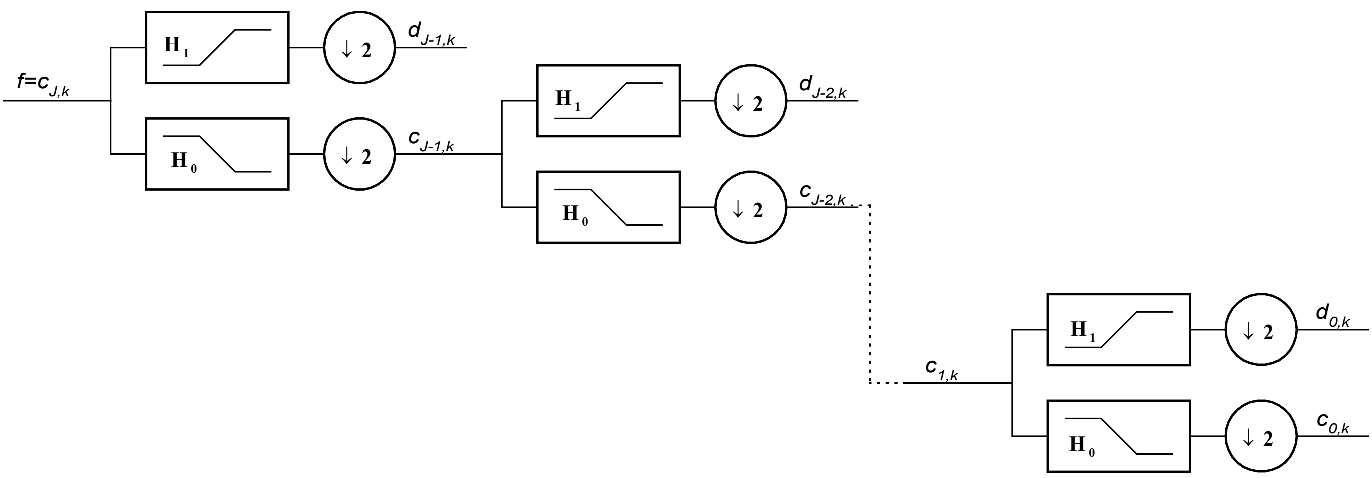

Fig. 1. Discrete Wavelet Transform Tree

combines two linear filters with up-sampling operation. Fig. 1 shows the operation involved in the wavelet decomposition and synthesis of the signal.

At present, there exist no theoretical results that can predict which wavelet is suitable for a particular type of signal. Usually, the best wavelet is chosen by comparing the performances of several types of wavelets.

Wavelet Shrinkage

The most popular form of wavelet-based filtering is commonly known as *Wavelet Shrinkage*. The basic wavelet shrinkage algorithm involves computing of the discrete wavelet transform of the observation y (w = DWT(y)). The contribution of a particular wavelet basis function in the signal expansion can be filtered by weighting the corresponding coefficient w_i by a number $0 \le h_i \le 1$. That is, the wavelet coefficients are modified according to:

$$\hat{w}_i = w_i \cdot h_i \tag{5}$$

In the wavelet shrinkage program, the shrinkage filter corresponds to either the "hard threshold" nonlinearity

$$h_i^{(\mathrm{hard})} = \begin{cases} 1, & \text{if } |w_i| \ge \tau \\ 0, & \text{if } |w_i| < \tau \end{cases} \tag{6}$$

or the "soft threshold" nonlinearity

$$h_i^{(\mathrm{soft})} = \begin{cases} 1 - \dfrac{\tau\,\mathrm{sgn}(w_i)}{w_i}, & \text{if } |w_i| \ge \tau \\ 0, & \text{if } |w_i| < \tau \end{cases} \tag{7}$$

with τ a user-specified threshold level.

Finally, the signal is reconstructed (estimated) by computing the inverse wavelet transform from the processed data: $\hat{f}$ = IDWT($\hat{w}$).

3. FILTRATION OF CHEST REGION IMAGES

Chest region images contain quantum noise, which obeys a Poisson law and is highly dependent on the underlying light intensity pattern being imaged [6]. For denoising purposes, it is often advantageous instead of working in the spatial (pixel) domain to work in a transform domain. One possible choice for image transform is the discrete wavelet transform (DWT) domain. The DWT tends to concentrate the energy of a signal into a small number of coefficients, while a large number of coefficients have low SNR.

Motivated by the DWT tendency to produce coefficients with high and low SNR, we apply the soft thresholding from the wavelet shrinkage program. But, if the noise was additive white Gaussian, the noise level would be uniform throughout the image and hence uniform across all the wavelet coefficients. Therefore, in additive white Gaussian noise a simple global noise threshold could be determined independently on the signal [5]. Unfortunately, the Poisson noise is signal-dependent and therefore the wavelet-domain filtering based on a global threshold is inappropriate. Hence, for denoising this type of images we use the Anscombe (1948) variance-stabilizing transformation:

$$y_{i_1,i_2} = \sqrt{N_{i_1,i_2}} \tag{8}$$

As a result, the transformed coefficients are characterized with a white Gaussian noise model [4] and we calculate the Donoho's level dependent threshold:

$$\tau_j = \sigma\sqrt{2\log N} \cdot 2^{(j-J)/2}, \quad j = 0,...,J, \tag{9}$$

where σ is the noise standard deviation (to be estimated), J is the number of decomposition levels, j is the scale level and N is the total number of image pixels [4].

In addition, due to the wavelet shrinkage program, some of the wavelet coefficients are discarded, so the perfect reconstruction is not possible. Hence, we propose to give up the perfect reconstruction at the very beginning. It means instead of using wavelet filters, to decompose the data using a filter bank with linear phase filters that have better characteristics. At the same time the QMF bank should be designed to achieve near perfect reconstruction (NPR).

The algorithm for denoising chest region images can be summarized as following:

- transform the image using (8);
- apply DWT using QMF NPR bank;
- calculate the Donoho's level dependent threshold using (9);
- apply the standard soft-threshold wavelet-domain filter;
- apply inverse DWT;
- square the result.

4. EXPERIMENTAL RESULTS

As a sample image in our experiments we use one NM image matrix of resolution 128x128. Fig. 2 shows the original image and the image obtained after applying the proposed wavelet filtering.

To design a suitable QMF bank we use the method described in [7]. The obtained QMF bank has overall reconstruction error minimized in the minimax sense; the corresponding QMF filters have least-squares stopband error. The filters have good passband and narrow transition band. The decomposition filters magnitude response and the prototype filter coefficients are given in Fig. 3 and Table 1, respectively.

To calculate the noise standard deviation in (9) we use Donoho's estimate MAD/0.6745 [5], where MAD is the median of the magnitudes of all the coefficients at the finest decomposition scale.

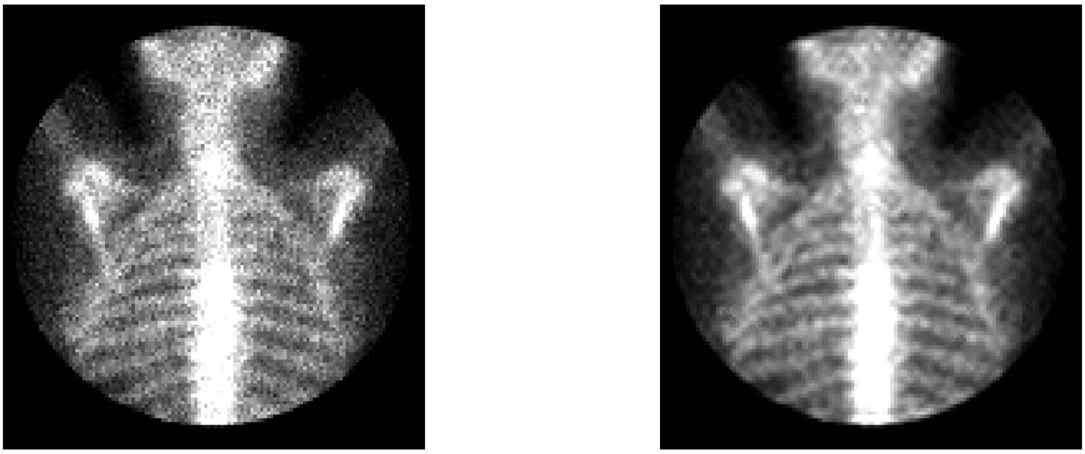

Fig. 2 a) The original image, b) The soft threshold filtered image

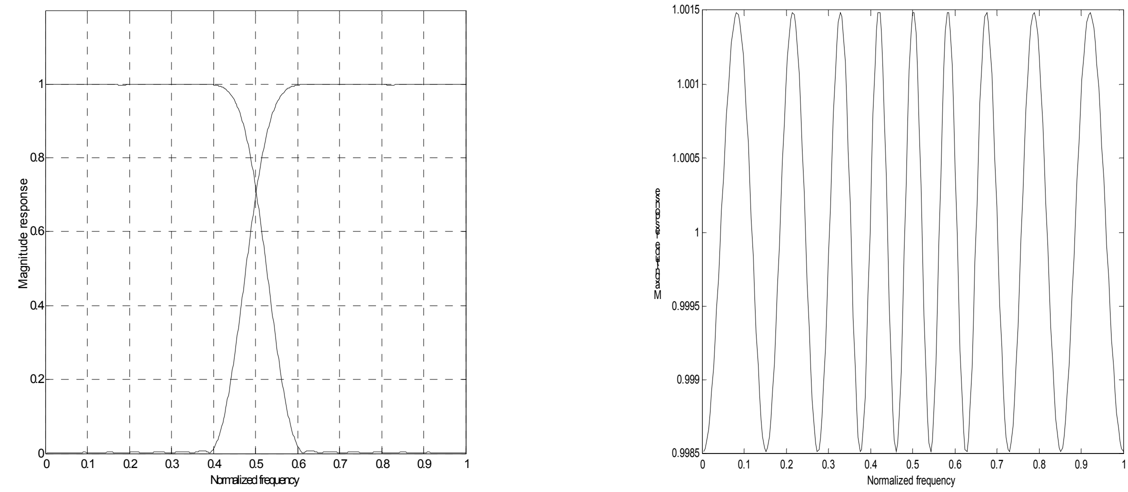

Fig. 3 Magnitude response of the used QMF bank: a) Magnitude response of the prototype filter, b) Magnitude response of the QMF bank

$h_0[0-15] =$ $h_0[31-16]$	0.002722 -0.002856 -0.003194 0.007698 0.002690 -0.015823 0.000046 0.027907 -0.007397 -0.046104 0.023106 0.075651 -0.058667 -0.140412 0.184563 0.657174
$h_1[0-15] =$ $-h_1[31-16]$	0.002722 0.002856 -0.003194 -0.007698 0.002690 0.015823 0.000046 -0.027907 -0.007397 0.046104 0.023106 -0.075651 -0.058667 0.140412 -0.184563 -0.657174
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Table 1 Filter coefficients of QMF bank filters

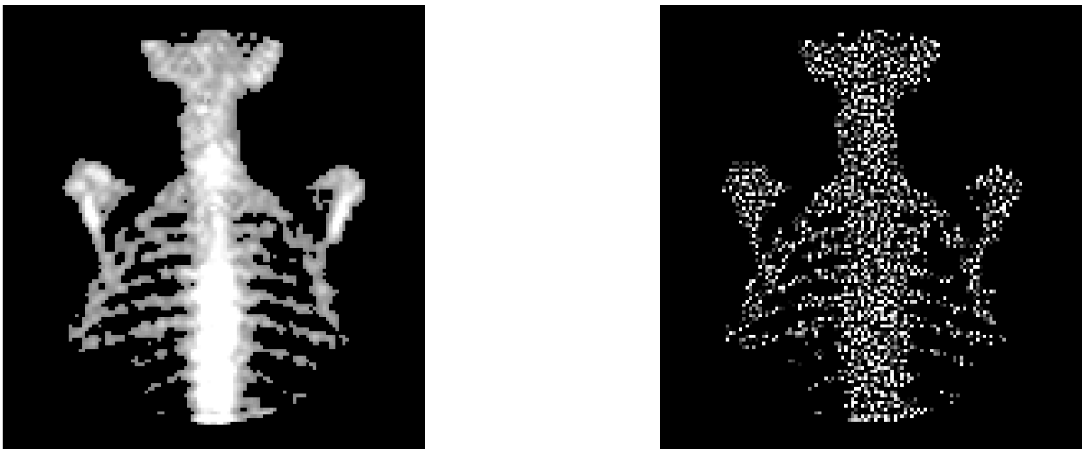

Fig. 4 a) The filtered image without shadow, b) The removed noise

After applying the algorithm given in Section 3, we remove the shadow in the resultant image. Fig. 4 shows the resultant image without shadow and the image of the removed noise. The intensity of the pixels in the image of removed noise in Fig. 4 is amplified by a factor of 10.

5. CONCLUSION

In this paper an approach on pre-processing of NM chest region images is presented. The images are processed in the wavelet transform-domain using linear phase QMF filters designed to achieve near perfect reconstruction. Due to the signal-dependence of the Poisson noise, the Anscombe variance-stabilizing transformation is applied and the Donoho's level dependent threshold is used. The performance of the proposed method is demonstrated on real NM images. The obtained results could be used an expert system to be created. Utilizing this system, physicians could be able to analyze regions of interests and make physiological investigation.

6. REFERENCES

[1] General Electric, *Gamma Camera Technical Reference Manual*, 1980;

[2] Цветко Д. Митровски, "Квантитативно одредување на лево десен шант кај срцеви болни", *Зборник на трудови на ТФ-Битола*, стр. 327-335, 1996;

[3] G. Strang and T. Nguyen, *Wavelets and Filter Bank*s. Wellesley-Cambrige Press, 1996;

[4] D. L. Donoho, "Wavelet Thresholding and W.V.D.: A 10-minute Tour", *Int. Conf. on Wavelets and Applications*, Toulouse, France, June 1992;

[5] D. L. Donoho and I. M. Johnstone, "Ideal spatial adaptation via wavelet thresholding", *Biometrika*, vol. 81, pp. 425-455, 1994;

[6] Robert D. Nowak, Richard G. Baraniuk, "Wavelet-Domain Filtering for Photon Imaging Systems", *IEEE Trans. Image Processing*, vol. 8, Iss. 5, p. 666-678, May 1999;

[7] Sofija Bogdanova, Mitko Kostov, and Momcilo Bogdanov, "Design of QMF Banks with Reduced Number of Iterations", *IEEE Int. Conf. on Signal Processing, Application and Technology, ICSPAT '99,* Orlando, Nov. 1999.