QMF Filtering Of Nuclear Medicine Heart Region Images

Cvetko D. Mitrovski[1] and Mitko B. Kostov[2]

Abstract – **In the paper we present our approach on pre-processing of NM heart-region images. The proposed method combines Discrete Wavelet Transform realized via near perfect reconstruction QMF bank with a specific strategy for selecting an appropriate threshold. The performance of the proposed method is demonstrated on real NM images.**

Keywords – **Nuclear medicine image, wavelets, thresholding, QMF.**

I. INTRODUCTION

Nuclear Medicine (NM) images are diagnostic digital images, which provide both anatomical and functional information. They present the projection of the distribution of radioisotope(s) in a body of a patient after injection of adequate dose of radioisotope(s). The raw NM images are created by accumulating the emitted gamma rays from a patient over a fixed observation period by computerized gamma cameras. They have a low signal-to-noise ratio (SNR) 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). 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.

In [7], [8], [9] and [10] we proposed several approaches to cope with this problem. In [7], the whole process of spreading the radionuclide is divided in three successive phases and the images that belong to one specific phase are processed separate from the others. In addition, the image resolution is changed and autocorrelation technique is applied. In [8], the images are filtered by utilizing the wavelet shrinkage program, where the threshold is set to be same for all the wavelet coefficients in one level. In [9] the images processing is carried out by modifying images histogram. In [10] the denoising is tried by filtering the images in the direction that is normal to the spreading of the radionuclide.

In [5] a new method for designing optimal wavelet-domain filters for noise removal in photon imagery is proposed. The threshold adapts to the local noise level of the spatially varying Poisson process underlying the image and is different for every wavelet coefficient.

This paper presents a new approach on pre-processing of NM heart-region images. The images are processed in the discrete wavelet transform domain with linear phase QMF filters. The filters are designed to achieve both good image decomposition and near perfect reconstruction. The threshold in the wavelet shrinkage program is selected as proposed in [5].

The paper is organized as follows. In Section II the NM images creation process is modelled, and the problems due which raw NM images should be pre-processed, are formulated. Section III outlines the scheme used in wavelet filtering of NM images. Section IV presents suitable NM images filtration technique. The performance of the proposed method is demonstrated on real NM images in Section V. Conclusion is given in Section VI.

II. NM IMAGES CREATION PROCESS

The process of generating the NM images starts after injection of certain, small dose (for safety reasons) of suitably chosen radioactive material, into the body of a patient. The radionuclide spreads and mixes with the blood on its way to the heart through the vena cava superior. This results with some very complicated, fast changing function, $\rho(x, y, z, t)$. After passing through the heart, the blood-radioactivity mixture passes through the lungs, returns to the heart and proceeds with spreading toward each cell of the patient body through its arteries. This process could be recorded as a set of *N*, NM images (Fig. 1). Each image contains rather high level of noise caused by: a) mixing the radionuclide with the blood and the spreading of this mixture, b) hydrodynamic processes in the blood vessels caused by the pumping work of the heart, and c) by the randomness of the gamma rays emission and their detection by the gamma camera. Considering this, the raw images should be adequately preprocessed in order to extract the anatomy information about the position of the vena cava superior and the heart. According to this information, the optimal position (and the shape) of the regions of interest (ROI's) for the heart study could be proposed [1].

III. 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 [2]. The orthogonal components are generated by dilations and translations of a prototype function ψ called *mother wavelet:*

[1]Cvetko D. Mitrovski is with the Faculty of Technical Sciences, I.L.Ribar bb, 7000 Bitola, Macedonia, E-mail: cvetko.mitrovski@uklo.edu.mk

[2]Mitko B. Kostov is with the Faculty of Technical Sciences, I.L.Ribar bb, 7000 Bitola, Macedonia, E-mail: mitko.kostov@uklo.edu.mk

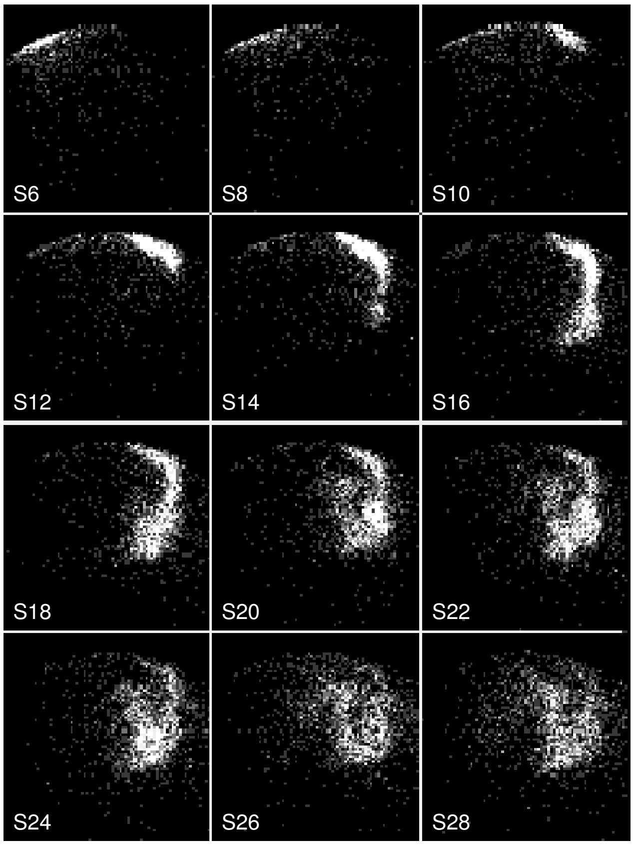

Fig. 1. Sequence of enhanced noised images (τ=0.4 s)

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

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 a 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 coefficients 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) [3]. The 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 [2]:

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

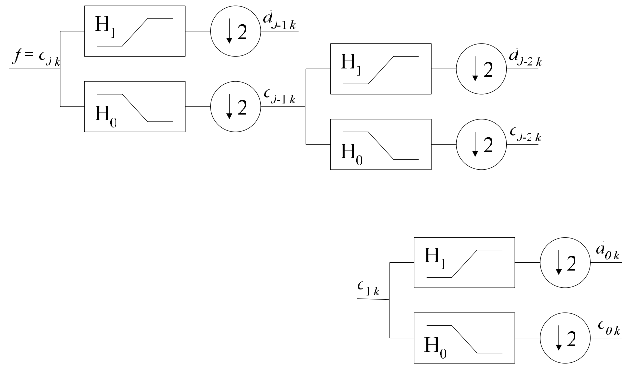

Fig. 2. Discrete Wavelet Transform Tree

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

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 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

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

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($\hat{w}$).

IV. Filtration of NM Images

The heart region images contain quantum noise, which obeys a Poisson law and is highly dependent on the underlying light intensity pattern being imaged [5]. 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 images 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 a 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 a case when a signal contains additive white Gaussian noise a simple global noise threshold could be determined independently on the signal [4]. Unfortunately, the Poisson noise is signal-dependent and therefore wavelet-domain filtering based on a global threshold is inappropriate. Hence, for denoising this type of images we use the wavelet filter described in [5]:

$$h_I = \left(\frac{\hat{\theta}_I^{\,2}}{\hat{\theta}_I^{\,2} + \hat{\sigma}_I^{\,2}} \right)_+ \quad (8)$$

with

$$I = (i,j,m,n)$$

an abstract index for the four indices of the 2-d wavelets basis $\psi_{i,j,m,n}(k,l)$ and

$$\hat{\sigma}_I^{\,2} = \sum_{k,l} \psi_I^{\,2}(k,l) f_I(k,l)$$

an unbiased estimate of the noise power in the I-th wavelet coefficient, and

$$\hat{\theta}_I^{\,2} = \omega_I^{\,2} - \hat{\sigma}_I^{\,2}$$

an unbiased estimate of the signal power in the I-th wavelet coefficient, and $(\cdot)_+$ denoting the positive part (negative values set to zero).

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 filters that have better characteristics. At the same time the QMF bank should be designed to achieve near perfect reconstruction (NPR). One possible choice for designing QMF NPR bank is using the algorithm in [6].

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

- apply the autocorrelation technique to the dynamical images [7];
- create a resultant image from the images obtained in the previous step;
- compute DWT of the image using a QMF NPR bank;
- compute the wavelet filter given with Eq. (8);
- apply the standard soft-thresholding;
- compute the inverse DWT by using modified wavelet coefficients.

V. Experimental Results

We use a set of real NM image matrices of resolution 128x128 shown in Fig. 1. Autocorrelation technique [7] is applied to remove the salt and paper noise from the images.

To design a suitable QMF bank we use the algorithm described in [6]. 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 linear phase, zero at π, 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.

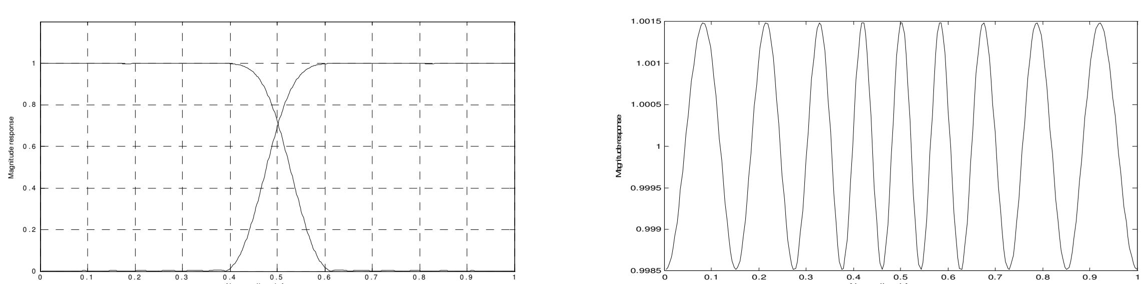

Fig. 3 a) Magnitude responses of the decomposing filters, b) Magnitude response of the QMF NPR bank

$h_0[0-15] = h_0[31-16]$	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
$f_0[0-15] = f_0[31-16]$	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
$f_1[0-15] = -f_1[31-16]$	-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

Table 1 Filter coefficients of QMF bank filters

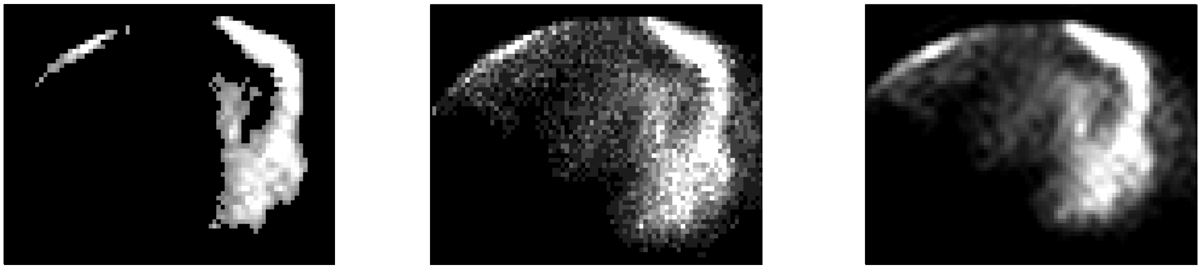

Fig. 4. The vena and the heart a) proposed approach b) conventional approach c) lowpass filtering of the image in b)

After applying the algorithm given in Section 4, we remove the shadow (pixels with low intensity) in the resultant image. Fig. 4 shows the resultant image without the shadow and the resultant image obtained by the conventional way of extracting anatomic information i.e. summing a number of sequential raw images. The image in Fig. 4-a) has sharp edges of the vein and the heart, while the image in Fig. 4-b) contains relatively high level of noise that blurs the edges of these objects. Therefore, the image in Fig. 4-a) is more suitable for an upgrading expert system that could provide automatic identification of optimal shapes and positions of regions of interest needed for further physiological diagnostics.

The quality of the image in Fig. 4-b) could be further improved by using certain low pass filtering techniques as shown in Fig. 4-c), but the projections of the vein and the heart would still suffer from certain deformations. These deformations could degrade the effects of an expert system for automatic identification of the optimal positions and shapes of regions of interest needed for further investigations.

VI. Conclusion

We present an approach on pre-processing heart region dynamical NM images. The aim of this approach is to determine anatomical data in order to upgrade the software with an expert system that could identify the optimal positions and the shapes of the regions of interest needed for the heart study. The images are processed in the wavelet transform-domain using linear phase QMF NPR filters. Due to the signal-dependence of the Poisson noise, an alternative approach for selecting the threshold is used. The performance of the proposed method is demonstrated on real NM images.

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