A WAVELET DOMAIN APPROACH ON NOISE FILTRATION OF NUCLEAR MEDICINE IMAGES

Cvetko D. Mitrovski, Ph.D. and Mitko B. Kostov, M.Sc.

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

Abstract – *In this paper an approach on pre-processing of dynamic nuclear medicine images is proposed. The method is based on conventional threshold level detection, applied on adequately pre-processed set of dynamic images. A combination of autocorrelation low-pass filtering technique and wavelet transform-domain processing is used. The performance of the proposed method is demonstrated on real NM images.*

I. INTRODUCTION

Nuclear Medicine (NM) images are diagnostic digital images, which can provide both anatomical and functional information. They present the projection of distribution of radioisotope(s) in a body of a patient after injection of adequate dose of radioisotope(s). The raw nuclear medicine images are based directly on the total counts detected over a fixed observation period by computerized gamma cameras and have a low signal-to-noise ratio (SNR). There are several sources of noise in nuclear medicine: low count levels, scatter, attenuation, and electronic noises in the detector/camera. Therefore, a certain image pre-processing must precede the NM images analysis, which ought to provide an accurate recognition of anatomic data of the patient (the boundaries of the various objects – organs, on the images). This process of separating signal from noise is a very difficult task and it could be much diversified, since it should be adjusted to the organs and tissues, which physiology is to be investigated.

This paper presents our approach on pre-processing of dynamic chest-region NM images, captured immediately after injection of the radioactive material into the vein of a patient. A combination of autocorrelation low-pass filtering technique and wavelet transform-domain processing is used.

The paper is organized as follows. In Section II the dynamic NM images creation process is modelled, and the problems due which raw NM images should be pre-processed, are formulated. In Section III, we propose our approach for extracting the boundaries of the anatomical data in the chest region from a set of raw sequential images. Section IV presents suitable NM images non-linear filtration techniques used in the proposed approach. In Section V the proposed algorithm for noise removal is given. The performance of the proposed method is demonstrated on real NM images captured with our own gamma camera upgrading system. Conclusions and future research are discussed in Section VI.

II. MODEL OF THE PROCESS

The process of generating the NM images starts after injection of small dose (for safety reasons) of suitably chosen radioactive material

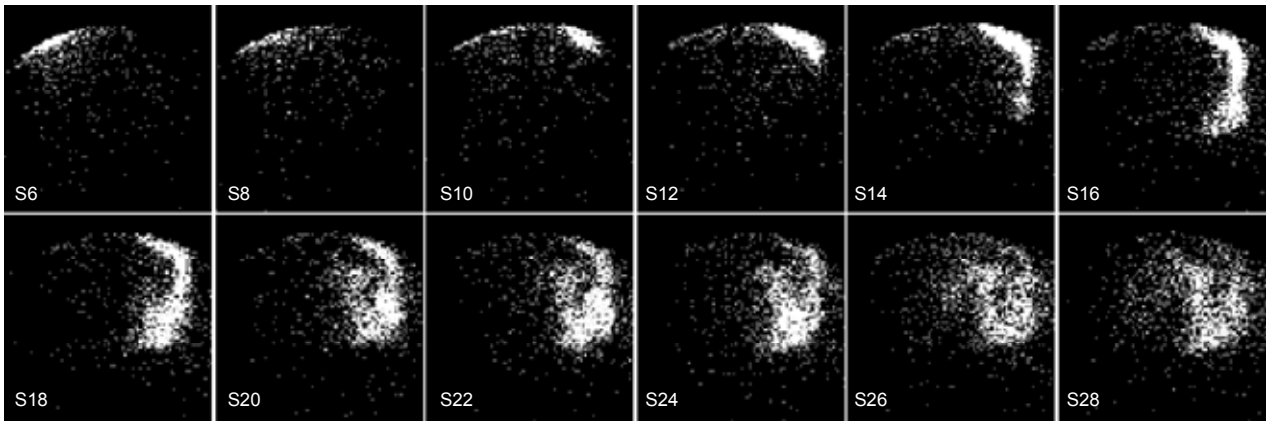

Fig. 1 Sequence of enhanced noised images (τ=0.4 s)

$$Q = \int_0^T q(t)dt \tag{1}$$

into the body of a patient where $q(t)$ is injection flow of the radionuclide and T is total injecting time. The injected radionuclide starts to spread, generating some space and time varying *radionuclide density function* (r.d.f.), $\rho(x, y, z, t) \geq 0$, into the body of the patient ($t > 0$; $x, y, z \in B$, B – body of the patient).

After injection of the radioactive material in the patient vein (right hand), the blood-radioactivity mixture passes through the heart and 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):

$$S_k^r(i,j,t_k,\tau), \qquad k = 1,2,...,N \tag{2}$$

where r (power of 2) is image resolution index; $i, j = 1,2,...,r;$ are indexes of the image matrix that correspond to a set of $r \times r$ imaginary rectangular cells of the gamma camera detector plane; t_k is moment of beginning of generation of the image; τ is accumulation time.

Each image $S_k^r(i,j,t_k,\tau)$ (in the further text $S_k^r(t_k,\tau)$ or S_k^r) is formed by counting the detected gamma rays in the cells of the image matrix in the interval $[t_k, t_{k+1}]$ ($t_{k+1} = t_k + \tau$; $k = 1, 2, \ldots N$; $t_1 = 0$). This type of images, usually has a very short accumulation time ($\tau \leq 0.5$) in order to record the very fast spreading of the radionuclide. Therefore, the accumulated energy (counts) per image is very small. As a consequence of that, the images captured with higher resolution will have relatively lower level of image dynamics defined by

$$d_k^r = \max_{i,j}(S_k^r(i,j)) - \min_{i,j}(S_k^r(i,j)). \tag{3}$$

Since for this type of NM images, the lowest pixel intensity is 0, the image dynamics is defined by $d_k^r = \max_{i,j}(S_k^r(i,j))$.

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 pre-processed in order to extract the anatomy information about the position of the vena cava superior and the heart.

III. Anatomical Data Extraction

On the set of NM images, the following arithmetic operations can be defined:

$$S_k^{r1}(t_k,\tau) = f(S_k^r(t_k,\tau)); \qquad r1 = 0.5r \tag{4}$$

$$S_{k,j}^r(t_k, j\tau) = \sum_{i=k}^{k+j-1} S_i^r(t_i,\tau) \tag{5}$$

which helps in creation of new raw images with lower resolution (Eq. 4) and longer accumulation time (Eq. 5) (f(.) is a function for reducing the resolution of the original image by factor of two).

The conventional way for extracting anatomic information is by summing a number of sequential raw images. In some cases, this approach gives sufficiently good results, but in many situations the objects on the resultant image appear enlarged and deformed. Therefore, we have experimented with a modified approach based on superposition of the parts of the filtered images.

The process of spreading of the radionuclide after its injection in the vein of the patient can be divided in three successive phases. The first one is when the radionuclide passes through the vena and comes to the heart; the second one begins when it starts to spread through the heart and comes to the lungs; and the third one starts when the radionuclide begins to return to the heart and proceeds to spread through arteries toward each cell of the patient body. The determining of the break point between the phases is given in [3].

The images recorded in phase one, show the spreading of rather compact mass of radionuclide through the vena. In spite of that, these images contain high level of spatially distributed noise in a form of isolated pixels in the neighbourhood of the vein.

The images recorded in the beginning of the second phase consist of two objects: the vein and the heart. Later, the vein disappears, and only the heart remains. The projection of the heart in this phase is the best, but still its boundaries remain poorly shaped due to the lower concentration of the radionuclide in it. Also, the heart pulsation has NM image degrading effects. Hence, the filtering techniques cannot be successfully applied on the whole image. Therefore, we propose the set of all NM images to divide into two subsets: subset with images where the vein appears only (I phase) and subset with images where the vein and the heart appear (II phase). We

propose to remove the vein from the images of the second subset, and then to reduce resolution of the images. Then, we apply same techniques of filtration to the images of the first subset and to pre-processed images from the second subset.

Next, intuitively, it is obvious that each filtered image S_{fk} contains a part of global information about the anatomy of the body of the patient. In order to extract the desired information out from the image S_{fk}, we define and determine the image energy zone with energy above certain threshold (say $0.8 \cdot d_k$), and the image zone below the same threshold. Actually, we decompose the filtrated image into two sub-images:

$$S_{fk}^r = S_{hfk}^r + S_{lfk}^r \tag{6}$$

(S_{hfk}^r -high energy sub-image, S_{lfk}^r -low energy sub-image), after what we proceed with composition of the resultant image according to the following formula:

$$S_{af}^r = \sum_{k=0}^{k_3} \frac{d_{k_1}^r}{d_k^r} S_{hfk}^r + \omega \sum_{k=0}^{k_3} \frac{d_{k_1}^r}{d_k^r} S_{lfk}^r \tag{7}$$

where $0 < \omega < 1$ and $k_3 = k_1 + \varepsilon(k_2 - k_1)$; $0.6 < \varepsilon < 0.8$ (k_1 and k_2 are break-points between I and II phase and between II and III phase, respectively). We choose the coefficient ε to lie in the interval [0.6, 0.8], because we want to process the images with the heart only, not the images with the heart and the lungs together.

The process of decomposition could be continued with decomposing the sub-image S_{lfk}^r into two new sub-images.

IV. Filtration Of Dynamical Images

A combination of autocorrelation low-pass filtering technique and wavelet transform-domain processing is used. The autocorrelation low-pass filtering technique is applied to the images in order the isolated pixels to be removed. The main motivation to apply this technique was our assumption that there is a bigger chance any isolated pixel(s) to be a part of the noise than to be a part of the image information [3]. The motivation for applying the wavelet transform-domain processing is that the Discrete Wavelet Transform (DWT) tends to concentrate the signal energy into a few coefficients (which are kept) and there is a large number of coefficients with low SNR (which are discarded). After discarding the noisy coefficients, the image is reconstructed using the inverse DWT.

Wavelet Shrinkage

The most popular form of wavelet-based filtering is commonly known as *Wavelet Shrinkage*. The basic wavelet shrinkage algorithm first involves computing of the discrete wavelet transform of the observation y (w = DWT(y)). Having wavelet coefficients of the observation, w_i, we can filter contribution of a particular wavelet

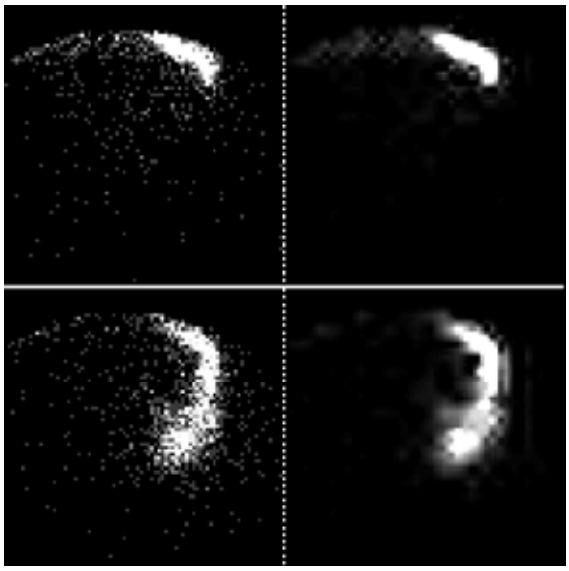

Fig. 2 Original and filtered images S_{12}, S_{17}

Fig.3 The final image of the vena and the heart

basis function in the signal expansion by weighting the corresponding coefficient w_i by a number $0 \le h_i \le 1$. That is, we modify the wavelet coefficients according to:

$$\hat{w}_i = w_i \cdot h_i \tag{8}$$

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

$$h_i^{(\text{hard})} = \begin{cases} 1, & \text{if } |w_i| \ge \tau \\ 0, & \text{if } |w_i| < \tau \end{cases} \tag{9}$$

or the "soft threshold" nonlinearity

$$h_i^{(\text{soft})} = \begin{cases} 1 - \dfrac{\tau \operatorname{sgn}(w_i)}{w_i}, & \text{if } |w_i| \ge \tau \\ 0, & \text{if } |w_i| < \tau \end{cases} \tag{10}$$

with τ a user-specified threshold level.

Finally, we invert the modified wavelet transform to obtain our signal estimate $\hat{f}$ = IDWT($\hat{w}$). In the case of NM images, the noise power will differ between wavelet coefficients according to the image intensity. This spatial variation must be accounted for in the wavelet-domain filter design. The wavelet shrinkage program is illustrated in Fig. 2.

V. The Proposed Algorithm

Considering the previous, we propose the following algorithm for noise removal in nuclear medicine images:

- Decomposing the set of images into two subsets: subset with images of the vein (I phase, indexes 5-14) and subset with images of the vena, the heart and the lungs (II phase, indexes 15-28);

- The autocorrelation technique to the images from the first subset [3];
- The wavelet shrinkage (Eqs. 8 and 9) to the obtained images;
- Decomposing the filtrated images obtained in the previous step according to Eq. 6 and composition the resultant images according to Eq. 7;
- Superposition of the images from the first subset and obtaining a final image about the vein;
- Extracting the segment with the heart from the images of the second subset using the final image about the vein;
- Reducing the resolution of the extracted segment by a factor of 2;
- The autocorrelation technique to the obtained images [3];
- The wavelet shrinkage (Eqs. 8 and 9) to the obtained images;
- Decomposing the filtrated images obtained in the previous step according to Eq. 6 and composition the resultant images according to Eq. 7;
- Increasing the resolution of the filtrated images by a factor of 2;
- Superposition of the images obtained in the previous step and obtaining a final image about the heart;
- Superposition of the image of the vein and the image of the heart.

The resultant image about the vena and the heart (obtained from 24 sequential images, with indexes 5-28) is shown in Fig. 3.

V. Conclusion

In this paper we present our approach on pre-processing of dynamic nuclear images. The proposed method is based on conventional threshold level detection, applied on adequately pre-processed set of dynamic images (nonlinear enhancement of the originals and their filtrations). A combination of autocorrelation low-pass filtering technique and wavelet transform-domain processing is used. The performance of the proposed method is demonstrated on real NM images recorded and processed by our own gamma camera upgraded system, developed at the department of NM in Bitola. 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.

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] Cvetko D. Mitrovski and Mitko B. Kostov, "On the Preprocessing of Dynamic Nuclear Medicine Images", *International Scientific Conference on Information, Communication and Energy Systems and Technologies ICEST 2002*, Nis, 2002;