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DE-BLURRING SINGLE PHOTON EMISSION COMPUTED TOMOGRAPHY IMAGES USING WAVELET DECOMPOSITION

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Abstract
Single photon emission computed tomography imaging is a popular nuclear medicine imaging technique which generates images by detecting radiations emitted by radioactive isotopes injected in the human body. Scattering of these emitted radiations introduces blur in this type of images. This paper proposes an image processing technique to enhance cardiac single photon emission computed tomography images by reducing the blur in the image. The algorithm works in two main stages. In the first stage a maximum likelihood estimate of the point spread function and the true image is obtained. In the second stage Lucy Richardson algorithm is applied on the selected wavelet coefficients of the true image estimate. The significant contribution of this paper is that processing of images is done in the wavelet domain. Pre-filtering is also done as a sub stage to avoid unwanted ringing effects. Real cardiac images are used for the quantitative and qualitative evaluations of the algorithm. Blur metric, peak signal to noise ratio and Tenengrad criterion are used as quantitative measures. Comparison against other existing de-blurring algorithms is also done. The simulation results indicate that the proposed method effectively reduces blur present in the image.

Keywords:
Blind De-Convolution, Nuclear Medicine Imaging, Single Photon Emission Computed Tomography Imaging, Wavelet Transform

1. INTRODUCTION

Cardiovascular disease is a main cause of death globally. About 17.5 million people died from heart diseases in 2012, representing 31% of all global deaths [1]. According to the estimates of world health organization, 45% of non-communicable disease deaths in India are due to heart diseases [2]. This emphasizes the need for early detection of heart disorders. Many techniques are available for the diagnosis of heart diseases and nuclear medicine imaging is one among them. Nuclear medicine imaging is a non-invasive imaging technique. Single photon emission computed tomography (SPECT) and positron emission tomography (PET) are popular nuclear medicine imaging techniques that find extensive application in imaging cardiac functioning [3, 4]. In this paper we propose a method for improving the quality of cardiac SPECT images using image processing techniques.

Cardiac SPECT and PET images allow a visual analysis of blood flow through heart muscles. Acquiring a SPECT image is comparatively cheaper as compared to that of a PET image. But the uses of SPECT images are counterbalanced by the relative low image quality as compared to PET images. Significant efforts have been expended in past few years to improve the quality of SPECT images by incorporating image processing techniques. Among these we focus on the de-blurring techniques in this paper. De-blurring is an important issue to be addressed for improving the quality of cardiac SPECT images. De-blurring techniques can be applied during the reconstruction process of the SPECT images or on the reconstructed SPECT images. This paper describes a method for de-blurring reconstructed SPECT images making use of image processing methods.

In SPECT technique, a radioactive tracer is administered to the patient's body. The amount of tracer taken up by the heart muscles is then estimated by measuring the emitted gamma rays. This is then imaged using a scintillation camera. Scattering of photons and patient motion introduces blur in images. This phenomenon can be expressed using Eq.(1), where $r(x,y)$ is the blurred image, $q(x,y)$ is the true image, $h(x,y)$ is the distortion operator and $n(x,y)$ is the noise. The distortion operator is also known as the point spread function (PSF) of the system. The image degradation model is given in Fig.1.

$$r(x,y) = q(x,y)*h(x,y)+n(x,y) \tag{1}$$

As the block diagram in Fig.1 suggests, image de-blurring is an inverse filtering problem, which seeks an estimate of the true image and the original PSF. But in the case of SPECT images these information are totally unknown. The main aim of blind image de-convolution is to reconstruct the original image without using any prior data [5]. Many iterative blind image de-convolution methods with different assumptions on the prior information are also available in literature [6]. A non-negativity support constraints recursive inverse filtering (NAS-RIF) algorithm was proposed in [7]. Its three dimensional extension is explained in [8]. In [9] and [10] the authors proposed Bayesian tomographic reconstruction methods using structural information. In SPECT image the blur transfer function is approximated with a two dimensional symmetric Gaussian function [11]. The approximation is done using a known PSF in [12]. In [13] and [14] the authors described blind de-convolution methods using maximum likelihood estimation.

Fig.1. Image degradation model

Lucy Richardson algorithm proposed by Richardson [15] and Lucy [16] is a potentially better approach for de-blurring images.

Lucy Richardson algorithm considers images with Poisson statistics and maximizes the likelihood function in an iterative manner. In [17] this is described as,

$$p(r/q) = \prod_{x,y} \frac{(h*q)^r e^{-(h*q)}}{r!} \tag{2}$$

This paper proposes a de-blurring algorithm for cardiac SPECT images in which Lucy Richardson algorithm is applied on selected wavelet coefficients of the image. The paper is organized as follows. Section 2 gives a brief description of the fundamentals of wavelet transform. Proposed method is detailed in section 3. Section 4 discusses the results and the paper is concluded in section 5.

2. FUNDAMENTALS OF WAVELET TRANSFORM

The wavelet transform (WT) is a tool for time-frequency analysis [18,19]. It is similar to short time Fourier transform (STFT) except that STFT uses constant length window functions but WT uses wider window functions for low frequencies and narrower window functions for high frequencies as shown in Fig.2. This ensures constant time frequency resolution. In WT the transformation is done using special type of functions called wavelets. A wavelet ψ is a function with average zero. A single wavelet with its dilations and translations, also known as bases functions, are used to represent a signal.

$$\int_{-\alpha}^{\alpha} \psi(t)dt = 0 \tag{3}$$

The wavelet ψ which is dilated with a scale parameter a and translated by b is,

$$\psi_{b,a}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \tag{4}$$

The wavelet transform of the signal f at the scale a and position b is,

$$Wf(b,a) = \int_{-\alpha}^{\alpha} f(t) \frac{1}{\sqrt{a}} \psi^*\left(\frac{t-b}{a}\right) dt \tag{5}$$

Discrete wavelet transform analyzes the signal using discrete scales with a number of translations at each scale. Sampling Eq.(5) at discrete values of scales and translations is done by substituting $a = 2^{-j}$, j and k are integers representing discrete translations and dilations. Eq.(5) becomes,

$$W(j,k) = \int_{-\alpha}^{\alpha} f(t) 2^{j/2} \psi\left(2^j t - k\right) dt \tag{6}$$

In discrete wavelet transform wavelet coefficients are found out at a very few number of points and the corresponding wavelets are given as,

$$\psi_{j,k}(t) = 2^{j/2} \psi\left(2^j t - k\right) \tag{7}$$

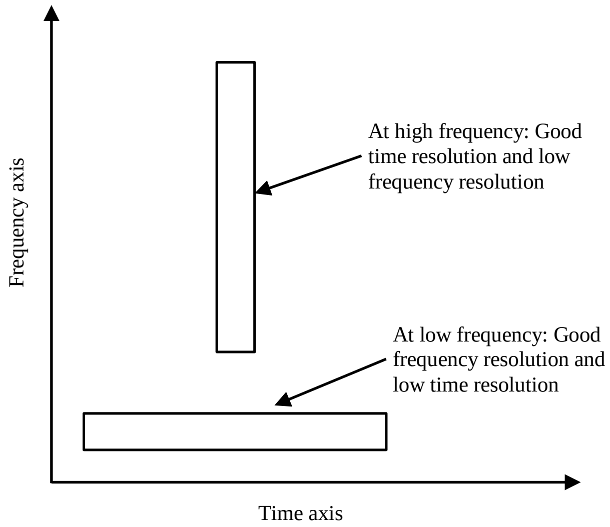

Fig.2. Time frequency tiling in wavelet transform

Here the mother wavelet is $\psi_{0,0}(t) = \psi(t)$. Putting values for all integers j and k, other wavelets are generated. All these wavelets form orthogonal bases.

Two dimensional discrete wavelet transform is applied on images by performing one dimensional transform in two stages. In the first stage one dimensional transform is applied on each row generating the approximation and detail coefficients in each row (L and H sub-bands). In the second stage, one dimensional transform is applied on these L and H sub-band column-wise to obtain LL, LH, HL and HH sub-bands. LL denotes the approximation coefficients or the low frequency part and LH, HL and HH denote the detail coefficients or the high frequency part.

3. PROPOSED METHOD

In this paper we propose a method for de-blurring cardiac SPECT images. The method applies Lucy Richardson algorithm on wavelet coefficients. Lucy Richardson algorithm gives best results for cases with a known distortion operator or PSF. In the case of SPECT images the distortion operator is totally unknown. In our method an estimate of PSF and true image is obtained using maximum likelihood approach. The estimated image is decomposed using discrete wavelet transform into approximation and detail coefficients. Lucy Richardson algorithm is applied on the approximation coefficients. The PSF estimated using maximum likelihood approach acts as the initial PSF to Lucy Richardson algorithm. The detailed algorithm is given below and the block diagram is shown in Fig.3.

Step 1: In a cardiac SPECT image the functioning of the heart at different instances of time can be visualized in different slices or tiles. Each heart tile shows the amount of blood in the heart region at an instant of time. The first step is to extract each tile from the image. The further processing is done on each tile.

Step 2: Maximum likelihood estimation and Lucy Richardson algorithm are implemented using Discrete Fourier Transform, which may introduce high frequency drops. Pre-filtering is done to reduce this ringing effect.

Step 3: Using Bayesian principles, the PSF and the true image are estimated by maximizing the likelihood function,

$$\{q_{ML}, h_{ML}\} = \underset{q,h}{\arg\max}\ p(r/q, h) \tag{8}$$

- An initial guess on PSF is made.

$$\hat{h}^{(0)}(x,y) = ones(arbitrarysize) \tag{9}$$

- An initial guess on the true image is made.

$$\hat{q}^{(0)}(x,y) = r(x,y) \tag{10}$$

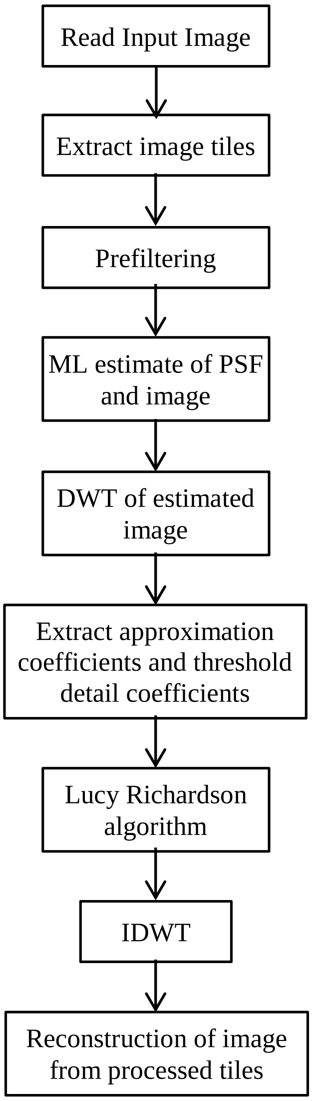

Fig.3. Block diagram of the proposed method

- Set the number of iterations to be performed, P.
- Using iterative steps, maximum likelihood estimate of PSF and the true image are computed.

$$\hat{q}^{p+1}(x,y) = \hat{q}^{p}(x,y)\left[\hat{h}^{p}(x,y)^{*} * \frac{r(x,y)}{\hat{h}^{p}(x,y) * \hat{q}^{p}(x,y)}\right] \tag{11}$$

$$\hat{h}^{p+1}(x,y) = \hat{h}^{p}(x,y)\left[\frac{r(x,y)}{\hat{h}^{p}(x,y) * \hat{q}^{p}(x,y)} * r(x,y)^{*}\right] \tag{12}$$

- Non negativity constraints are applied on $\hat{q}(x,y)$ and $\hat{h}(x,y)$ during each iteration step.
- Stop the iterations when the number of iterations reaches P.

Step 4: Using discrete wavelet transform, $\hat{q}^{p}(x,y)$ is decomposed into four sub band images as shown in Fig.4, where LL denotes the approximation coefficients and LH, HL and HH denote the detail coefficients.

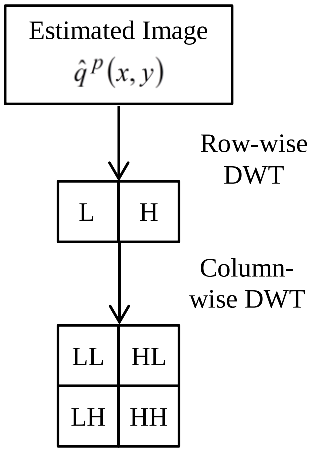

Fig.4. Wavelet decomposition (single level)

Step 5: Lucy Richardson algorithm is applied on the approximation coefficients.

Step 6: Detail coefficients are thresholded using universal thresholding.

Step 7: Inverse discrete wavelet transform is taken with the processed approximation coefficients and the thresholded detail coefficients.

4. RESULTS AND DISCUSSION

The proposed method is applied to cardiac SPECT images obtained from a two collimator single photon emission computed tomography device. The database used for testing the algorithm consists of 40 images taken from 40 different patients in the age group 45-65 years, 952 × 510 gray scale images, each with 40 heart tiles are used in the experiments. The tiles include both short axis and long axis views of the heart. The Fig.5 shows a portion of the blurred input image with 4 tiles from short axis view. The corresponding output de-blurred image is shown in Fig.6. The Fig.7 shows tiles corresponding to long axis view of the heart. The corresponding de-blurred image is shown in Fig.8.

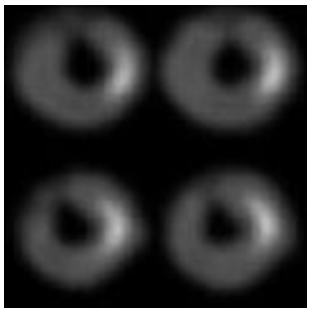

Fig.5. Blurred image- short axis slice

The proposed method is also evaluated quantitatively. Blur metric [20], peak signal to noise ratio (PSNR) and Tenengrad criterion are used as quantitative measures. Blur metric gives a measure of blur. Higher the value of blur metric, higher will be the amount of blur. The proposed method is also compared with existing de-blurring techniques. The results in Table.1 show the effectiveness of the proposed method in reducing blur. The proposed method gives the lowest amount of blur as compared to conventional de-blurring techniques including blind de-convolution and Lucy Richardson algorithm.

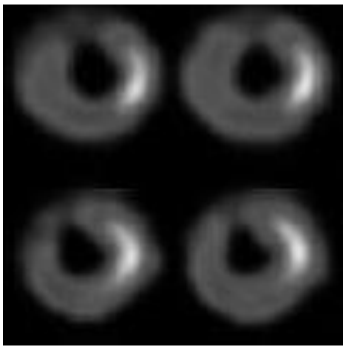

Fig.6. De-blurred image- short axis slice

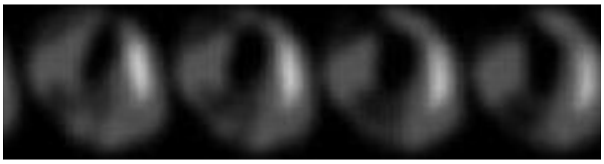

Fig.7. Blurred image- long axis slice

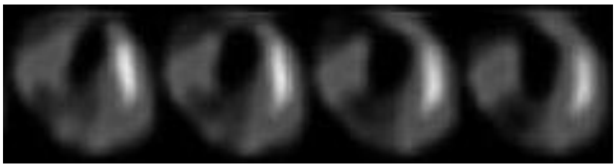

Fig.8. De-blurred image- long axis slice

Table.1. Performance comparison of de-blurring techniques

Methods	Blur Metric
Blurred image	0.8427
Blind deconvolution	0.8151
Lucy Richardson	0.8168
Proposed method	0.7768

The Fig.9 shows the amount of blur present in the blurred image and in the de-blurred image. The proposed method is used for the de-blurring process. From the graph it is clear that there is reduction in blur after applying the proposed method.

The Fig.10 shows a comparison in peak signal to noise ratio (PSNR) between the blurred image and the image de-blurred using the proposed method. The PSNR value is more for de-blurred image. The performance of the proposed method in terms of PSNR is also compared with that of Lucy Richardson algorithm. The Fig.11 shows that PSNR value is more for the images obtained by the proposed method as compared to the images obtained by Lucy Richardson algorithm.

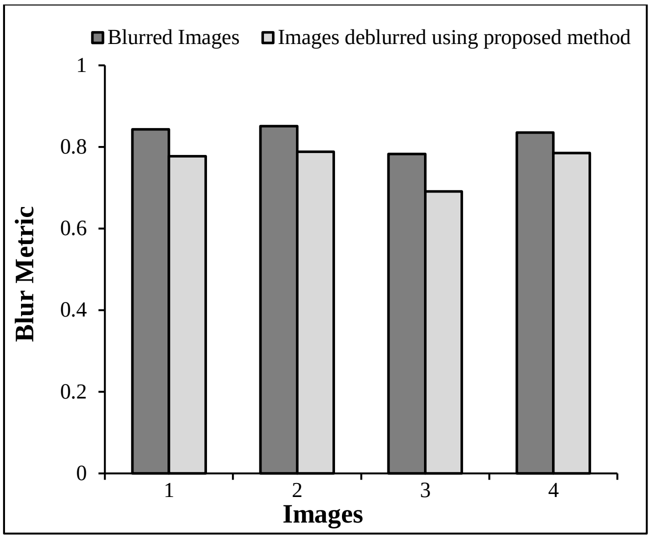

Fig.9. Reduction in blur

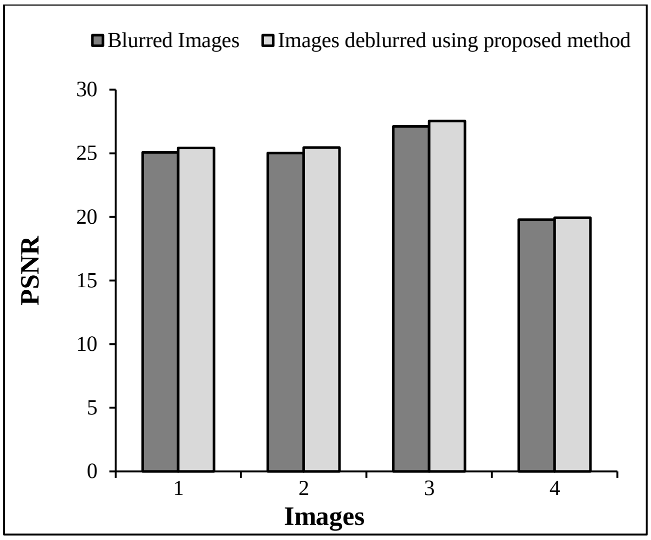

Fig.10. Improvement in PSNR

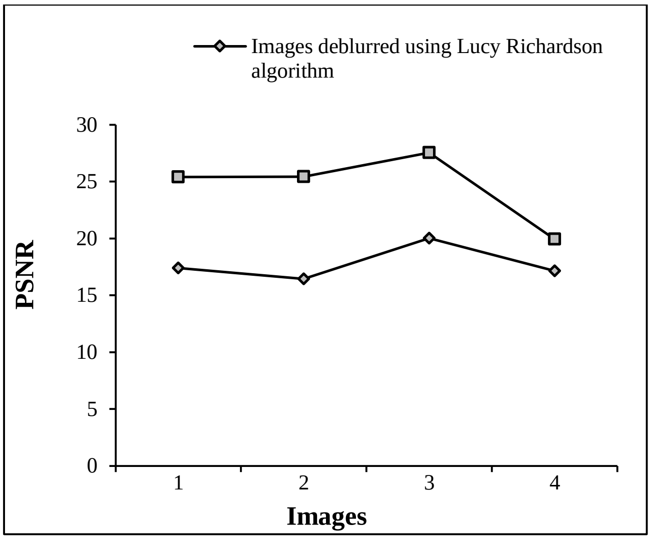

Fig.11. Comparing proposed method with Lucy Richardson algorithm in terms of PSNR

Tenengrad criterion [21] gives a measure of image sharpness. It is based on Sobel gradient operator. A comparison between the blurred image and the image de-blurred using the proposed method is presented in Fig.12. The results show that the value of Tenengrad criterion is more for the de-blurred image. This means that the quality of the image, in terms of sharpness, has improved.

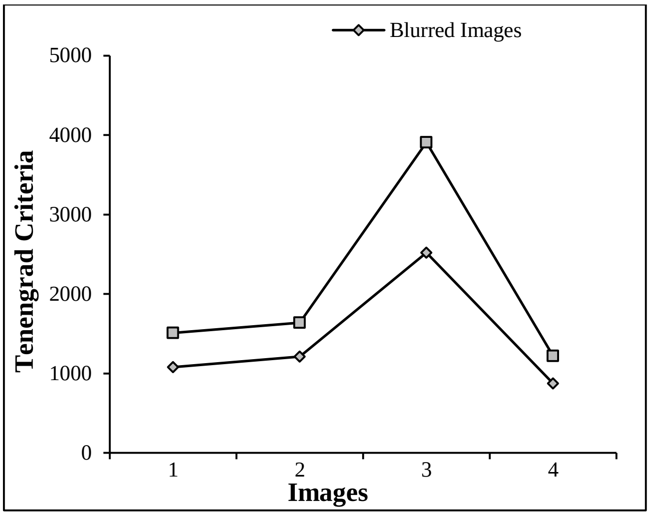

Fig.12. Improvement in image sharpness

5. CONCLUSION

The paper proposes an enhancement method for nuclear images. It presents a de-blurring technique based on Lucy Richardson algorithm. The proposed method differs from the conventional de-blurring techniques in that here the operation is done on the wavelet coefficients. The point spread function is estimated from the image using maximum likelihood estimation. Lucy Richardson algorithm is performed on the approximation coefficients extracted from the image. It uses the estimated point spread function. Real cardiac SPECT images are used to carry out the simulations. The performance of the proposed method is analyzed both qualitatively and quantitatively. Blur metric, peak signal to noise ratio and Tenengrad criterion are used as quantitative measures. The performance of the algorithm is also compared with other conventional de-blurring techniques. The results show that the proposed method yields better output in reducing blur.

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