Denoising of SPECT-Image Sinogram-Data Before Reconstruction

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ABSTRACT
Nuclear medicine images have low signal-to-noise ratio (SNR) due to several physical limitations which degrade the image quality considerably. In this study, the Gaussian filter and the patch confidence Gaussian filter (PCG) were used to improve the image quality for Single Photon Emission Computed Tomography (SPECT). The new approach applies these filtering methods on the acquired 2D-projections before reconstructing the image. The new approach was evaluated on a SPECT dataset and the performance was compared with several conventional methods presented in the literature.

Keywords: Low SNR, SPECT, Sinogram, 2D Projections, PCKNN, Patch Confidence Gaussian Filter PCG.

1. INTRODUCTION
Nowadays, a lot of filters are used to reduce the noise in reconstructed SPECT-images in order to improve the image SNR to fulfill the demands of clinical diagnosis and body functional research [1, 2, 3]. On the other hand, SPECT-image noise is initially generated during the acquisition process of gamma photons and added to the acquired projections which form the sinograms of the slices that can be reconstructed. During the scanning process, each gamma-photon detector measures the intensity of discrete incident photons over a certain time interval. The photons arrive on the sensor in a random and independent way and generate photon noise which can be described by the Poisson distribution (also called Poisson noise) corresponding to the statistically expected incident photon counts [5].

In conventional SPECT imaging systems, the images are reconstructed from the acquired sinogram data, then these images are denoised with various kinds of filters (i.e. post-reconstruction denoising is performed) in order to reduce Poisson noise and to enhance the image quality. Therefore, reconstructing the noisy sinogram data will spread out the distortion effect of the noise over the whole reconstructed image. Furthermore, since none of the existing reconstruction methods is a simple aggregation of the detected signals, the contamination of the reconstructed image with noise will occur and result in an unpredictable noise type which in its turn depends on the chosen reconstruction algorithms.

Therefore, in this work, a novel denoising approach is proposed to apply the denoising filters directly on the 2D projections to reduce (and ideally eliminate) the Poisson noise before reconstructing the image (i.e. pre-reconstruction denoising is performed here). The Gaussian filter and the patch confidence Gaussian filter (PCG), which is a special case and simplified variant of the patch confidence K-nearest neighbor filter (PCKNN) [8], are utilized for this purpose. This approach is tested and evaluated on a SPECT dataset (2D gamma images or projections of a patient) and the resulting reconstructed images have been compared with the corresponding results of a number of existing conventional image-denoising methods.

2. METHOD
In the human body, the same type of tissue shows specific physical, chemical and physiological characteristics, such as absorption and accumulation of isotope-marked molecules and the attenuation coefficient which affects the penetration of gamma photons through this type of tissue. These factors generate the main information that can be captured by
the SPECT imaging technique. Therefore, regarding the denoising aspect for this kind of images, the statistical properties of surrounding voxels in SPECT images are expected to be similar. This makes it feasible to consider denoising approaches for SPECT images where a certain neighborhood around the currently filtered voxel is processed to contribute to the resulting voxel value. Therefore, in this work, the Gaussian [6] and the PCG filters are utilized for denoising purposes as follows in this section.

Gaussian Filter

When using the Gaussian filter [7], the whole image area will be modified by convolution with a Gaussian function given as follows:

\[ f(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \]  

(1)

where \( x \) is the distance from the origin (i.e. the central element) of the filter kernel in the horizontal axis, \( y \) is the distance from the origin in the vertical axis, and \( \sigma \) is the standard deviation of the Gaussian distribution.

Patch Confidence Gaussian Filter

The new filter proposed and coined as the PCG filter in this work is (as discussed previously in this section) a special case of the patch confidence K-nearest neighbor filter (PCKNN) [8, 9]. The PCG filtering approach can be seen as a combination of Principal Component Analysis (PCA) and Gaussian filtering.

The basic framework of the PCG filter is shown in Figure (1) and the filtering algorithm can be described according to the following steps:

1. Determine the patch size (n\(^2\)n) depending on the original image size in addition to the size of the details of interest.
2. Patch Denoising: for each pixel \( Z \) inside the patch, apply Gaussian Filtering to the selected patch area (\( Z^* \)):

\[ z^* = \frac{1}{\Sigma_{z\epsilon KNN(z)}(X)} \Sigma_{z\epsilon KNN(z)}(X)z \]  

(2)

Patch Denoising Confidence: compute a similarity measure showing the influence of the patch on the original pixel \( X \) as follows:

\[ c_f = \frac{(\Sigma_{z\epsilon Gaussian(z)}(X))}{\Sigma_{z\epsilon Gaussian(z)}(X)} \]  

(3)

4. After calculating all denoised patches and the confidence factors of the patches, the value of the currently filtered voxel can be set as:

\[ x_i = \frac{\Sigma_{i\epsilon gaussian(z)}(X)c_{f}}{\Sigma_{i\epsilon gaussian(z)}(X)c_{f}} \]  

(4)

where \( c_{i,n} \) is the confidence of patch \( n \) among the \( n\times n \) patches which contain pixel \( X_i \).

3. EXPERIMENT AND RESULTS

A set of SPECT images was used to validate the proposed methods. The dataset was provided from Karolinska Institute Hospital Solna, Stockholm, Sweden. It consists of 32 2D-projections with 128-slices in each projection. The median filter [10], Gaussian filter and the proposed PCG filter are implemented and used in our proposed approach, where these denoising filters are applied to the SPECT projections as a preprocessing step before the image reconstruction step. The Maximum Likelihood Expectation Maximization (MLEM) image reconstruction method [11, 12] is used with 20 iterations to produce all SPECT images to be able to compare the performance of all filtering approaches. In addition, a reference image (denoted as undeenoised) for each slice (there are totally 128 slices) is generated and reconstructed using the MELM reconstruction.
algorithm only without additional denoising. Furthermore, these reference images are denoised using the median filter for comparison with the results of the proposed approach in this work. Some slices are chosen for visual comparison of the reconstruction results.

Figures (2), (3) and (4) show comparisons of the reconstructed images for slices 48, 49 and 50, respectively. In these three figures, the reconstruction results are presented as follows: (a) is the undenoised image; (b) is the post-reconstruction denoising result using an additional median filter; (c), (d) and (e) are the pre-reconstruction denoising images obtained when using an additional median filter, Gaussian filter and PCG filter, respectively.

In these figures, two ischemia spots on the left ventricle (i.e. small regions of the heart muscle with reduced blood supply) can be easily recognized when using the two pre-reconstruction denoising approaches with the PCG filter and the median filter. Visual inspection and comparison of the resulting images presented in these three figures shows that the other approaches are not as accurate as these two. Furthermore, a quantitative evaluation and comparison of these four image denoising and reconstruction approaches is performed by employing the signal-to-noise ratio (SNR) of slice 50, as shown in Table (1).

**Figure 2.** Reconstructed SPECT images of slice 48 (a) undenoised image; (b) post-reconstruction denoising using median filter; (c) pre-reconstruction denoising using median filter; (d) Pre-reconstruction denoising using Gaussian filter; (e) Pre-reconstruction denoising using PCG filter.

**Figure 3.** Reconstructed SPECT images of slice 49 (a) undenoised image; (b) post-reconstruction denoising using median filter; (c) pre-reconstruction denoising using median filter; (d) Pre-reconstruction denoising using Gaussian filter; (e) Pre-reconstruction denoising using PCG filter.
Table 1. SNR of slice 50 using all four approaches.

<table>
<thead>
<tr>
<th>MLEM reconstruction method</th>
<th>SNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Undenoised</td>
<td>17.8</td>
</tr>
<tr>
<td>Pre-denoising method</td>
<td></td>
</tr>
<tr>
<td>Median filter</td>
<td>25.4</td>
</tr>
<tr>
<td>Gaussian filter</td>
<td>30.8</td>
</tr>
<tr>
<td>PCG filter</td>
<td>31.4</td>
</tr>
<tr>
<td>Post-denoising method</td>
<td></td>
</tr>
<tr>
<td>Median filter</td>
<td>21.4</td>
</tr>
</tbody>
</table>

The SNR is computed (in dB) and defined as:

$$\text{SNR} = 20 \log_{10} \frac{M_A}{S_A}$$  \hspace{1cm} (5)

where $M_A$ is the mean intensity value within the object of interest region and $S_A$ is the standard deviation of the intensity values of the same region.

Table (1) shows that among all four approaches, the pre-denoising reconstruction using the PCG filter can produce an image for slice 50 with the best SNR value (of 31.4 dB). Combining qualitative and quantitative performance evaluation indicates that the proposed approach using pre-denoising with a PCG filter can give the best reconstruction results.

4. DISCUSSION

In a SPECT imaging system, the noise is generated and added to the projections while acquiring them. Thus it sounds logical to try to purify these projections from noise before using them to reconstruct the corresponding SPECT images. In addition to that, the statistical properties of a group of voxels within a small neighborhood in a SPECT 2D-projection are expected to be of similar nature. Therefore, it also sounds logical to expect that it is efficient to use a denoising approach which considers and processes a certain neighborhood of voxels. Therefore, the PCG filter is proposed and utilized to denoise the 2D-projections taking into account the influence of a neighborhood on the filtering process. The final images that are reconstructed using this approach can give solid evidence that vital diagnostic information is enhanced and preserved.

5. CONCLUSIONS

Enhancing the quality SPECT images is a challenging task because of the poor resolution and low SNR of these images. The aim of image denoising is to enhance and sharpen the edges and to smooth the inner part of each segment that is supposed to be uniform. The filters are always producing results that are related to the average of the information in a certain way [13]. Therefore, after denoising, the resulting image will be smoothed including the edges that will be faded away. In SPECT imaging used for cardiology and oncology, disease-related spots in SPECT images that have abnormal intensities
(brighter or darker than healthy and normally functioning tissues) represent the vital diagnostic information that medical doctors wish to detect and recognize in these images. This goal could be achieved in this work by implementing and applying the PCG filter to the 2D projections (i.e. sinogram data) before performing the reconstruction task. The results show that it is possible to efficiently reduce the noise in the SPECT image while preserving and enhancing the useful diagnostic information. Future work will focus on optimizing and testing the proposed algorithm on more SPECT data as well as Positron Emission Tomography (PET) data since both types of data suffer from the same type of limitations and can be enhanced by the same type of algorithms.

6. ACKNOWLEDGMENT

The authors would like to thank Prof. Bjorn-Erik Erlandsson (KTH, Stockholm, Sweden) for his support.

7. REFERENCE
