DEVELOPMENT OF A PCA BASED METHOD FOR NOISE REDUCTION IN SCINTIGRAPHIC IMAGES

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Abstract: Poisson noise is one of the factors degrading quality of scintigraphic images, due to statistical nature of photon detection. The purpose of this study is the development of a method to reduce the Poisson noise contained in scintigraphic images preserving contrast and spatial resolution. The method is based on Principal Component Analysis (PCA), considering that a small number of independent components can successfully describe useful image information, whereas a large number of independent components contain statistical noise. In order to apply PCA the image is decomposed into 8×8 blocks, considering the gray level values of the block as components. The most significant independent image components, in terms of gray level variability, are automatically selected based on the derivative of the percent of cumulative variability curve, with remaining components discarded as noise. The method was evaluated in phantom images by means of noise, contrast, contrast-to-noise ratio (CNR) and spatial resolution metrics and applied in clinical planar images. Comparison with conventional noise reduction filters was performed. Noise is significantly reduced in all noise reduction methods studied (Student's t-test, $p<0.05$), whereas CNR is improved and spatial resolution is preserved only in the PCA. Improved visual performance is also demonstrated in clinical images.

1 INTRODUCTION

A scintigraphic image is the representation of a radioactive distribution inside regions of interest (ROIs) or the whole body[1]. Each pixel contains a discrete value, which is related to the number of γ-photons detected within a period of time. These discrete values follow a statistical distribution (Poisson distribution), due to the random nature of radioactive disintegration. The statistical variations of these values are considered responsible for the image Poisson noise. Thus it is obvious that the number of photon counts has to be increased in order the effect of Poisson noise to be reduced. This can be achieved by: (a) increasing the acquisition time with increased risk of patient motion, (b) increasing the amount of administered radioactive material, which will lead to higher patient's absorbed dose and (c) using gamma cameras with multiple detectors or very highly efficient detector with the drawback of increasing costs.

Considering the limitations of each of the above-mentioned methods, image-processing techniques are used instead to reduce the noise level without increasing photon counts. The simplest filtering technique is to replace each pixel value with the mean of its surrounding neighbors[2]. The immediate consequence of applying linear filters is degradation of contrast and resolution of the image, which appears smoothed. The median filter is another nonlinear filter option, which consists of replacing the value of each pixel by the median value of its neighbors. Both filters are stationary and non-adaptive, which means that the filtering operation is applied all over the whole image, without any consideration of noise level and count distribution[3]. Adaptive non-stationary procedures have been proposed in an attempt to reduce noise without degrading image quality. The common principle of this class of filters is to use statistical criteria for the selection of neighbors included in the smoothing procedure[4].

The aim of this study is the development of a statistical method, based on Principal Component Analysis (PCA) to specifically address and reduce Poisson noise in scintigraphic images, preserving image quality characteristics such as contrast and resolution. The performance of the proposed method was assessed by employing quantitative image quality characteristics (noise, contrast, contrast-to-noise ratio (CNR) and spatial resolution) and comparing four conventional noise reduction methods (smooth 3x3 and 5x5, median 3x3 and 5x5) to the proposed one. Additionally, the proposed method is evaluated in clinical planar scintigraphic images, by means of a preference study.

2 MATERIALS AND METHODS

2.1 Principal Component Analysis (PCA)

PCA is a multivariate correlation analysis technique which explains a variance-covariance structure of observed data sets with a few linear combinations of original variables[5-9]. The motivation behind PCA is to find a direction, or a few directions, that explain as much of the variability as possible. This is achieved because each direction is associated with a linear sum of the variables, which are linear sums of the old variables. Thus the first principal component is the linear sum corresponding to the direction of greatest variability. The search for the second principal component is restricted to variables that are uncorrelated with the first principal component.

Suppose that we want to perform a PCA upon variables $X_1,\ldots,X_p$. If we were dealing with only one variable, say variable X_j, we summarize its variability by the variance. Suppose that there are a total of n observations, so that for each of the p variables, we have n values. Let X_{ij} be the ith observation on the jth variable. Let $\overline{X_j}$ be the mean of the n observations on the jth variable. Then we estimate the variability that is the variance of the variable X_j:

$$\operatorname{var}(X_j) = \sum_{i=1}^{n} \frac{(X_{ij} - \overline{X_j})^2}{n-1} \quad (1)$$

The total variance V_k, denoted by V, for variables $X_1,\ldots, X_p$ is the sum of the individual variances. That is:

$$V = \sum_{j=1}^{p} \operatorname{var}(X_j) \quad (2)$$

Let $Y_1,Y_2,\ldots,Y_k$ be the first, second and subsequent principal components for the variables $X_1,\ldots,X_p$. In a sample, the variance of each Y_k is estimated by:

$$V_k = \operatorname{var}(Y_k) = \sum_{i=1}^{n} \frac{(Y_{ik} - \overline{Y_k})^2}{n-1} \quad (3)$$

where Y_{ik} is the value of the kth principal component for the ith observation. That is, we first estimate the coefficients for the kth principal component. The value for the ith observation uses those coefficients and the observed value of the ith X_j's to compute the value of the Y_{ik}. The variance for the kth principal component in a sample is then given by the sample variance for Y_{ik}, i=1,2,…,n. This variance is denoted as seen above by V_k. The percent of the variability expressed by the first m principal components is:

$$100 \sum_{k=1}^{m} \frac{V_k}{V} \quad (4)$$

where V is the total variance. As we chose the principal components successively to explain more and more of the variance, we have: $V_1 \geq V_2 \geq \ldots \geq V_p \geq 0$. The first m principal components explain as much of the total variability, as it is possible to explain by m linear functions of the X_j variables.

2.2 Application of PCA

The aim using PCA is to reduce the volume of data, preserving a large amount of useful information. In the case of scintigraphic images we consider that a small number of independent components contain useful information (signal), whereas a large number of independent components contain statistical noise. Therefore, applying PCA and discarding image components which correspond to noise, a significant noise reduction can be achieved. In this study PCA was applied to scintigraphic images according to the following steps:

PCA was applied to scintigraphic images according to the following steps:

(i) The image is decomposed into blocks of size 8x8, considering the gray-level values of the blocks as components. The rows of pixels in each block are arrayed into lines. In the matrix X_{ij}, j=1,…, 64 is the value of each pixel in the block and i=1,…, n is the number of block. In order to avoid 'block artifacts' on the reconstructed image, PCA is applied in a sliding way.

(ii) PCA is applied to the data X_{ij} in order to find the most significant independent image components p, where $1 \leq p \leq 64$. P is the value, for which the second derivative of the Percent of Cumulative Variability (PCV) curve tends to zero. This can be observed by the change of the slope of the PCV curve. Figure 1 presents the percent of the total variance explained cumulatively from principal components.

(iii) A denoised image is obtained by applying the inverse PCA and setting as zero the data that correspond to the 64-p less significant components.

2.3 Performance evaluation

To assess the performance of PCA with respect to noise reduction, and to test preservation of resolution and contrast, a quantitatively analysis was carried out based on hot spots and bar phantom images Specifically, a planar source of ^{57}Co, acting as background and two small circular ^{99m}Tc sources, acting as hot spots, were used for measuring noise[10], contrast and CNR quantitatively, for different acquisition times (figure 2). In addition, to measure spatial resolution in terms of full width at half maximum (FWHM), a bar phantom was used consisting of horizontal and vertical linear sources of ^{99m}Tc of 5 mCi activity (high contrast resolution). These measurements were obtained by means of profile (figure 3).

To test the applicability of the proposed method, the method was applied to planar scintigraphic images. Specifically, ten (10) bone, four (4) lung, (5) thyroid and six (6) parathyroid scintigraphic images of 256x256 pixels size were acquired, based on the clinical protocols of the Nuclear Medicine Department at the University Hospital of Patras. Two nuclear medicine doctors examined scintigraphic images, with respect to anatomical characteristics.

The proposed method was compared to four conventional noise reduction methods (median 3x3, median 5x5, smooth 3x3 and smooth 5x5) employing quantitative analysis, applying parametric statistical tests (Student's t-test) and clinical observation by means of a preference study.

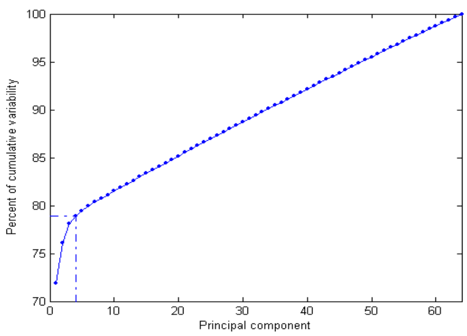

Figure 1: Estimation of *p* most significant components.

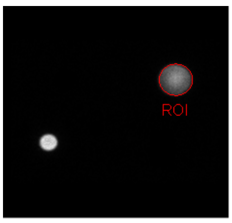

Figure 2: Original image of hot spots phantom.

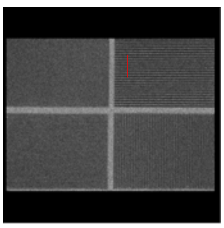

Figure 3: Original bar phantom image.

3 RESULTS

3.1 Quantitative analysis

The plots of noise and CNR as a function of time for the original and the five noise reduction methods are presented on figure 4 and 5, respectively[11]. Specifically, figure 4 demonstrates that noise is statistically significantly reduced in all methods studied (Students's t-test, p<0.0001), with the most effective methods are the smooth 5x5 filter and the PCA, whereas figure 5 presents that CNR is improved by the PCA-based method due to preservation of contrast.

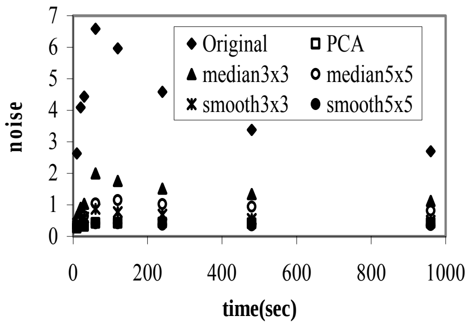

Figure 4: The reduction of noise as a function of time.

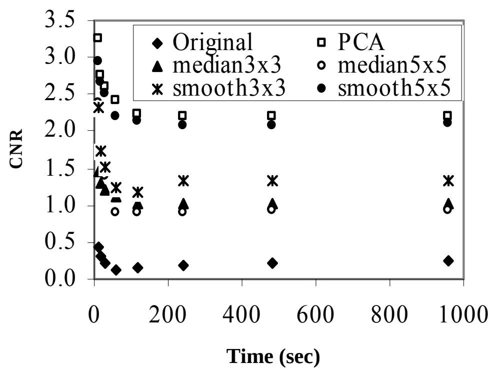

Figure 5: CNR for the five noise reduction methods.

In Table 1, the FWHM for original image and the five noise reduction methods are provided. It is observed that PCA is the only method which preserves the value of original FWHM.

Table 1: FWHM estimation for the original image and the five noise reduction methods.

Characteristic	FWHM
Original	2.9
PCA	3.0
Median 3x3	3.6
Median 5x5	4.3
Smooth 3x3	3.5
Smooth 5x5	3.4

3.2 Clinical examples

In figure 6 the original bone scintigraphic image and the corresponding processed images are presented. The most effective and most preferred method is the PCA-based, since statistical noise is significantly decreased, while visual performance of anatomical structures is considerably improved.

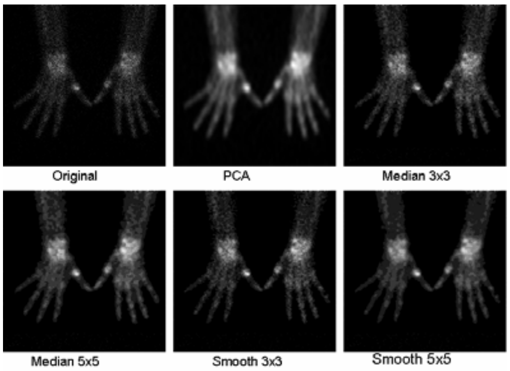

Figure 6: Representative example at a bone scintigraphic image after applying noise reduction methods.

4 DISCUSSION AND CONCLUSION

A PCA-based method is proposed aiming to reduce Poisson noise contained in scintigraphic images. Method's performance as compared to other four conventional noise reduction methods (median 3x3, median 5x5, smooth 3x3 and smooth 5x5 filter) has demonstrated improved denoising and spatial information preservation characteristics, by means of quantitative analysis. A future step is the combination of PCA with wavelet analysis for Poisson noise reduction, recently used in Positron Emission Tomography (PET) images with encouraging results[12].

5 ACKNOWLEDGMENT

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