International Journal of Bio-Science and Bio-Technology
Vol.6, No. 6 (2014), pp.13-20
http://dx.doi.org/10.14257/ijbsbt.2014.6.6.02

A Proposed Approach for Biomedical Image Denoising Using PCA_NLM

Mohit Bansal[2], Munesh Devi, Neha Jain[1] and Chinu Kukreja

[2]*Assistant Professor, Department of Electronics and Communication Engineering GIET, Sonepat-131001, India*
[1] *M.Tech. Scholar, Department of Electronics and Communication Engineering BMIET, Sonepat-131001, India*
M.Tech. Scholar, Department of Computer Science Engineering SGI, Samalka -131001, India
[2]*mohit.bansal0903@gmail.com, muneshsangwan@gmail.com,*
[1]*nehagupta2589@gmail.com, cheenu.chugh@gmail.com*

Abstract

The main problem faced during biomedical image diagnosis is the noise introduced due to the consequence of the coherent nature of the image. The noise interfered may be Gaussian noise, speckle noise or Poisson noise, during transmission. The capturing devices itself has a salt & pepper noise. These noises corrupt the image and often lead to incorrect diagnosis. These noises make it more difficult for the observer to discriminate fine detail of the images in diagnostic examinations. Thus, denoising these noises from a noisy image has become the most important step in medical image processing. In spite of the sophistication of the recently proposed methods, most algorithms have not yet attained a desirable level of applicability. Denoising techniques are aimed at removing noise or distortion from images while retaining the original quality of the image. In this work, we propose PCA_NLM approach which computes neighborhood similarities after PCA projection. Our algorithm is based on the assumption that image contains an extensive amount of self-similarity. The accuracy and computational cost of the PCA algorithm is improved by computing neighborhood similarities, i.e., averaging weights, after a PCA projection to a lower dimensional subspace. We evaluate and compare the performance of proposed technique with different existing methods by using six quality measures PSNR, SNR, MSE, NAE, Correlation Coefficient and SSIM. Comparative analysis shows our approach give the best performance results in terms of improved quality measures as well as visual interpretation.

Keywords: *Biomedical Images, PCA, NLM, Wavelet denoising*

1. Introduction

1.1 Biomedical Imaging

Medical imaging is the technique and process used to create images of the human body for clinical purposes (medical procedures seeking to reveal, diagnose, or examine disease) or medical science. Medical information, composed of clinical data, images and other physiological signals, has become an essential part of a patient's care, during screening, in the diagnostic stage and in the treatment phase [4]. Over the past three decades, rapid developments in information technology (IT) & Medical Instrumentation has facilitated the

ISSN: 2233-7849 IJBSBT

development of digital medical imaging. This development has mainly concerned Computed Tomography (CT), Magnetic Resonance Imaging (MRI), the different digital radiological processes for vascular, cardiovascular and contrast imaging, mammography, diagnostic ultrasound imaging, nuclear medical imaging with Single Photon Emission Computed Tomography (SPECT) and Positron Emission Tomography (PET) [6]. All these processes are producing ever-increasing quantities of images. These images are different from typical photographic images primarily because they reveal internal anatomy as opposed to an image of surfaces. In Natural monochromatic or color images, the pixel intensity of the image corresponds to the reflection coefficient of natural light. Whereas images acquired for clinical procedures reflect very complex physical and physiological phenomena, of many different types, hence the wide variety of images. Each medical imaging modality (digital radiology, computerized tomography (CT), magnetic resonance imaging (MRI), ultrasound imaging (US)) has its own specific features corresponding to the physical and physiological phenomena as shown in Figure 1.

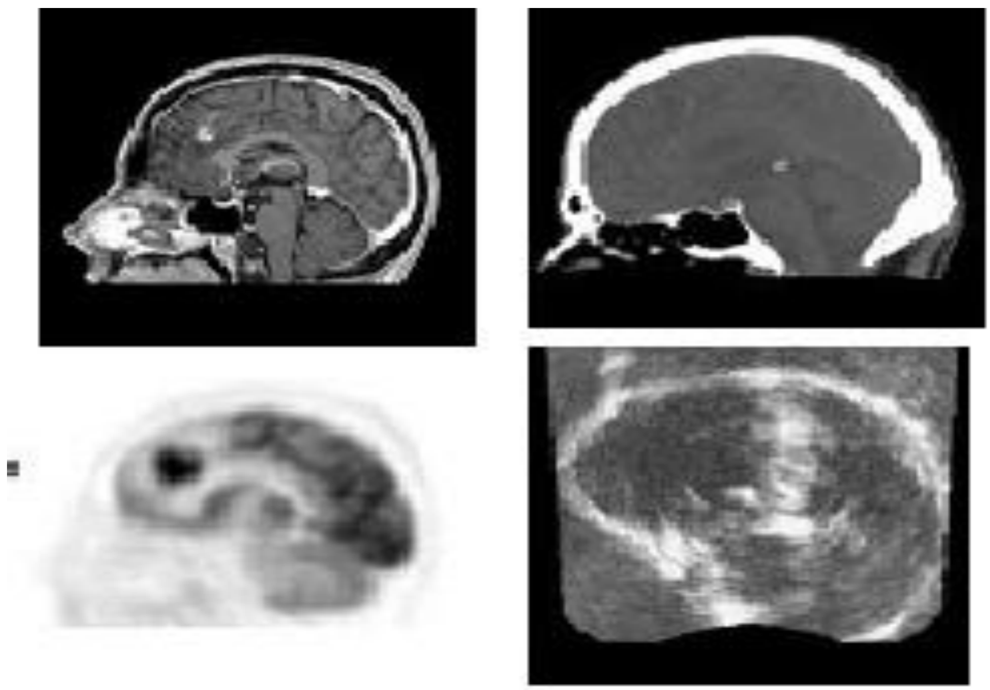

Figure 1. Sagittal Slices of the Brain by Different Imaging Modalities: a) Magnetic Resonance Imaging (MRI), b) Computed Tomography (CT), c) Positron Emission Tomography (PET)

2. Concepts and Theory of Problem

The advent of digital imaging technologies such as MRI has revolutionized modern medicine. Today, many patients no longer need to go through invasive and often dangerous procedures to diagnose a wide variety of illnesses. Medical Resonance Imaging is one of the popular techniques for imaging diagnosis and is preferred over other medical imaging modalities because it is noninvasive, portable and does not provide any harmful radiations. MRI Images possess the unique properties of distinctiveness and persistence [5]. The disadvantage of MRI is the poor quality of images which is due to the presence of additive and multiplicative noise. With the widespread use of digital imaging in medicine today, the quality of digital medical images becomes an important issue. To achieve the best possible diagnoses it is important that medical images be sharp, clear, and free of noise and artifacts. While the technologies for acquiring digital medical images continue to improve, resulting in images of higher and higher resolution and quality, noise remains an issue for many medical images [4]. Removing noise in these digital images remains one of the major challenges in the study of medical imaging. While noise in medical images presents a problem because they could mask and blur important but subtle features in the images, many proposed denoising techniques have their own problems. The denoising phenomenon goal is to remove the noise while retaining the maximum possible the important signal or image features. At the time of acquisition and transmission the images are often corrupted by additive noise [7]. The main aim of a denoising algorithm is to reduce the noise level, while preserving the image features. To achieve a good performance in this respect, a denoising algorithm has to adapt to image discontinuities.

The basic idea behind this research is the estimation of the uncorrupted image from the distorted or noisy image, and is also referred to as image “denoising”. There are various methods to help restore an image from noisy distortions. Selecting the appropriate method plays a major role in getting the desired image.

Wavelet transform (WT) has proved to be effective in noise removal. It decomposes the input signal into multiple scales, which represent different time-frequency components of the original signal. At each scale, some operations, such as thresholding and statistical modeling, can be performed to suppress noise. Denoising is accomplished by transforming back the processed wavelet coefficients into spatial domain. Late development of WT denoising includes ridge-let and curve-let methods for line structure preservation.

Although WT has demonstrated its efficiency in denoising, it uses a fixed wavelet basis (with dilation and translation) to represent the image [1]. For natural images, however, there is a rich amount of different local structural patterns, which cannot be well represented by using only one fixed wavelet basis. Therefore, WT-based methods can introduce many visual artifacts in the denoising output. To overcome the problem of WT, Muresan and Parks proposed a spatially adaptive Principal Component Analysis (PCA) based denoising scheme, which computes the locally fitted basis to transform the image. All these methods show better denoising performance than the conventional WT-based denoising algorithms.

Principal Component Analysis (PCA) is a classical de-correlation technique in statistical signal processing and it is pervasively used in pattern recognition and dimensionality reduction, etc [3]. An important property of PCA is that it fully de-correlates the original dataset X. The energy of a signal will concentrate on a small subset of the PCA transformed dataset, while the energy of noise will evenly spread over the whole dataset. Therefore, the signal and noise can be better distinguished in the PCA domain. By transforming the original dataset into PCA domain and preserving only the several most significant principal components, the noise and trivial information can be removed. In a PCA-based scheme was proposed for image denoising by using a moving window to calculate the local statistics, from which the local PCA transformation matrix was estimated.

However, this scheme applies PCA directly to the noisy image without data selection and many noise residual and visual artifacts will appear in the denoised outputs [1].

Motivation of Proposed Work

These denoising algorithms make two assumptions about the noisy image which can cause blurring and loss of detail in the resulting denoised images. The first assumption is that the noise contained [2] in the image is white noise. This means that the noise contains all frequencies, low and high. Because of the higher frequencies, the noise is oscillatory or non-smooth. The second assumption is that the true image (image without the noise) is smooth or piecewise smooth. This means the true image or patches of the true image only contain low frequencies.

Above methods attempt to separate the image into the smooth part (true image) and the oscillatory part (noise) by removing the higher frequencies from the lower frequencies. However, not all images are smooth. Images can contain fine details and structures which have high frequencies. When the high frequencies are removed, the high frequency content of the true image will be removed along with the high frequency noise because the methods cannot tell the difference between the noise and true image. This will result in a loss of fine detail in the denoised image. Also, nothing is done to remove the low frequency noise from the image. Low frequency noise will remain in the image even after denoising. Because of this loss of detail Baudes et al. have proposed the non-local means algorithm.

The recently proposed **Non-Local Means (NLM)** approach uses a very different idea from the above methods in noise removal. Unlike other local smoothing filters, non-local means, based on a non local averaging of all pixels in the image. It averages the similar image pixels according to their intensity distance to recover a single pixel. Each pixel is estimated as the weighted average of all the pixels in the image, and the weights are determined by the similarity between the pixels. The weight of each pixel depends on the distance between its intensity grey level vector and that of the target pixel [2]. Since image pixels are highly correlated while noise is typically independently and identically distributed, averaging of these pixels results in noise cancellation and yields a pixel that is similar to its original value.

Non Local Means (NLM), is very effective in noise removal but, high computational load limits its wide application. Also, as it processes noisy image patches, the non local means algorithm is not effective for large noise removal.

In the present work, we proposed a variation of the non local means (NLM) image denoising algorithm that uses Principal Component analysis (PCA) to achieve a higher accuracy while reducing computational load. Consequently, neighborhood similarity weights for denoising are computed using distances in this subspace rather than the full space. This modification to the non-local means algorithm results in improved accuracy and computational performance [8]. We present an analysis of the proposed method's accuracy as a function of the dimensionality of the projection subspace and demonstrate that denoising accuracy peaks at a relatively low number of dimensions. The edgy information that could not be retained by PCA approach is extracted back from its residue by denoising it with non local means algorithm. The proposed technique is compared both quantitatively as well as qualitatively by computing various quality measures besides the visual interpretation.

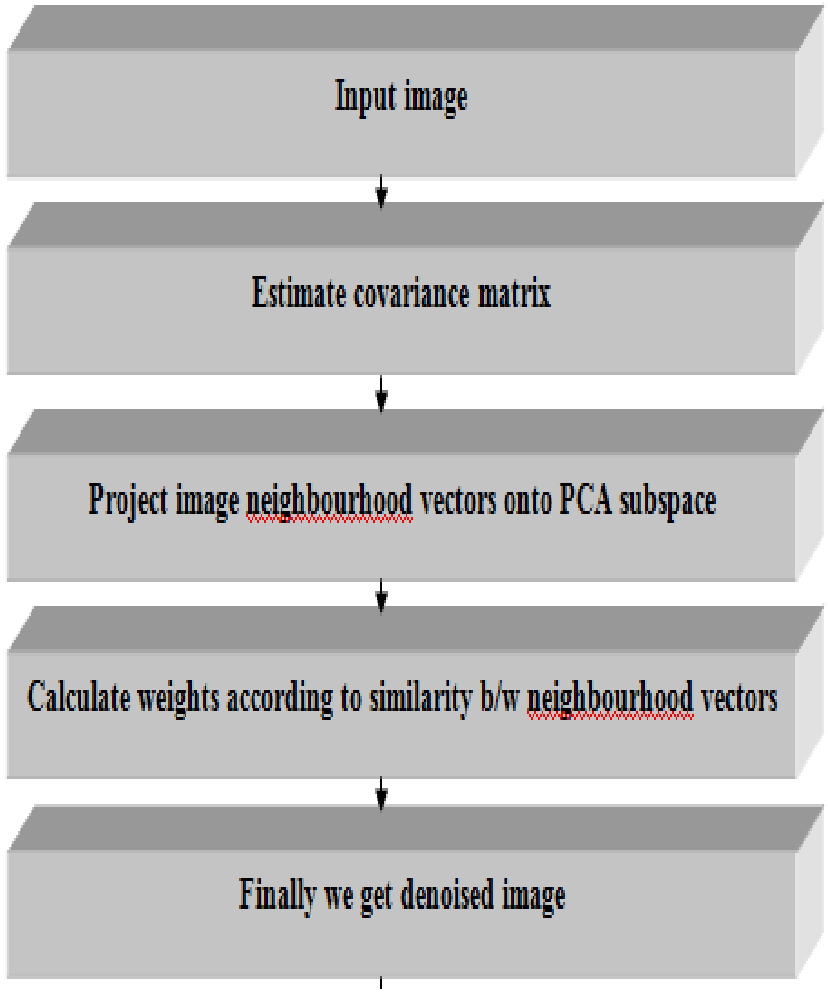

Figure 2. Flow Chart of Proposed Algorithm

3. Results and Discussion

We compare PCA_NLM with representative and state-of-the-art denoising algorithms, Wavelet and PCA. The six test images (size: 256X256) Anatomic imaging of the lungs haste, Anatomic imaging of the shoulder axial, Angulations of cardiac planes cine images of sepal infarct, MRI orbita, MRI pancreas, MRI thorax basal plane chest used in our experiments. Noise has been added to the original input image and three different denoising algorithms are used for noise removal. The evaluation and comparison of different methods by using six quality measures PSNR, SNR, MSE, NAE, Correlation Coefficient and SSIM has been done in this work. A single MRI image has been taken as input image as shown in Figure 3. For input MRI image, Figure 3 represents (a) Original image, (b) Noisy image, (c) Denoised image based on Wavelet Transform, (d) Denoised image based on PCA, (e) Denoised image based on our proposed method using PCA_NLM. A comparative analysis of the image denoising techniques is given in Table 1 in terms of PSNR, SNR, MSE, NAE, Correlation Coefficient and SSIM. It is evident from the given figure that PCA_NLM is much efficient algorithm as compared to other two algorithms. Also, figures given in Table 1 clearly indicate that PCA_NLM is much more effective and efficient as compared to Wavelet Transform and

PCA. Comparative analysis of different existing algorithms with the proposed approach shows proposed approach give the best performance results in terms of improved quality measures as well as visual interpretation.

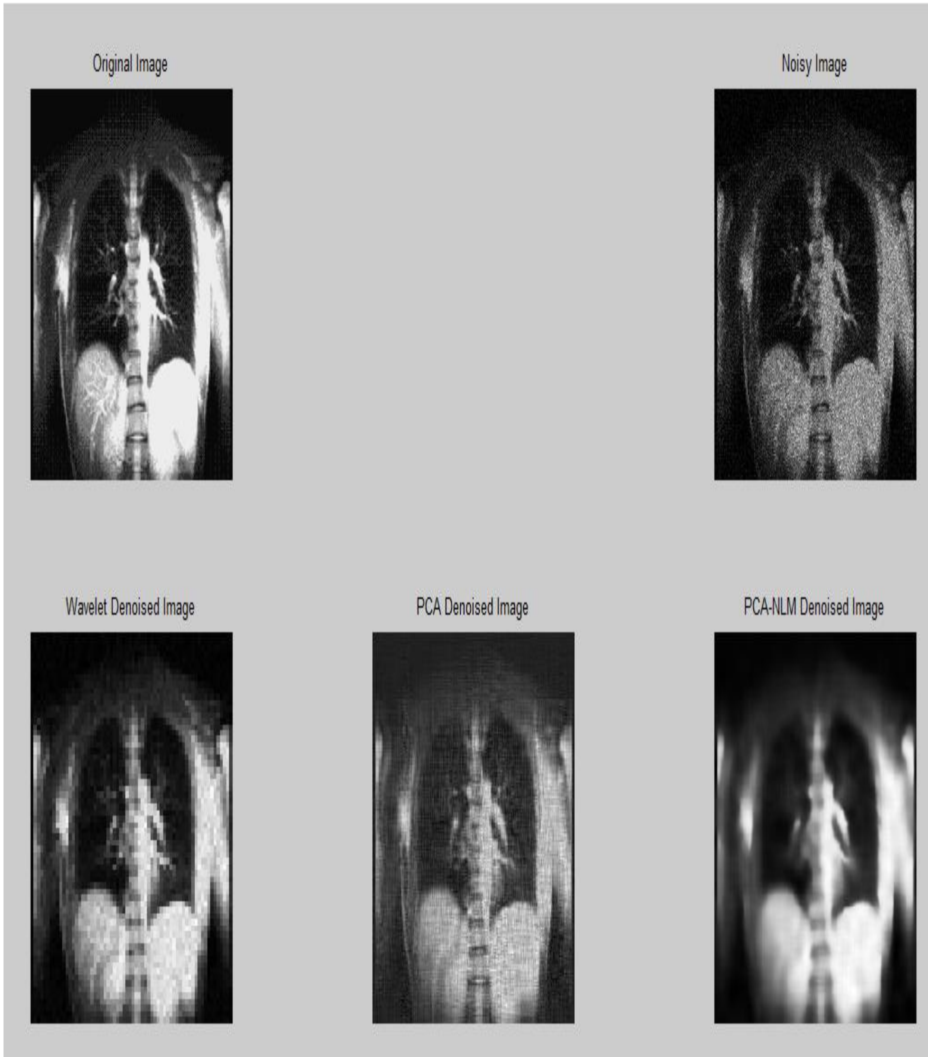

Figure 3 (a) Original Image of Anatomic Imaging of the Lungs Haste, (b) Noisy Image, (c) Denoised Image based on Wavelet Transform, (d) Denoised Image Based on PCA, (e) Denoised Image Based on our Proposed Method Using PCA_NLM

Table 3.1 Comparative Analysis of Different Denoising Techniques based on Different Quality Measures

		PSNR	SNR	MSE	NAE	Correlation	SSIM
NOISY IMAGE	**WAVELETS**	38.2826	9.1978	9.6564	0.2254	0.9446	0.8882
	PCA	38.3214	9.1727	9.5706	0.2248	0.9444	0.8849
	PCA_NLM	**38.3270**	**9.1783**	**9.5582**	**0.2249**	**0.9445**	**0.8847**
DENOISY IMAGE	**WAVELETS**	39.8420	10.7617	6.7435	0.1856	0.9571	0.9265
	PCA	42.4252	13.2764	3.7202	0.1489	0.9765	0.9472
	PCA_NLM	**42.6466**	**13.4979**	**3.5352**	**0.1385**	**0.9778**	**0.9567**

4. Conclusions & Future Scope

Biomedical image corrupted with noise is the main problem in medical science. So there is a need to denoise the medical image for better diagnosis. Mostly Wavelet Denoising methods are used for image denoising but it introduces many visual artifacts in the denoised output. To overcome the problem of Wavelet Denoising, Muresan and Parks proposed Principal Component Analysis (PCA) based denoising scheme, which computes the locally fitted basis to transform the image. However, PCA applies directly to the noisy image without data selection and many noise residual and visual artifacts will appear in the denoised outputs [1]. The accuracy and computational cost of the PCA algorithm is improved by computing neighborhood similarities, i.e., averaging weights, after a PCA projection to a lower dimensional subspace. In this work, we propose PCA_NLM approach which computes neighborhood similarities after PCA projection. Our algorithm is based on the assumption that image contains an extensive amount of self-similarity. PCA_NLM algorithm performed best as compared to other denoising techniques for preserving edges and improve visual appearance of the denoised image. Experimental results also show the better performance of our algorithm as compared to other algorithm in terms of PSNR, SNR, MSE, NAE, Correlation Coefficient and SSIM. In future, the proposed approach can be extended to color images by performing in the RGB image neighborhood space which is formed by concatenating image neighborhoods in the three channels into a single vector. Also the proposed approach can also be easily applied to other denoising and segmentation algorithms that use similarity measures based on image neighborhood vectors. Also some improvement can be done on PCA algorithm to give better results for denoising.

References

[1] R. Hari Kumar, B. Vinoth Kumar and S. Gowthami, "Performance Analysis of LPG-PCA Algorithm in Medical Images", IEEE, **(2012)**.

[2] A. Buades, B. Coll and J.M. Morel, "A Non-Local Algorithm for Image Denoising", Computer Vision and Pattern Recognition, IEEE Computer Society Conference, **(2005)**.

[3] Y. M. Mohan Babu, M.V. Subramanyam and M.N. Giri Prasad "PCA based image denoising", Signal & Image Processing : An International Journal (SIPIJ), vol. 3, no. 2, **(2012)**.

[4] Y. Wang and H. Zhou, "Total Variation Wavelet-Based Medical Image Denoising", International Journal of Biomedical Imaging, vol. 5, **(2006)**.

[5] N.J. Olawuyi, O.G. Iroju, C.S. Idowu and Olaleke, "Comparative Analysis Of Wavelet-Based Denoising Algorithms On Cardiac Magnetic Resonance Images (MRIs)", Comp & ICT, vol. 4, no.1, **(2011)**.
[6] G. Andria, F. Attivissimo, G. Cavone, N. Giaquinto and A.M.L. Lanzolla, "Linear Filtering of 2-D Wavelet Coefficients for Denoising Ultrasound Medical Images", Elsevier, **(2012)**.
[7] J. Quan, W.G. Wee and C.Y. Han, "A New Wavelet based Image Denoising Method", IEEE , Data Compression Conference (DCC), **(2012)**.
[8] S. D. Ruikar and D. D. Doye, "Wavelet Based Image Denoising technique", IJACSA, vol. 2, no. 3, **(2011)**.

Authors

Mohit Bansal is working as an Asst. Prof. at GIET, Sonepat, INDIA in the deptt. of Electronics and communication engineering. He has completed his M. Tech. in Electronics and communication engineering from MMU Mullana, INDIA in 2010. He is currently doing research on automatic diagnose and analysis of Bio-medical images. Also, wireless communication and digital signal processing are the key fields of his research.

Neha Gupta is working as an Asst. Prof. at MAIT, Delhi, INDIA in the deptt. of Electronics and communication engineering. She completed her M. Tech. in Electronics and communication engineering from DCRUST Murthal, INDIA in 2013. She has done research work on denoising of Bio-medical images and is currently working on automatic diagnose and analysis of biomedical images.

Munesh Devi is working as an Asst. Prof. at GIET, Sonepat, INDIA in the deptt. of Electronics and communication engineering. She completed her M. Tech. in Electronics and communication engineering from MDU Rohtak, INDIA in 2014. She is currently doing research on analysis of Bio-medical images. She has done research work on enhancement of performance of MANETs during my M.Tech.

