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A RESEARCH PAPER ON DENOISING MULTI-CHANNEL IMAGES IN PARALLEL MRI BY LOW RANK MATRIX DECOMPOSITION AND LOCAL PIXEL GROUPING WITH PRINCIPAL COMPONENT ANALYSIS

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ABSTRACT

Parallel magnetic resonance imaging has emerged as an effective means for high-speed imaging in various applications. The reconstruction of parallel magnetic resonance imaging (pMRI) data can be a computationally demanding task. Signal-to-noise ratio is also a concern, especially in high-resolution imaging. We present a patch-wise Denoising method for pMRI by exploiting the rank deficiency of multichannel images. For each processed patch and pixel, similar patches are searched with pixel in spatial domain and throughout all coil elements, and arranged in appropriate matrix forms. Then, noise and aliasing artifacts are removed from the structured matrix by applying sparse and low rank matrix decomposition method with Local Pixel Grouping using Principal Component Analysis (PCA). The proposed method has been validated using both phantom and in vivo brain data sets, producing encouraging results. Specifically, the method can effectively remove both noise and residual aliasing artifact from pMRI reconstructed noisy images, and produce higher peak signal noise rate (PSNR) and structural similarity index matrix (SSIM) than other state-of-the-art Denoising methods. The Denoising of pMRI is implemented using Image Processing Toolbox. This work has been tested and found suitable for its purpose. For the implementation of this proposed work we use the Matlab software.

KEYWORDS: Denoising, Low rank matrix decomposition, Multi-channel coil, parallel MRI (pMRI), Local Pixel Grouping Technique, Principal Component Analysis (PCA).

INTRODUCTION

Magnetic resonance imaging (MRI) of living human tissue started in the 1970s with the introduction of gradient magnets fields, by Paul Lauterbur. Due to its recentness, MRI is a very fruitful area of research in the bioengineering and signal processing fields, as it addresses the problem of developing an imaging tool that does not use ionizing radiation, and enables further studies in the image reconstruction and data acquisition areas. The advent of parallel MRI over recent years has prompted a variety of concepts and techniques for performing parallel imaging. A main distinguishing feature among these is the specific way of posing and solving the problem of image reconstruction from under sampled multiple-coil data. The clearest distinction in this respect is that between k-space and image-domain methods. The present paper reviews the basic reconstruction approaches, aiming to emphasize common principles along with actual differences. To this end the treatment starts with an elaboration of the encoding mechanisms and sampling strategies that define the reconstruction task. Based on these considerations a formal framework is developed that permits the various methods to be viewed as different solutions of one common problem.

The basic idea of parallel MRI dates back to the late 1980s when first concepts were proposed by Carlson, Hutchinson and Kelton followed by further contributions by Kwiat, Carlson and Ra in the early 1990s. However, only in the late 1990s was parallel detection first successfully used for actually accelerating an MRI procedure. This second era of parallel MRI development was triggered by the introduction of the SMASH technique (Simultaneous acquisition of spatial harmonics, followed by the SENSE approach (sensitivity encoding). Since then the family of parallel imaging methods has quickly grown, now including a range of further variants such as PILS (parallel imaging with localized sensitivities), SPACERIP (sensitivity profiles from an array of coils for encoding and reconstruction in parallel), generalized SMASH, GRAPPA (generalized auto calibrating partially parallel acquisitions), and PARS (parallel imaging with augmented radius in k-space). The increasing use of parallel detection in MRI has far-reaching consequences with respect to radiofrequency instrumentation, data acquisition, and data processing and image properties. Many of these implications are quite similar for the various parallel imaging techniques. One distinguishing feature, however, is the specific way of posing and solving the problem of image reconstruction from multiple-coil data. Parallel MRI (pMRI) is a way to increase the speed of the MRI acquisition by skipping a number of phase-encoding lines in the k-space during the MRI acquisition. Data received simultaneously by several receiver coils with distinct spatial sensitivities are used to reconstruct the values in the missing k-space lines. Our task is to propose and implement a robust pMRI algorithm that will reconstruct the original image using a set of images with incomplete information. We focus on the minimizing of the presence of noise in the reconstructed image and also on removing of the aliasing artifacts from the reconstructed image (artifacts caused by skipping some phase-encoding lines in the k-space during the acquisition).

G.Hari Priya[1] proposed Noise Removal in Image Using LPG-PCA (Local Pixel Grouping Principle Component Analysis) Algorithm in 2014. In this paper an effective algorithm for noise removal in an image is obtained by using PCA (principal component analysis) with LPG (Local Pixel Grouping). This technique ensures the preservation of image local structure. Here the pixels and its neighbors are treated as vector variables whose training samples are selected from local windows using block matching based LPG. This ensures only the similar samples are selected for the PCA transformation so that the desired local characteristics are only preserved with considerable noise reduction. The LPG –PCA algorithm is performed twice to enhance the quality of an image. Lei Zhang[4] presents Two-stage image denoising by principal component analysis with local pixel grouping in 2010. This paper presents an efficient image denoising scheme by using principal component analysis (PCA) with local pixel grouping (LPG). For a better preservation of image local structures, a pixel and its nearest neighbors are modeled as a vector variable, whose training samples are selected from the local window by using block matching based LPG. Such an LPG procedure guarantees that only the sample blocks with similar contents are used in the local statistics calculation for PCA transform estimation, so that the image local features can be well preserved after coefficient shrinkage in the PCA domain to remove the noise.

The remainder of this paper is organized as the following. At first, in Section II we illustrate the various components of our proposed technique to image encryption then compression. Further, in Section III we present some key experimental results and evaluate the performance of the proposed system. At the end we provide conclusion of the paper in Section IV and state some possible future work directions.

PROPOSED TECHNIQUE

This section illustrates the overall technique of our proposed image compression. In our propose work we present "Denoising Multi-Channel Images in Parallel MRI by Low Rank Matrix Decomposition and Local Pixel Grouping with Principal Component Analysis". In previous purposed work, the Denoising method for parallel MRI by exploiting the self-similarity between multi-channel coil images and inside themselves. This proposed method removes noise simultaneously and aliasing artifacts by leveraging sparse and low rank matrix factorization. In this method there are only one type of image dimension is uses and by this method we can't denoise DICOM Images. In my proposed method that extended to multiple dimensions imaging by exploiting the redundancy and similarity between multi-slice and DICOM images to obtained a higher SNR by the using of LPG-PCA. The main objective of our proposed work id given below:

1. Denoise DICOM Images and MRI Images.
2. Obtained higher PSNR value with respect to previous work.
3. We can use any dimension of image.

Magnetic Resonance Imaging (MRI)

Noninvasive imaging method used in medicine. Imaged object is placed in a strong magnetic field. All protons in the tissue align with the direction of the magnetic field. The protons are excited to a higher energy state using a radio-frequency electromagnetic pulse. Excited protons return back to the energy equilibrium. The accepted energy is retransmitted back and can be measured. The electromagnetic pulses have to have an exact frequency (called the resonance frequency - in order of MHz) that depends on the chemical properties of the tissue, strength of the main magnetic field and temperature. The spatial position of the signal cannot be resolved -> the signal need to be spatially encoded in order to retrieve images. Magnetic gradient fields are used to locally change the resonance frequency -> the frequency of the MRI signal become dependent on the spatial position of the signal source. A k-space image is

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formed by measuring the retransmitted signal. The k-space image corresponds to the image in the Fourier space. The real image of the object is obtained by Fourier transform of the k-space image (it resolves the correspondence of the frequency and spatial position of the signal).

Parallel MRI (pMRI)

In MRI, signal is usually received by a single receiver coil with an approximately homogeneous sensitivity over the whole imaged object. In pMRI, MRI signal is received simultaneously by several receiver coils with varying spatial sensitivity -> this brings more information about the spatial position of the MRI signal. The task of pMRI is to speed up the acquisition in order to:

1. be able to image dynamic processes without major movement artifacts (i.e. reduce the speed of the acquisition so the movement during the acquisition time does not cause significant artifacts),
2. Shorten the MRI acquisition time that could be very long (for example - acquisition of a high resolution 3D scan may take up time in order of minutes).

The bottleneck of the MRI acquisition is the number of retrieved lines in k-space and the time needed to acquire one line in k-space. In pMRI, only a fraction 1/M of k-space lines is acquired while preserving spatial resolution.

1. The acquisition is M times faster.
2. It causes an aliasing in the images - M points from the original image overlaps over themselves in the image with aliasing.

Linear combination of at least M images with aliasing retrieved by the coils with varying sensitivity is used to reconstruct the original image (the coil configuration is supposed to be suitable for pMRI reconstruction - the coil sensitivities should be distinct, all parts of the imaged slice should be covered by at least one coil with reasonable SNR in this part of the slice). The parameters of the reconstruction are estimated using the exact knowledge of the coil sensitivities.

Low rank Matrix decomposition

Matrix representations of complex systems and models arising in various areas often have the character that such a matrix is composed of a sparse matrix and a low-rank matrix. Such applications include the model selection in statistics, system identification in engineering, partially coherent decomposition in optical systems, and matrix rigidity in computer science.

Local Pixel Grouping (LPG)PCA

In this paper we present LPG-PCA technique for noise removal in an image. PCA is a de-correlation technique in statistical signal processing used pervasively in pattern recognition. By transforming the image data set into PCA domain and preserving only the desired components the noise and other trivial information can be removed considerably. In the proposed LPG-PCA algorithm the input dataset to PCA is obtained using the block match LPG technique. Here the pixels and its neighbors are modeled as vectors and the training samples are determined by selecting the pixels with similar properties within the local window. This algorithm ensures effective noise removal and edge preservation. The algorithm is computed in two stages for effectiveness. Here we assume that the noise (u) in the image is additive, with zero mean and standard deviation σ. Let this noise be added to the original image say F. Therefore the new image value is determined as Fu= F+u. The goal of our project is to find an image F1 which is approximately equal to the original image F. Pixels are identified based on the spatial coordinates and their grey scale value(intensity value) whereas of different intensity values. Here we assume the pixels in local structure as vectors and improvise the edge preservation process. The image F and noise u are uncorrelated. For removing noise from an underlying pixel, according to the fig, a K×K matrix centered on the pixel and denote by X=[x1, x2…xm] T with total no of elements m=k2. The window is centered on the image X. Since the image is prone to noise u we represent the new image vector as Xu=X+u. The noisy image where U=[u1,u2….um] T . The statistical PCA is used on these vectors. To remove the noise from an image the covariance matrix Xu and PCA transformation matrix are to be calculated. Therefore, we use a LL training block centered on Xu, such that L×L is greater than K×K. From the training block we need to estimate the required pixels for the PCA. This selection of different pixels from training blocks is a complex process and may sometimes leads to inaccurate results.

EVALUATION AND RESULTS

To verify the effectiveness (qualities and robustness) of the proposed Denoising Multi-Channel Images in Parallel MRI by Low Rank Matrix Decomposition and Local Pixel Grouping with Principal Component Analysis. We conduct several experiments with this procedure on several images. There are some steps of our proposed technique are given below:

Phase 1: Firstly we develop a particular GUI for this implementation. After that we develop a code for the loading the MRI image in DICOM format from the database of the images.

Phase 2: Develop a code for the add noise in the load image from the database of the images.

Phase 3: Develop a code for the Denoising by the uses of Denoising Low Rank Matrix Decomposition and Local Pixel Grouping with Principal Component Analysis.

Phase 4: After that we calculate PSNR and processing time.

Flow Chart of proposed method

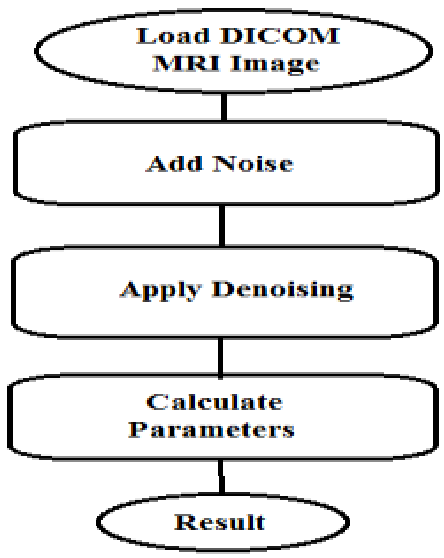

Figure: 1. Flow chart of proposed method

Results

When we simulate our implementation then we got these result which more accurate than previous work:

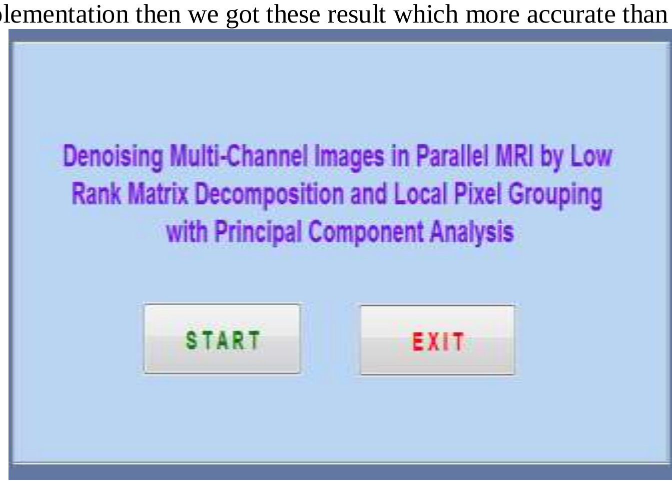

Fig.2. Main Figure window

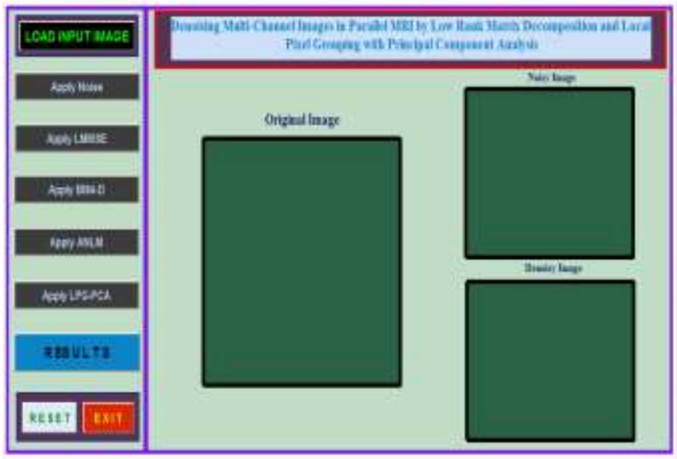

Fig.3. Work Figure window

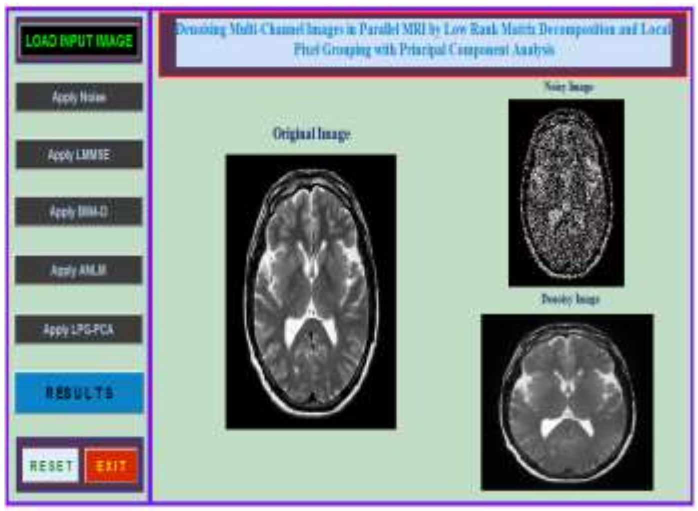

Fig.4. Running Figure window

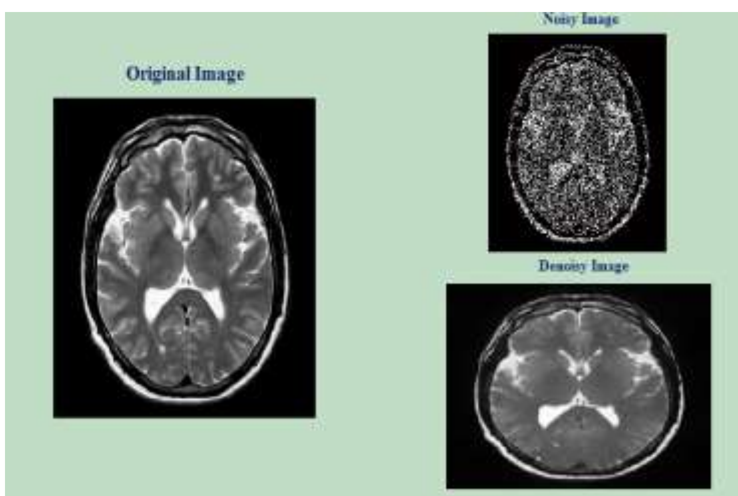

Fig.5. LMMSE Technique

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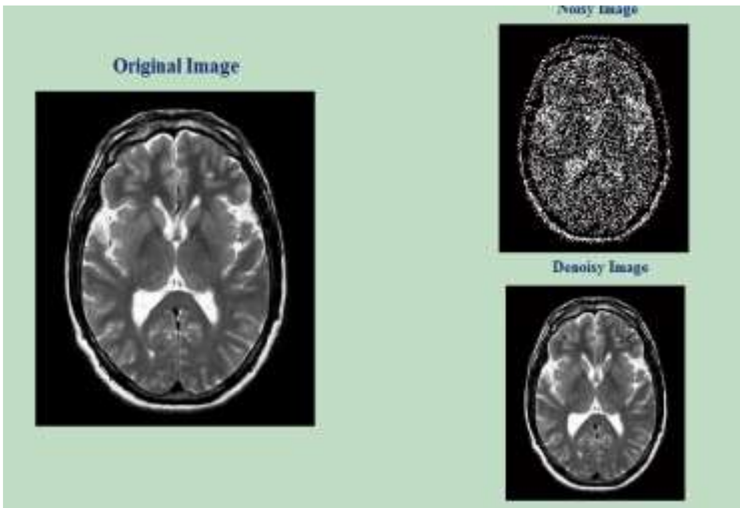

Fig.6. BM4-D Technique

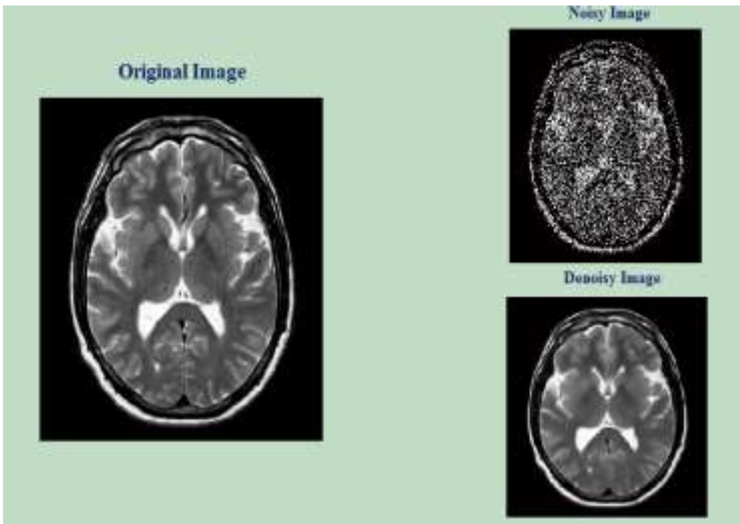

Fig.7. ANLM Technique

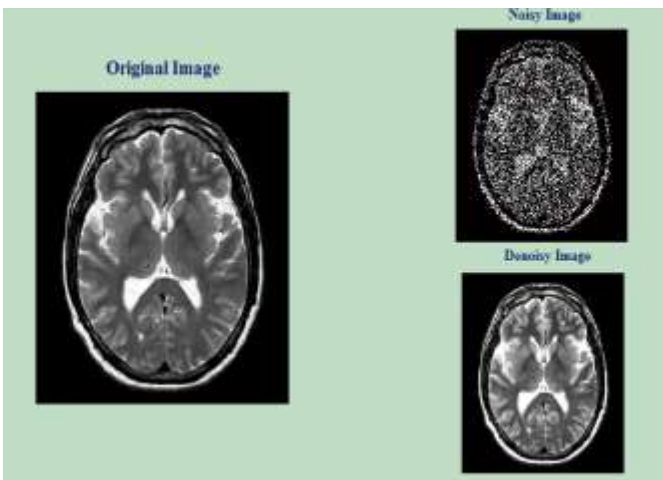

Fig.8. LPG-PCA Technique

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CONCLUSION

In this paper we "Denoising Multi-Channel Images in Parallel MRI by Low Rank Matrix Decomposition and Local Pixel Grouping with Principal Component Analysis". In this paper we selects grey scale image to stimulate for denoising purpose. The LPG-PCA algorithm will adaptively adjust the noise level of an image unlike WT (Wavelet Transformation). Several experimental results show the effectiveness of the proposed algorithm. The LPG-PCA denoising procedure is iterated one more time to further improve the denoising performance, and the noise level is adaptively adjusted in the second stage. Experimental results on benchmark test images demonstrate that the LPG-PCA method achieves very competitive denoising performance, especially in image fine structure preservation, compared with state-of-the-art denoising algorithms.

REFERENCES

[1] G.Hari Priya1, B.Venkatesh2, A.Srivani3, G.Sowmya4, N.Rajasekhar5,"Noise Removal in Image Using LPG-PCA (Local Pixel GroupingPrinciple Component Analysis) Algorithm"IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)e-ISSN: 2278-2834,p- ISSN: 2278-8735.Volume 9, Issue 1, Ver. V (Feb. 2014).
[2] R.R Coifman, D.L Donoho, Translation-invariant-de-noising,sprinjer,Berlin Journal 1995
[3] M.KMichhack,I.Kozenstev,K.Ramachandran,P.Moulin Low complexity image de-noising based on statistical modelling of wavelet co-efficient, IEEE signal processing Letters 6(12) 1999,300-303.
[4] Lei Zhang a,, Weisheng Dong a,b, David Zhang a, Guangming Shi b"Two-stage image denoising by principal component analysis with local pixel grouping"Pattern Recognition 43 (2010) 1531–1549
[5] A. Pizurica,W. Philips, Estimating the probability of the presence of a signal of interest in multi resolution single- and multiband image denoising, IEEE Transaction on Image Processing 15 (3) (2006) 654–665.
[6] jing bian, yaming wang, huaxiong zhang, litao zhu, mingfeng jiang"parallel mri reconstruction using svd-andlaplacian Transform based sparsityregularization"school of information science and technology, zhejiang sci-tech university, hangzhou 310018, china,10th january 2013. Vol. 47 no.1
[7] G.Y. Chen, B. Ke´ gl, Image de-noising with complex ridgelets, Pattern Recognition 40 (2) (2007) 578–585.
[8] Sathish Ramani*, Member, IEEE, and Jeffrey A. Fessler, Fellow, IEEE"Parallel MR Image Reconstruction using Augmented Lagrangian Methods"2010.
[9] M. Aharon, M. Elad, A.M. Bruckstein, The K-SVD: an algorithm for designing of over complete dictionaries for sparse representation, IEEE Transaction on Signal Processing 54 (11) (2006) 4311–4322.
[10] A. Foi, V. Katkovnik, K. Egiazarian, Point wise shape-adaptive DCT for high- quality de-noising and de-blocking of grayscale and color images, IEEE Transaction on Image Processing 16 (5) (2007).
[11] C. Tomasi, R. Manduchi, Bilateral filtering for gray and color images, in: Proceedings of the 1998 IEEE International Conference on Computer Vision, Bombay, India, 1998, pp. 839–846.
[12] D. Brash, A fundamental relationship between bilateral filtering, adaptive smoothing, and the nonlinear diffusion equation, IEEE Transaction on Pattern Analysis and Machine Intelligence 24 (6) (2002) 844–847.
[13] A. Buades, B. Co, J.M. Morel, A review of image de-noising algorithms, with a new one, Multiscale Modeling Simulation 4 (2) (2005) 490–530.
[14] C. Kervrann, J. Boulanger, Optimal spatial adaptation for patch based image de-noising, IEEE Transaction on Image Processing 15 (10) (2006) 2866–2878.
[15] K. Dabov, A. Foi, V. Katkovnik, K. Egiazarian, Image de-noising by sparse 3D transform-domain collaborative filtering, IEEE Transaction on Image Proces- sing 16 (8) (2007) 2080–2095.
[16] D.D. Muresan, T.W. Parks, Adaptive principal components and image denoising, in: Proceedings of the 2003 International Conference on Image Processing, 14–17 September, vol. 1, 2003, pp. I101–I10
[17] R.C. Gonzalez, R.E. Woods, Digital Image Processing, second ed., Prentice- Hall, Englewood Cliffs, NJ, 2002