

## Rician Noise Reduction with SVM and Iterative Bilateral Filter in Different Type of Medical Images.

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**ABSTRACT:** Parallel magnetic resonance imaging (pMRI) techniques can speed up MRI scan through a multi-channel coil array receiving signal simultaneously. Nevertheless, noise amplification and aliasing artifacts are serious in pMRI reconstructed images at high accelerations. Image Denoising is one of the most challenging task because image denoising techniques not only posed some technical difficulties, but also may result in the destruction of the image (i.e. making it blur) if not effectively and adequately applied to image. This study presents a patch-wise de-noising method for pMRI by exploiting the rank deficiency of multi-Channel coil images and sparsity of artifacts. For each processed patch, similar patches a researched in spatial domain and through-out 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. 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 De-noising methods. We propose image de-noising using low rank matrix decomposition (LRMD) and Support vector machine (SVM). The aim of Low Rank Matrix approximation based image enhancement is that it removes the various types of noises in the contaminated image simultaneously. The main contribution is to explore the image denoising low-rank property and the applications of LRMD for enhanced image Denoising, Then support vector machine is applied over the result.

**Keywords:** pMRI, De-noising, Multi channel coil array, Low Rank Matrix Decomposition (LRMD) and Support Vector Machine (SVM)

### I. INTRODUCTION

Magnetic resonance imaging (MRI), nuclear magnetic resonance imaging (NMRI), or magnetic resonance tomography (MRT) is a medical imaging technique used in radiology to investigate the anatomy and physiology of the body in both health and disease. MRI scanners use strong magnetic fields and radio waves to form images of the body. The technique is widely used in hospitals for medical diagnosis, staging of disease and for follow-up without exposure to ionizing radiation. Parallel magnetic resonance imaging (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.

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 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). It also 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 arrival of digital medical imaging technologies like Positron emission tomography, Medical Resonance Imaging, Computerized tomography and Ultrasound Imaging has revolutionized modern medicine. Many patients no longer need to go through dangerous procedures to diagnose a wide variety of diseases. Because of increased use of digital imaging in medicine today the quality of digital medical images becomes an important issue and to achieve the best possible diagnosis it is important for medical images to be sharp, clear,

and free of noise. While the technologies for acquiring digital medical images continue to improve and resulting in images of higher resolution and quality but removal of noise in these digital images remains one of the major challenges in the study of medical imaging because they could mask and blur important features in the images and many proposed de-noising techniques have their own problems. Image de-noising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. The factors which affect noise modeling in medical imaging are capturing instruments, information transmission media, image quantization and separate sources of radiation. So differential algorithms are used depending on the noise model that is why it is important to reduce noise and other artifacts in images, as various types of noise generated reduces the effectiveness of medical image diagnosis.

So this study concentrate on a patch-wise de-noising method for pMRI by exploiting the rank deficiency of multi-Channel coil images and sparsity of artifacts. For each processed patch, similar patches a researched in spatial domain and through-out 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. 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 De-noising methods. We propose image de-noising using low rank matrix decomposition (LRMD) and Support vector machine (SVM). The aim of Low Rank Matrix approximation based image enhancement is that it removes the various types of noises in the contaminated image simultaneously. The main contribution is to explore the image denoising low-rank property and the applications of LRMD for enhanced image Denoising, Then support vector machine is applied over the result.

Structural similarity index matrix (SSIM) is a method for measuring the similarity between two images. The SSIM index is a full reference metric; in other words, the measuring of image quality based on an initial uncompressed or distortion-free image as reference. SSIM is designed to improve on traditional methods like peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proven to be inconsistent with human eye perception.

**The SSIM is calculated on various windows of an image. The measure between two windows x and y of common size  $N \times N$  is:**

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (1)$$

Where  $\mu_x$  the average of x;  $\mu_y$  the average of y;  $\sigma_x^2$  the variance of x;  $\sigma_y^2$  the variance of y;  $\sigma_{xy}$  the covariance of x and y;  $c_1 = (k_1L)^2$ ,  $c_2 = (k_2L)^2$  two variables to stabilize the division with weak denominator; L the dynamic range of the pixel-values;  $k_1 = 0.01$  and  $k_2 = 0.03$  by default.

The difference with respect to other techniques mentioned previously such as MSE or PSNR is that these approaches estimate perceived errors; on the other hand, SSIM considers image degradation as perceived change in structural information. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene. PSNR is most easily defined via the mean squared error (MSE). Given a noise-free  $m \times n$  monochrome image  $I$  and its noisy approximation  $K$ ,

**MSE can be defined as:**

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i, j) - K(i, j)]^2 \quad (2)$$

And the PSNR (in dB) can be defined as:

$$PSNR = 10 \cdot \log_{10} \left( \frac{MAX_I^2}{MSE} \right) \quad (3)$$

## II. TECHNIQUES USED

**There are three main techniques are used to enhance the results of this thesis. These techniques are discussed below:**

## 2.1 Low-Rank Matrix Decomposition

Low-Rank Matrix Decomposition It is derived from compressed sensing theory has been successfully applied various matrix completion problems, e.g., image compression video denoising and dynamic MRI Compared with classical denoising methods. Denoising methods based on low rank completion enforce fewer external assumptions on noise distribution. These methods rely on the self-similarity of three dimensions (3-D) images across different slices or frames to construct a low rank matrix. Nonetheless, significantly varying contents between different slices or frames may lead an exception to the assumption of low-rank 3-D images, and discount the effectiveness of these methods. In this paper, we propose to remove both noise and aliasing artifacts in pMRI image by using a sparse and low rank decomposition method. By exploiting the self-similarity between multi-channel coil images and inside themselves, we formulated the denoising of pMRI image as a non-smooth convex optimization problem that minimizes a combination of nuclear norm and L1norm. The proposed problem is efficiently solved by using the alternating direction method of multipliers (ADMM). Experimental results of phantom and in vivo brain imaging are provided to demonstrate the performance of the proposed method, with comparisons to the related denoising methods.

## 2.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) is basically a classifier in which width of the edge between the classes is the advancement standard that is unfilled zone around the decision boundary characterized by the separation to the closest training patterns. These are called support vectors. The support vectors change the models with the main difference between SVM and traditional template matching systems is that they characterize the classes by a decision limit. This decision boundary is not simply characterize by the minimum distance function. The concept of (SVM) Support Vector Machine was introduced by Vapnik. The objective of any machine that is capable of learning is to achieve good generalization performance, given a finite amount of training data. The support vector machines have proved to achieve good generalization performance with no prior knowledge of the data. The principle of an SVM is to map the input data onto a higher dimensional feature space nonlinearly related to the input space and determine a separating hyper plane with maximum margin between the two classes in the feature space. The SVM is a maximal margin hyper plane in feature space built by using a kernel function. This results in a nonlinear boundary in the data space. The optimal separating hyper plane can be determined without any computations in the higher dimensional feature space by using kernel functions in the input space. There are some commonly used kernels include:- a) Linear Kernel  $K(x, y) = x \cdot y$  b) Polynomial Kernel  $K(x, y) = (x \cdot y + 1)^d$  SVM Algorithm i. Define an optimal hyper plane. ii. Extend the above definition for nonlinear separable problems. iii. Map data to high dimensional space where it is simpler to order with direct choice surfaces.

## 2.3 FILTERS:

In image processing filters are mainly used to suppress either the high frequencies in the image that is smoothing the image, or the lower frequencies that is enhancing or detecting edges in the image. The image can be filtered in frequency domain or in the spatial domain. . In spatial domain there are two types of filters namely linear filters and non linear filters. The bilateral filter is a non-linear filter and edge-preserving noise-reducing smoothing filter for medical images. In this the weight can be based on a Gaussian distribution. Weights depend not only on Euclidean distance of pixels, but also on the radiometric differences (e.g. range differences, such as color intensity, depth distance, etc.). The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. The bilateral filter can blur an image while respecting strong edges. The ability of bilateral filter to decompose an image into different scales without causing haloes after modification has made it ubiquitous in computational photography applications such as tone mapping, style transfer, relighting, and denoising of medical images. This text provides a graphical, intuitive introduction to bilateral filtering, a practical guide for efficient implementation and an overview of its numerous applications, as well as mathematical analysis. The formulation of it is simple and each pixel is replaced by a weighted average of its neighbours. This aspect is important because it makes it easy to acquire intuition about its behaviour, to adapt it to application-specific requirements, and to implement it.

## III. CONCLUSIONS

The formalism presented in this paper demonstrates that the LRMD and SVM techniques are combined to propose a new technique to further reduce the noise in medical images. The proposed approach drastically improves the quality of Parallel MRI scanning in particular medical images. Future work may be further applied new formulas or algorithm for the enhancement of denoised images. The proposed algorithm has been

implemented on MATLAB tool. This approach can also be an effective technique to denoise the images used for digital image processing.

### REFERENCES

- [1]. Abuzoum Mohamed Saleh “Efficient analysis of medical image de-noising for MRI and Ultrasound Images”, Engineering University of Malaysia, 2012.
- [2]. Akutagawa Mastake, ChanYongjia, Katayama Masato, “Additive and multiplicative noise reduction by back propagation neural network”, IEEE 29th Annual International Conference, 2007.
- [3]. Al-Sobou Yazeed A. “Artificial neural networks as an image de-noising tool”, World Applied Sciences Journal, 2012.
- [4]. Amritpal Kaur, Dr. Pankaj Kumar Verma “An Efficient Technique of Noising and De-Noising Medical Images Using Neuro– FUZZY and LDA”, IJCSIT International Journal of Computer Science and Information Technologies, 2014.
- [5]. Dr. T.Santhanam, S.Radhika, “Applications of neural networks for noise and filter classification to enhance the image quality”, IJCSI International Journal of Computer Science, 2011.
- [6]. E.Salari, S. Zhang ,“Image de-noising using neural network based non-linear filter in wavelet domain”, IJARCSSE International Journal of Advanced Research in Computer Science and Software Engineering, 2014.
- [7]. F.Marvasti, N.sadati, S.M.E Sahraeia, “ Wavelet image De-noising based on neural network and cycle spinning”, IJIRCCE International Journal of Innovative Research in Computer and Communication Engineering, 2007.
- [8]. Gupta Manoj, Kumar Papendra, Kumar Suresh “Performance comparison of median and the weiner filter in image de-noising”,IJCSIT International Journal of Computer Science and Information Technologies, 2010.
- [9]. Kaur Jappreet, Kaur Manpreet, Kaur Manpreet, Kaur Poonamdeep “Comparative analysis of image de-noising techniques”, IJETAE International Journal of Emerging Technology and Advanced Engineering, 2012.
- [10]. Leavline E.Jebamalar Sutha S, Singh D.Asir Anton Gnana “Wavelet domain shrinkage methods for noise removal in mages”, IJCA International Journal of Computer Applications, 2011.
- [11]. Mr. S. Hyder Ali, Dr.(Mrs.) R. Sukanesh, Ms. K. Padma Priya “ Medical image de-noising using neural networks”, ICIA International Conference on Information and Automation, 2005.
- [12]. Rehman Amjad, Sulong Ghazali, Saba Tanzila “An intelligent approach to image denoising”, JATIT Journal of Theoretical and Applied Information Technology, 2010.
- [13]. Sontakke Trimbak R, Rai RajeshKumar, “Implementation of image de-noising using thresholding techniques”, IJCTEE International Journal of Computer Technology and Electronics Engineering, 2007.
- [14]. Toshihiro Nishimura, Masakuni Oshiro, “US Image Improvement Using Fuzzy Neural Network with Epanechnikov Kernel”, IJIRCCE International Journal of Innovative Research in Computer and Communication Engineering, 2015.
- [15]. V Naga Prudhvi Raj, T Venkateswarlu “Ultrasound Medical Image denoising using Hybrid Bilateral filtering” ,IJCAInternational Journal of Computer Applications, 2012.
- [16]. V N Prudhvi Raj and Dr. T Venkateswarlu “Denoising Of Medical Images Using Image Fusion Techniques”, SIPIJ Signal and Image Processing : An International Journal, 2012.