Image Denoising and Rician Noise Reduction by LRMD, SVM and Iterative Bilateral Filter in different type of Medical Images

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Abstract: Digital image processing remains a challenging domain of programming for several reasons. First the issue of digital image processing appeared relatively late in computer history, it had to wait for the arrival of the first graphical operating systems to become a true matter.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 reconstruct The main challenge in digital image processing is to remove noise from the original image. This paper reviews the existing denoising algorithms of various medical images and performs their comparative study in image denoising. This technique not only some self-possessed technical difficulties, but also may result in the demolition of the image (i.e. making it blur)ed images at high accelerations. Image Denoising is one of the most challenging task because image denoising techniques not only poised 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 (LMRD) 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: ***Image denoising, Rican noise, pMRI, De-noising, PSNR, MSE, SSIM, Bilateral Filter, 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).

II. IMAGE PROCESSING FACILITIES AND MATLAB

History of digital image processing dates back to 1960s. At that time DIP or say digital picture processing techniques were developed at various research facilities such as Jet Propulsion Laboratory, University of Maryland, Bell Laboratory, Massachusetts institute of Technology and many more. The computing equipments at that time were not as much advanced as are now-a- days so the processing cost at that time was very high. MATLAB is a multi-paradigm numerical computing environment and forth generation programming language. It allows matrix manipulations, plotting of functions and data, implementations of algorithms and interfacing with the programmes.Although MATLAB is intended primarily for numerical computing and also allowing access to symbolic computing abilities.The function of the MATLAB software is very simple to implement complex image processing applications, especially for fast prototyping. The image processing toolbox provides a comprehensive set of reference- standard algorithms, functions and applications.
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 different 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 (LMRD) 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*×*N* is:

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

Where μ_x the average of x; μ_y the average of y; σ_x^2 the variance of x; σ_y^2 the variance of y; σ_{xy} the covariance of x and y; $c_1 = (k_1 L)^2$, $c_2 = (k_2 L)^2$ two variables to stabilize the division with weak denominator; L the dynamic range of the pixel-values; $k_1 = 0.01$ and $k_1 = 0.03$ 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*×*n* monochrome image *I* and its noisy approximation *K*,
MSE can be defined as:

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

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

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

The PSNR algorithm performs an exhaustive search for the maximum Y-channel PSNR over plus or minus the horizontal and vertical spatial uncertainties (in pixels) and plus or minus the temporal uncertainty.The processed video segment is fixed and the original video segment is shifted over the search range

III. TECHNIQUES USED

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

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.

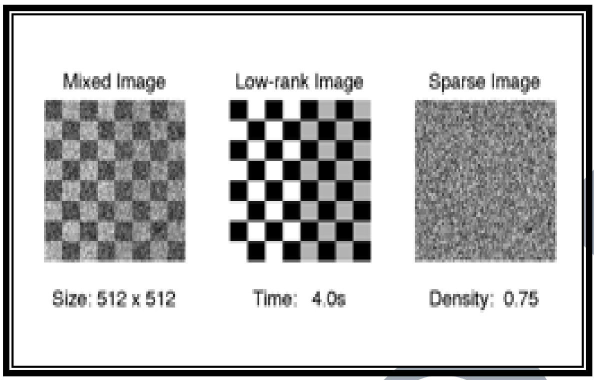

Fig 2.1: Mixed image, low-rank image and sparse image

Features of LMRD:

- It considered noisy low-rank and sparse decomposition, which is the most situation of real data.
- The LMRD directly control the rank of the low-rank part and the sparsity of the sparse part, thus brings great savings in time and space costs (by trade-off between efficiency and accuracy).
- It develop therandomized low-rank approximation method "bilateral random projection (BRP)" to further accelerate the update in the algorithm.
- The linear convergence and robustness to the noise can be theoretically proved by the scheme of "alternating projections on manifolds" by Lewis and Malick.
- The effective extensions to other problems such as matrix completion and multi-label learning.

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.

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.

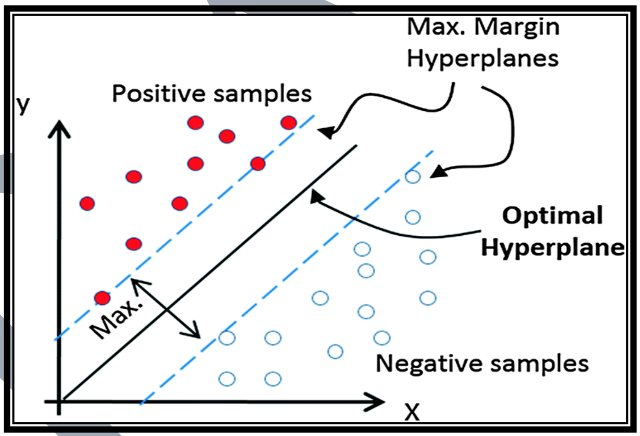

Fig 2.2: Support Vector Machine with positive and negative samples

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, y b) Polynomial Kernel K(x, y) = (x. 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.

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

ITERATIVE BILATERAL FILTER:

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. Bilateral filter is known for its effectiveness in edge-preserved image denoising and iterative bilateral filter for filtering the Rician noise in the magnitude magnetic resonance images .The iterative bilateral filter improves the denoising efficiency and also preserves the fine structures and also reduces the bias due to Rician noise. In our research an iterative bilateral filtering scheme is used for Rician noise removal. The visual and diagnostic quality of the image is well preserved.

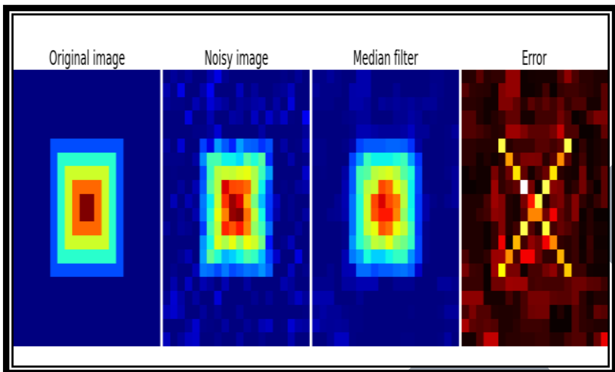

Fig 2.3: Digital original image, noisy image and filter image

IV. PARAMETERS USED

Following are the two main parameters that are used to calculate the results of the proposed work in this thesis. These parameters are:

Peak Signal-to-Noise Ratio (PSNR):

Peak signal-to-noise ratio is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a wide dynamic range and PSNR is usually expressed in terms of the logarithmic decibel scale. Peak signal-to-noise ratio is the maximum gray scale value of the pixels in the fused image. Higher the value of the PSNR is better the performance of the fusion algorithm.

Mean Square Error (MSE):

The mean square error (MSE) of a procedure for estimating an unobserved quantity measures the average of the squares of the errors that is, the difference between estimator and what is estimated. It would have the same effect of making all the values positive as the absolute value. There are two basic techniques used to compare the various image are the mean square error (MSE) and the peak signal-to-noise ratio (PSNR). A commonly utilized reference based assessment metric is the Mean Square Error (MSE). The MSE between a reference image and a fused image is given by the reference and fused images respectively and image dimensions. The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. Smaller the value of the MSE is better the performance of the fusion algorithm.

3.3 Structure Similarity Index Matrix (SSIM)

Structure similarity index matrix is a method for measuring the similarity between two images and it is a full reference matrix. In other words the measuring of image quality based on an initial uncompressed or distortion free image. This parameter is employed for measure the similarity between two images. SSIM enforced to recover on ancient ways like peak signal-to-noise ratio and mean square error. The distinction with reference to different parameters like MSE or PSNR is that it estimates perceived.

V. 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.

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