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A REVIEW PAPER ON DENOISING MULTI-CHANNEL IMAGES IN PARALLEL MRI BY LOW RANK MATRIX DECOMPOSITION AND BACTERIAL FORAGING ALGORITHM

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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) [1] 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 Bacterial Foraging Algorithm (BFA). The proposed method validates 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 [3].The Denoising of pMRI is implemented using Image Processing Toolbox. This work test 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), Bacterial Foraging Algorithm (BFA).

INTRODUCTION

MRI system is working on the principles of nuclear magnetic resonance (NMR), to map the spatial location and associated properties of specific nuclei or protons in a subject using the interaction between an electromagnetic field and nuclear spin [1,2]. It detects and processes the signals generated when hydrogen atoms are placed in strong magnetic field and excited by a resonant magnetic excitation pulse. The human body is largely composed of fat and water molecules. Each water molecule has two hydrogen nuclei or protons. These hydrogen protons are usually imaged to demonstrate the physiological or pathological alterations of human tissues. A critical issue in image restoration is the problem of noise removal while keeping the integrity of relevant image information. Denoising is a crucial step to increase image quality and to improve the performance of all the tasks needed for quantitative imaging analysis. 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 [3,4] 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) [6] 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. Wright, Magnetic resonance imaging [1] proposed Noise Removal in Image Using BFA Algorithm in 2014. In this paper an effective algorithm for noise removal in an image is obtained by using BFA. 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 optimization. O. Dietrich, J. Raya, S.B. Reeder, M. Ingrisch, M. Reiser, S.O. Schoenberg [6], Influence of multichannel combination, parallel imaging and other reconstruction techniques on MRI noise characteristics.

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 pMRI image denoising. 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 Bacterial Foraging Algorithm". In previous purposed work, the Denoising method for parallel MRI by exploiting the self-similarity between multi-channel coil images and inside themselves was using LRMD. 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 MSE & PSNR by the using of BFA. 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)

Magnetic resonance imaging (MRI) is a technique that uses a magnetic field and radio waves to create detailed images of the organs and tissues within your body. Most MRI machines are large, tube-shaped magnets. When you lie inside an MRI machine, the magnetic field temporarily realigns hydrogen atoms in your body. 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. A k-space image is 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.

Noise in MRI

MRI, even if the scanner technology has undergone tremendous improvements in spatial resolution, acquisition speed and signal-to-noise ratio (SNR), the diagnostic and visual quality of MR images are still affected by the noise in acquisition. However,

MRIs contain varying amount of noise of diverse origins, including noise from stochastic variation, numerous physiological processes, and eddy currents, artifacts from the magnetic susceptibilities between neighboring tissues, rigid body motion, non-rigid motion and other sources. Identifying and reducing these noise components in MR images is necessary to improve the validity and accuracy of studies designed to map the structure and function of the human body. The main noise in MRI is due to thermal noise that is from the scanned object. The variance of thermal noise can be described as the sum of noise variances from independent stochastic processes representing the body, the coil and the electronics. Such a noise degrades the acquisition of any quantitative measurements from the data. The signal-to-noise ratio depends on static field intensity, pulse sequence design, tissue characteristics, and RF coil and sequence parameters, such as voxel size [8] (limiting spatial resolution), number of averages in the image acquisition and receiver bandwidth. In this section, the noise distribution in MRI for both single coil and multiple coils acquisition are explained.

A. 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.

B. Bacterial Foraging Algorithm (BFA)

In this paper we present BFA technique for noise removal in an image. Bacterial Foraging Algorithm (BFA) based optimization techniques for Image Denoising is proposed in this work. The Bacterial Foraging Algorithm belongs to the field of Bacteria Optimization Algorithms and Swarm Optimization, and more broadly to the fields of Computational Intelligence and Metaheuristics. It is related to other Bacteria Optimization Algorithms such as the Bacteria Chemotaxis Algorithm and other Swarm Intelligence algorithms such as Ant Colony Optimization and Particle Swarm Optimization. There have been many extensions of the approach that attempt to hybridize the algorithm with other Computational Intelligence algorithms and Metaheuristics such as Particle Swarm Optimization, Genetic Algorithm, and Tabu Search. The Bacterial Foraging Optimization Algorithm is inspired by the group foraging behavior of bacteria such as E.coli and M.xanthus. Specifically, the BFOA is inspired by the Chemotaxis behavior of bacteria that will perceive chemical gradients in the environment (such as nutrients) and move toward or away from specific signals. Bacteria perceive the direction to food based on the gradients of chemicals in their

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environment. Similarly, bacteria secrete attracting and repelling chemicals into the environment and can perceive each other in a similar way. Using locomotion mechanisms (such as flagella) bacteria can move around in their environment, sometimes moving chaotically (tumbling and spinning), and other times moving in a directed manner that may be referred to as swimming. Bacterial cells are treated like agents in an environment, using their perception of food and other cells as motivation to move, and stochastic tumbling and swimming like movement to re-locate. Depending on the cell-cell interactions, cells may swarm a food source, and/or may aggressively repel or ignore each other.

EVALUATION AND METHODOLOGY

To verify the effectiveness (qualities and robustness) of the proposed Denoising Multi-Channel Images in Parallel MRI by Low Rank Matrix Decomposition and Bacterial Foraging Algorithm. 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

Phase 2: we develop a code for the loading the Noisy MRI image in DICOM format from the database of the images. from the database of the images.

Phase 3: Develop a code for the Denoising by the uses of Denoising Low Rank Matrix Decomposition and BFA.

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

Flow Chart of proposed method

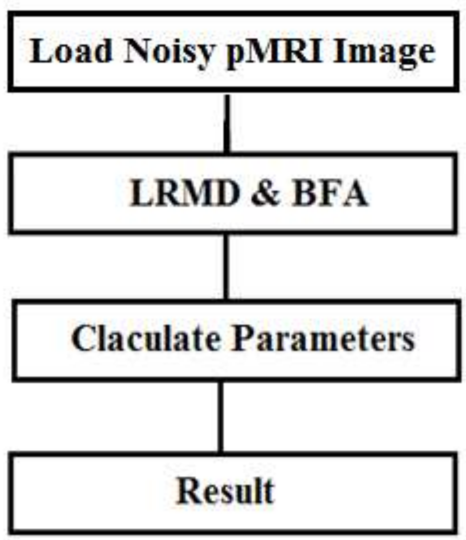

Figure: 1. Flow chart of proposed method

CONCLUSION

In this paper we "Denoising Multi-Channel Images in Parallel MRI by Low Rank Matrix Decomposition and Bacterial Foraging Algorithm". This paper summarized the MRI denoising techniques and compared with one another based on their performance which is measured using quantitative performance metrics such as PSNR, SNR, RMSE, SSIM, MSE and as well as in terms of the visual quality of the images. Many of the denoising methods are dealing with the spatially uniform noise distribution in parallel MR Images. But for parallel imaging MRI, the noise has spatially non-uniform distribution. To deal this, the denoising procedure requires a priori knowledge of the noise map and adaptability. In this paper we selects grey scale image to stimulate for denoising purpose. This paper presents a methodology to estimate the noise parameters of the pMRI image using Bacterial Foraging Algorithm (BFA). Bacterial foraging algorithm (BFA) has been widely accepted as a global optimization algorithm of current interest for optimization and control. BFOA is inspired by the social foraging behavior of Escherichia coli. Experimental results on benchmark test images demonstrate that the BFA method achieves very competitive denoising performance, especially in image fine structure preservation, compared with state-of-the-art denoising algorithms. In future we can use genetic algorithm with BFA for more accuracy and to improve the quality of image. The aim of this survey is to provide an overall view of the available MRI denoising techniques. This will help for the researchers who are willing to develop a new denoising technique for MR images. And also, from this survey, one can choose the best denoising method for further processes like image segmentation, image registration and image classification which are used for computer aided diagnosis.

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