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Analysis of MRI Image De-noising Technique

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Abstract: The Image processing is the technique which can store the information stored in the form of pixels. The noise is the extra pixels on the image which reduce image quality. The MRI images are medical images on which raisin noise is present. The PNLM is the algorithm which can denoise the MRI image. The PNLM algorithm is the parallel non local mean filter. In this review paper, various image denoising techniques are reviewed in terms of certain parameters.
KEYWORDS: PNLM, NLM, PSNR, MSE

I. Introduction

A major part of studies in digital image processing is devoted to image denoising. Image denoising is a classical research topic in image processing [1]. The transformation of images has become a major method of communication in the modern era, but the image obtained after transmission is often corrupted with noise. The corrupt image needs to be processed or denoised before it can be used, because it decreases the image quality and brings lots of inconvenience for the diagnosis purpose [2]. MRI (magnetic resonance imaging) plays an important role in medical and research procedures. It is one of the most effective medical equipment that has been proved to be less harmful for patients as compared to the other medical modalities [3]. MRI is more accurate for imaging soft tissues such as brain and muscles. It can diagnose a broad range of abnormality conditions like cancer, tumor, blockages, internal injuries etc. It does not depend on the ionizing radiation, hence is a non–invasive technique. The MRI technique provides excellent contrast between the normal tissues and the diseased tissues [4]. In the pre-processing technique of enhancement, the unwanted atmospheric noise removed and it can correcting the data from irregularities in the image and enhance the original image while segmentation, image divides into several parts but the main difficulties in segmenting the images are noise, blur, low contrast and a pixel contributing to multiple tissue types. In case of children and patients that need multiple imaging examinations, MRI scan is preferred as it does not utilize the ionizing radiation. The availability of soft tissue contrast is higher in case of MRI. This scan is more sensitive and provides particular abnormalities within the brain only [5]. Without moving the patient physically, the MRI scanning can be performed within imaging plane. There is less risk of causing potentially lethal allergic reaction as well in case of MRI in contrast to other technologies. The structured of obscured artifacts from the bone can be evaluated with the help of images generated from MRI scan. MRI is the scanner technology, has undergone tremendous improvements in spatial resolution, acquisition speed and signal-to-noise ratio (SNR). But the diagnostic and visual qualities of MRI images are still affected by the noise in acquisition [4]. The main noise in 6RI is due to thermal noise which comes from scanned objects. This type of noise degrades the acquisition of any quantitative measurements from the data [5]. The signal-to-noise ratio (SNR) depends on the static field intensity, pulse sequence design, RF coil and tissue character SNR also depends on sequence parameters , such as voxel size and average number in the image acquisition and receiver bandwidth. Noise is introduced into the MRI image due to some technical limitation, which includes non-uniform radio frequency (RF) fields. This noise includes intensity variations, partial volume effects and some random image noise. Two stages are very important in medical image processing, image filtering and enhancement. The pre-processing stage is utilized for lessening noise in the image, highlighting the desired regions, enhancing the contrasts and modifying various shapes. The enhancement stage may include resolution and contrast enhancement [6]. This is used to suppress the noise in MRI image and after removing noise from MRI image it can be converted into standard image [7]. Rician noise is used to refer the error between the image intensities and the observed data. Almost every denoising method mainly relies on the local pixels within a small neighbour to remove noise [8]. While this process, large scale structures are preserved while small structures are considered as noise and are removed. The NLM filter exploits the redundancy of information contained within the images to get rid of the noise [9]. The improved intensity value of the voxel is calculated because the weighted average of all the voxel intensities within the images.

II. Literature Review

Xu Mingliang et al (2016) [10] improved in this paper, the classical NLM algorithm to denoise medical images by including a novel noise weighting function and parallelizing. In the experiment, plenty of medical images have been tested and experiment results demonstrate that the algorithm can accomplish better results and higher efficiency compared with the original NLM method. This paper improves the weighted kernel function in NL-means algorithm to denoise the medical image, and furthermore propose a GPU-based parallel non-local means denoising algorithm. Results demonstrate that compared with the traditional sequential algorithm, this new method can have great performance on different levels of noise. The algorithm has been improved two orders of magnitude, in the aspect of processing speed.

Jing Zhang et al (2016) [11] performed in this paper ROC bend analysis to estimate the cut-off values for separating patients with various liver functions. In this study, D* and f values predicted the severity of liver dysfunction. Notwithstanding, D* values just facilitated the differentiation between patients with Child–Pugh class and Child–Pugh class B and C; it did not help differentiate the Child–Pugh class B from class C. Besides, f values predicted liver function more efficiently than did D* values. Despite the fact that we estimated the function of the entire liver, our research has set out a decent foundation for the assessment of regional or remnant hepatic function. In conclusion, perfusion-related parameters (particularly for f) are helpful for showing the severity of liver disease, and may can possibly turn into a novel tool for checking liver function.

Samuel St-Jean et al (2016) [12] proposed in this paper, a novel diffusion MRI denoising method that can be utilized on every single existing data, without adding to the scanning time. The method first applies a statistical system to change over both stationary and non stationary Rician and non focal Chi conveyed noise to Gaussian dispersed noise, adequately removing the bias. Further, there is an introduction of a spatially and angular adaptive denoising procedure, the Non Local Spatial and Angular Matching (NLSAM) calculation. This method restores perceptual information, removes the noise bias in like manner diffusion metrics, restores the extracted peaks coherence and improves reproducibility of tractography on the synthetic dataset. On the 1.2 mm high resolution in-vivo dataset, this type of denoising improves the visual quality of the data and reduces the number of spurious tracts when compared to the noisy acquisition.

Sila Kurugol et al (2016) [13] proposed in this paper, a probability distribution model of incoherent movement that uses a mixture of Gamma distributions to fully characterize the multi-scale nature of diffusion inside a voxel. Further, the robustness of the distribution parameter estimates is enhanced by integrating spatial homogeneity prior into the probability distribution model of incoherent movement (SPIM) and by utilizing the fusion bootstrap solver (FBM) to estimate the model parameters. Further, the improvement in quantitative DW-MRI analysis accomplished with the SPIM model is enhanced in terms of accuracy, precision and reproducibility of parameter estimation in both re-enacted data and in 68 abdominal in-vivo DW-MRIs. Results demonstrate that the SPIM model not just substantially reduced parameter estimation errors by up to 26% it additionally altogether improved the robustness of the parameter estimates (paired

Ms. Pallavi L. Patil et al (2016) [14] presented in this paper, comparison of different wavelet at different families increased, and further more utilizing wavelet thresholding strategies and comparing the different parameters like PSNR, structural similarity index(SSIM), MSE(Mean square error) and Image quality of original and denoise image. Wavelet thresholding has proven to be efficient edge-preserving denoising method for gray scale images particularly for removal the Rician noise. Wavelet transform gives localization in spatial and spectral domain. From that experimental result and comparison of parameters, it demonstrates that this strategy works exceptionally well when utilized for Rician noise and Gaussian noise, having the highest PSNR, less MSE. While comparing with wavelet families, coiflet4 has having better results as compared the other.

Donatella Granata et al (2016) [15] proposed in this paper performance is boost by an efficient algorithm to GPU hardware architectures. This algorithm adapts itself to many variants of the methodologies in terms of different strategies for estimating the involved filtering parameter, sort of noise affecting data, multi-component signals, spatial dimension of the images. Numerical experiments on brain Magnetic Resonance images are also provided. From one side it can be effectively adapted to the next generation Kepler NVIDIA GPU engineering featuring Compute Capability 3.0 and higher with a few limitations in the multi-GPU environment, because of the exclusive ownership of the gadget memory. This fixes the fundamental drawback of the present NLM algorithm given by the administration of the memory use. From the opposite side any advancement in the NLM methodology that is intrinsically massively parallel can be implemented in the algorithm.

Table of Comparison

Authors Names	Year	Description	Outcomes
Xu Mingliang, Lv Pei, Li Mingyuan, Fang Hao, Zhao Hongling, Zhou Bing, Lin Yusong, Zhou Liwei	2016	The classical NLM algorithm is designed to denoise medical images by including a novel noise weighting function and parallelizing.	Results demonstrate that compared with the traditional sequential algorithm, this new method can have great performance on different levels of noise.
Jing Zhang, Yihao Guo, Xiangliang Tan, Zeyu Zheng, Mengqi He, Jun Xu, Yingjie Mei, Jiajun Zhang, Xixi Zhao, Chunhong Wang, Yanqiu Feng, Queenie Chan, Yuankui Wu, Yikai Xu	2016	In this study, D* and f values predicted the severity of liver dysfunction. Notwithstanding, D* values just facilitated the differentiation between patients with Child–Pugh class and Child–Pugh class B and C.	In conclusion, perfusion-related parameters (particularly for f) are helpful for showing the severity of liver disease, and may can possibly turn into a novel tool for checking liver function.
Samuel St-Jean, Pierrick Coupé, Maxime Descoteaux	2016	A novel diffusion MRI denoising method is proposed that can be utilized on every single existing data, without adding to the scanning time.	On the 1.2 mm high resolution in-vivo dataset, this type of denoising improves the visual quality of the data and reduces the number of spurious tracts when compared to the noisy acquisition.

Sila Kurugol, Moti Freiman, Onur Afacan, Jeannette M. Perez-Rossello, Michael J. Callahan, Simon K. Warfield	2016	A probability distribution model is proposed of incoherent movement that uses a mixture of Gamma distributions to fully characterize the multi-scale nature of diffusion inside a voxel.	Results demonstrate that the SPIM model not just substantially reduced parameter estimation errors by up to 26% it additionally altogether improved the robustness of the parameter estimates (paired).
Ms. Pallavi L. Patil, Mr. V.B. Raskar	2016	Comparison of different wavelet is presented at different families increased, and further more utilizing wavelet thresholding strategies and comparing the different parameters.	From that experimental result and comparison of parameters, it demonstrates that this strategy works exceptionally well when utilized for Rician noise and Gaussian noise, having the highest PSNR, less MSE.
Donatella Granata, Umberto Amato, Bruno Alfano	2016	Algorithm is designed that adapts itself to many variants of the methodologies in terms of different strategies for estimating the involved filtering parameter, sort of noise affecting data, multi-component signals, spatial dimension of the images.	This fixes the fundamental drawback of the present NLM algorithm given by the administration of the memory use. From the opposite side any advancement in the NLM methodology that is intrinsically massively parallel can be implemented in the algorithm.

III. Conclusion

In this paper, it is concluded that noise is the factor which reduce quality of the image. The MRI images have the raisian noise which affect quality of MRI image. The NLM filter is the approach which can denoise the MRI images. The PNLM is the improved version of NLM for the image denoising. The approach of textual feature analysis can be applied with PNLM filter for the image denoising in future.

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