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NOISE REMOVAL FROM MEDICAL IMAGES USING COMPRESSIVE SENSING

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***Abstract*— Image Denoising is a fundamental image processing step for improving the overall quality of images. This paper is elaborating noise reduction method using compressive sensing. The conventional method consists of two phases: noise detection and noise filtering. The filtering is applied to only corrupt pixels of the noisy image. To overcome this problem, present a novel compressive sensing (CS)-based noise removing algorithm using adaptive multiple samplings and reconstruction error control. Compressive sensing is an emerging methodology in computational signal processing. Compressed sensing reconstruction achieves better image quality in terms of signal-to-noise ratio, local contrast, and contrast-to-noise ratio, compared to the classical averaging method while reducing the total amount of data required reconstructing the images.**

***Index Terms*— Image Denoising, Compressive Sensing, Orthogonal Match Pursuit Algorithm, Image Processing.**

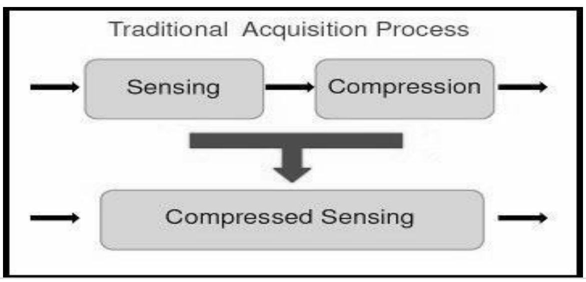
I. INTRODUCTION

Image denoising is an open problem and has received considerable attention in the literature for several decades. Most of the conventional spatial filtering techniques as the mean filter and Gaussian filter have the disadvantage of blurring the edges when reducing noise. Image sensors are of increasing importance in applications such as biomedical imaging, sensor networks, hand-held digital cameras, as well as cameras in cell phones, computers, and for (CCTV) monitoring systems. The increasing demand for both high resolution and high frame rate cameras leads to a large amount of image data. With these large amounts of data, fast and accurate image compression algorithms to represent the data in a compact form are required. Typically, compression algorithms use the spatial and temporal correlations in image and video signals to remove redundant information while concurrently keeping the essential features intact. Different algorithms such as Huffman, arithmetic, dictionary, differential, sub-band and wavelet-based coding as well as quantization methods has been presented. These algorithms perform the compression after the image acquisition. In the compressive sensing (CS) method, instead of sensing the entire image and then subsequently removing redundant information during the compression step, only the required or non-redundant information is sensed. The CS paradigm has attracted increased interest in past decade because it intrinsically avoids sensing redundant information that exists in image or video data. In CS, a number of random projections of the image are being sensed as the compressed version of the image, thus leading to the faster image acquisition system.

II. COMPRESSIVE SENSING

Compressed sensing is a new rapidly growing research field emerging primarily in the USA, which investigates ways in which we can sample signals at roughly the "information rate" rather than the Nyquist rate. The foundations for compressed sensing emerged over the last two years from theoretical work developed within the field of sparse signal representations. A sparse representation is one which accounts for most or all of the information of a signal with a linear combination of a small number of elementary signals called atoms. The Fourier transform, for example, can represent a signal containing a single frequency with a single non-zero frequency component. This sparseness is one of the reasons for the extensive use of popular transforms such as the discrete Fourier transform (DFT) and the wavelet transform in practical signal source coding schemes. The aim of these transforms is often to reveal certain structures of a signal and to represent these structures in a compact form. Sparse representations extend this idea by also considering more flexible redundant representations (called dictionaries) where the linear analysis transform is replaced by a nonlinear sparse representation operator. There are two main components to compressed sensing: the sampling strategy and the reconstruction algorithm.

Basic block diagram of compressive sensing:



Sampling - While conventional sampling involves measuring a quantity at regular intervals (so as to satisfy Nyquist), the concept of sampling in compressed sensing is much more general. Sampling in compressed sensing consists of making a random linear projection of the signal into a low dimensional space. While this is essentially what is required for the theory researchers have found empirically that the same ideas can often be used in much more conventional sampling scenarios. For example MRI scanners sample lines within the spatial Fourier domain of the image and there are already initial examples of compressed sensing techniques for MRI using randomized trajectories and even deterministic trajectories (sampling a small number of radial lines) in the Fourier space.

Reconstruction - The key difference between conventional sampling and compressed sensing is that the reconstruction operator is nonlinear. Essentially this selects the significant coefficients for the data in some sparse representation and then calculates a Least squares approximation using the associated basis functions. While this sounds relatively easy it should be noted that finding the significant coefficients is a combinational search problem and in practice cannot be solved directly. Instead much of the theory of compressed sensing has concentrated on proving that near optimal performance is possible by using either a convex relaxation that boils down to solving a linear or quadratic program or greedy algorithms that iteratively select the coefficients in a greedy way one at a time or in groups.

III. LITERATURE REVIEW/RELATED WORKS

In 2006, M. Elad and M. Aharon, proposed an approach of "*Image denoising via learned dictionariesand sparse representation,*" in Conference on Computer Vision and Pattern Recognition.

In 2008, Roummel F. Marcia and Rebecca M. Willett, Department of Electrical and Computer Engineering Duke University, Durham, NC 27708 proposed an approach of "*COMPRESSIVE CODED APERTURE SUPERRESOLUTION IMAGE RECONSTRUCTION*".

In 2010, Marcio Marim, Elsa Angelini and Jean-Christophe Olivo-Marin proposed an approach of "*Denoising in Fluorescence Microscopy Using Compressed Sensing with Multiple Reconstructions and Non-Local Merging*".

In July 2011, T. Tony Cai and Lie Wang propsed an approach of "Orthogonal Matching persuit for Sparse signal recovery with Noise"

In 2012, Amin Tavakoli and Ali Pourmohammad, Member, IACSIT proposed an approach of "*Image Denoising Based On Compressing Sensing".*

In 2013 , Richter D, Basse-Lüsebrink TC, Kampf T, Fischer A, Israel I, Schneider M, Jakob PM, Samnick proposed an approach of *"Compressed Sensing for reduction of noise and artefacts in direct PET image reconstruction".*

IV. IMAGE DENOISING METHOD

For image denoising, we first transform the image corrupted with noise to sparse domain using:

$$\Phi = \Psi \times (x + z)$$

Where z is the Additive noise. Then we sample from $\Phi$by mixing matrix $Mm \times n$ where M is stable and incoherence with the matrix transform:

$$\Psi\, y = M \times \Phi = M \times \Psi \times (x + z)$$

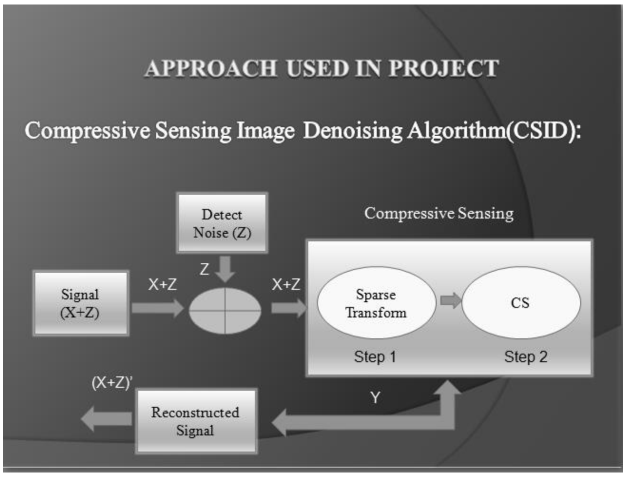
and $Mm \times n \times \Psi n \times n$ which would be called the compressed sensing matrix A. According to the observation vector $y = A \times x$, we need to reconstruct the original image from this observation. It is known that sparsity is a basic principle infidelity reconstruction. Also it is known the noise is not sparse in common domain. Hence most of part will be removed by compressed sensing due to recovery a just M dimensional vector of noise which is reconstructed. Also we can reconstruct the exact signal due to sparsity. Stated principle is basic idea for compressed sensing image denoising (CSID).

CSID algorithm:

- Firstly, Do sparse transform for signal X + Zformed by mixing signal $X$and noise Z, and obtain $\Phi = \Psi \times (X + Z)$.

- Secondly, Design a $M \times N$dimensional observation matrix M which is stable and unrelated with the transform basis Ψ, then use $\boldsymbol{M}$ to measure $\Phi$and acquire the observation vector

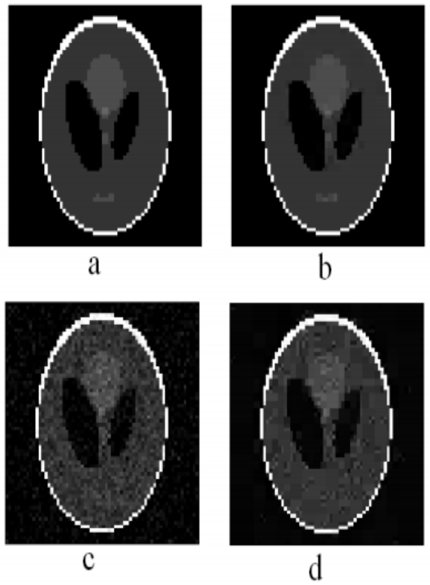
$$Y = M \times \Phi = M \times \Psi \times (X + Z).$$



 Finally, Restore signal X' by reconstructing Y (There are many reconstruction algorithm, such as orthogonal matching pursuit method, etc.) which complete the denoising of signal X.

V. SIMULATION AND RESULT

Several noisy monochrome images which corrupted with Additive Gaussian White noise are sampled with Gaussian Random compressive sensing matrices, and reconstructed with the corresponding algorithms. Representative results obtained with three of these images appear . The used procedure was as follows. First, each original image was sparsified by computing its wavelet transform (Haar) and then retained pre-determined fraction (e.g., 5%, 10%, or 15%) of its wavelet coefficients via keeping the largest and setting the rest to zero. Typically, images were distorted by these operations, especially when the number of coefficients retained was small. None of the tested images exhibited natural sparsity in this wavelet basis (or in any of a few other bases tried) below 5– 10%. depicts results for a 64 ×64 pixel synthetic image (the "Shepp-Logan phantom") commonly used as a surrogate for MRI brain images. Distortion of the original image due to the sparsifying transformation is not evident at 15% sparsity and rather severe at 10% sparsity. By added AWGN noise with zero mean and variance to the 15% sparsified images. Then constructed the related image by IHT algorithm and performed similar step for the 10% sparsified images .Due to increasing the sparsity in the image, we can reconstruct the image using fewer measurements. Hence the complexity decreases. Fig.3 examine this algorithm for 10% sparsify image and then reconstruct the image with 3200 samples. After that compared IHT and OMP algorithms. Simulation results show that these algorithms have same performance but the run-time in IHT algorithm is 45 seconds and for OMP algorithm is 60 seconds, which inform IHT is faster than OMP. we have compared some known classic filters and CISD algorithms. These filters and achieving PSNR results indicate the compressive sensing can remove then white nose from the image as same as the classical filter. But with noticeable difference which inform in the compressive sensing method don't need to adapt the algorithm when the parameter of noise or signal have been changed.



a) original 64×64 phantom image,
b) %15 sparsify image
c) Noise-polluted image PSNR is 15dB
d) Denoised image using CSID algorithm, PSNR of denoised image is 24dB and number of measurements are 3800 samples.

VI. CONCLUSION

This paper, presented and simulated a new approach for image denoising based on compressed sensing. In this method, an unknown noisy image of interest is observed (sensed) through a limited number linear functional in random projection, then original image is reconstructed using the observation vector and the existed recovery algorithms such as L1_minimization. Simulation results indicate the reduce additive Gaussian white noise from the image using compressive sensing. Sampling and compression accomplishing is one of steps of this method. Also, the reconstructing and denoising will are implementing in another step of this method. Using classical filter for image denoising, we need to redesign algorithm parameters owing to the change of signal parameters such as frequency, amplitude, etc. But CISD algorithm, don't need to change the algorithm parameters when the image or noise parameters have been changed. Simulation results show that the performance of compressive sensing denoising is the same as classic filter or in some occasion fairly better than those.

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