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A novel blind source separation technique using fractional Fourier transform for denoising medical images

A. Mustafi[a,*], S.K. Ghorai[b]

[a] Department of CSE, Birla Institute of Technology, Mesra, Ranchi 835215, India
[b] Department of ECE, Birla Institute of Technology, Mesra, Ranchi 835215, India

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ABSTRACT

In this paper we propose a novel algorithm to denoise medical images. The proposed method provides enhanced visual clarity to experts for utilizing such images during diagnosis. Medical images are unique in the fact that they are often low contrast and extremely noisy in nature because of the circumstances under which they are captured. Denoising these images without a priori knowledge of the noise PDF is always difficult and successful denoising of such images should not induce other artifacts or blurring of edges in the images. The proposed algorithm utilizes the technique of blind source separation (BSS) and the fractional Fourier transform to provide superior and stable denoising of medical images. The performance of the algorithm is compared with the recent genetic algorithm based wavelet thresholding method and the results are presented.

1. Introduction

Medical imaging has proved to be a great asset to medical practitioners, improving tremendously the reliability and speed of diagnosis [1]. Unfortunately many medical images are captured under low light and low exposure conditions. Interference in the acquisition system also causes substantial corruption of the images due to the addition of noise. In many cases, the noisy images are deteriorated to such an extent that offering medical judgment based on such images might be extremely hazardous. Also in many medical conditions, only small but significant differences exist between normal and abnormal tissues and the presence of noise or artifacts can considerably reduce the usefulness of such images for medical diagnosis [2]. Consequently, improving the quality of such images through the process of denoising, brightness adjustment and enhancement of contrast has become an area of prime research in the field of medical imaging.

An abundance of simple but highly competent algorithms for contrast enhancement, e.g. histogram based methods [3], homomorphic methods [4,5], adaptive algorithms [6] work very well for medical image as they do for natural images, however denoising medical images has proved to be a much greater challenge. Standard methods applicable to natural images are usually not suitable for application to medical images. This is primarily because of the propensity of these methods to induce some sort of blurring of edges when applied to noisy images. Edge preservation is a prime requirement in medical images allowing experts to visualize with clarity tissues which have been compromised from normal tissues. Even sophisticated methods like the Weiner's filter [7], median filtering [8], alpha trimming [9], etc. are also not devoid of this drawback when applied in the spatial or frequency domain.

The inability of these algorithms to properly denoise medical images has shifted attention to multi resolution methods and in particular wavelets [10]. Wavelets demonstrate excellent localization properties and are computationally simple to apply. However, the application of wavelets is having other complications, most notably the choice of a suitable threshold to truncate the wavelet coefficients. Various methods have been reported in the literature to choose a suitable threshold. These include blind thresholding, thresholding based on image statistics, Bayesian methods [11] and more recently heuristic and meta-heuristic algorithms, i.e. genetic algorithm [2]. The complexity in choosing a good threshold is further enhanced by the fact that medical images may contain different kind of noises dependent on the acquisition method being employed. Ultrasound images are more prone to having speckle noise which is multiplicative in nature, while MRI images tend to have more of Rician noise which is additive. A successful algorithm must be able to accommodate all kinds of noises and should still produce acceptable denoising.

In this paper, we present a novel algorithm to denoise medical images based on the technique of blind source separation. The use of the blind source separation technique proves to be extremely useful in removing the major component of additive or multiplicative noise from the acquired image. To further ensure that

* Corresponding author. Tel.: +91 6512275444; fax: +91 6512275401.
E-mail address: abhijit@bitmesra.ac.in (A. Mustafi).

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no abnormal loss of sharpness is observed in the edges, the BSS method is assisted by the use of filtering in the fractional Fourier domain. This added step provides the proposed method the desired localization property which is the strength of ***space-frequency algorithms. The combined application of the two steps ensures that the output images are well denoised but still retain the sharpness of edges. It will help medical practitioners to visualize the effect and extent of tissue damage and offer diagnosis.

2. Denoising medical images

2.1. Noise in medical images

Noise in digital images is induced principally during the acquisition process, though some noise may also be introduced during transmission of digital images across network channels. In this paper, we only consider acquisitional noise as it is of more interest in medical images. The performance of imaging sensors can be affected by many factors, e.g. environmental conditions during the process of acquisition, quality of the sensor elements, etc. [6]. The process of denoising often involves estimating the parameters of the noise induced in a digital image and then devising an algorithm to cancel the effects of such noise in the most non destructive manner possible. The spatial characteristics of the noise and its correlation with the image itself are critical factors in producing robust denoising algorithms. More formally the process of denoising refers to the process of extracting the signal f from noisy observation f' in a non destructive manner so as no other artefacts are introduced and the structures still maintain the clarity of their boundaries. The noise induced in digital images is usually additive or multiplicative. A digital image corrupted by additive noise is represented mathematically as

$$f'(x, y) = f(x, y) + \eta(x, y) \tag{1}$$

while images corrupted by multiplicative noises are represented as

$$f'(x, y) = f(x, y)[1 + \eta(x, y)] \tag{2}$$

where $\eta(x, y)$ is a random function that represents the induced noise and is the component that denoising algorithms try to remove.

2.2. Blind source separation of images

Blind source separation [12] refers to a the extraction of source signals from a linear or non linear mixture without any apriori knowledge about the sources. In recent times, the problem of BSS has received a lot of interest, particularly because of its usefulness in a wide spectrum of domains. BSS finds applications in various activities ranging from scanning of documents, seismic activity monitoring, sensor networks, etc. Even though seemingly complex to solve, various methods have been cited in history to solve the BSS problem with a considerable degree of reliability. Some of the methods that have been employed to solve the BSS problem are joint diagonalization based methods [12], higher order statistical based methods [13], PCA [14], methods based on the principles of thermodynamics [15], etc. More recently the advent of Independent Component Analysis (ICA) has paved the way for solving the BSS problem accurately and with remarkable efficiency [16,17]. ICA and its variants use the concept of independence of the constituent signals to perform the separation and this is one of the major reasons for applying BSS to denoise images. For many noise models, it is valid to assume that the induced noise is independent of the original image. Methods using wavelets [18] and multi state methods are also known to exist to solve the BSS problem. Mathematically we conceptualize the discrete linear BSS problem as

$$X = AS \tag{3}$$

where S is a matrix representing the collection of N source signals known to exist at M discrete points. Thus S can be visualized as

$$S = \begin{Bmatrix} s_{11} & s_{12} & \cdots & s_{1m} \\ \vdots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ s_{n1} & s_{n2} & \cdots & s_{nm} \end{Bmatrix} \tag{4}$$

The term A in Eq. (3), is an unknown matrix of dimension $n \times n$ made of real coefficients. It is obvious that X is a linear mixture of all the source symbols s_i, $1 \le i \le n$. The extension to the case of two dimensional signals is straightforward. To solve the BSS problem we must find the coefficients of the matrix S, however in doing so we work without any knowledge about A. Consequently, the only observed quantity available with us is matrix X. It can be observed that a solution to the linear BSS problem reduces to finding the coefficients of the matrix A. Mathematically, it can be written as

$$\begin{aligned} X &= AS \\ A^{-1}X &= A^{-1}AS \\ S &= A^{-1}X \end{aligned} \tag{5}$$

Thus, knowledge about the coefficients of A is sufficient to completely recover S which is the goal of any BSS algorithm. The linear BSS problem is the one that has found the most relevance in real world applications though, of late a lot of research has also focused on solving the non-linear BSS problem [19]. The mathematics for the non-linear case is much more complex, and finding a solution is a much more computationally intensive activity than the linear case.

We employ BSS for denoising of medical images as it is a robust method of removing induced noise from the images, when the noise is not correlated to the original image. This is usually the case for Rician noise which is additive and consequently quite easily removed by the application of BSS. However, BSS by itself would not be sufficient to denoise images to the desired level. This is because of its inability to remove multiplicative noise, i.e. speckle noise which is widespread in ultrasound images. To obtain a higher degree of denoising we use the fractional Fourier transform to remove the speckle noise component.

2.3. Fractional Fourier transform

The fractional Fourier transform (FRT), is a generalization of the Fourier's transform, and provides a means of going from the time domain to the frequency domain in a step wise manner [20]. The FRT is characterized by the parameter α (where $0 \le \alpha \le 1$), known as the order of the FRT. When $\alpha = 0$, the FRT is the same as the time domain signal while when $\alpha = 1$, the FRT is analogous to the Fourier transform of the signal. For any intermediate value of α, the FRT is composed of both temporal and frequency components and thus gives us an added degree of freedom for processing signals. The discrete form of the FRT can also be shown to exist for all signals under some mild assumptions. Mathematically, the FRT of a signal f can be written as

$$F^{\alpha} = W^{\alpha} f \tag{6}$$

The term W in Eq. (6) is a matrix comprising exponential coefficients that represents the forward kernel of the ordinary Fourier transform. Each term in W has a form $e^{-(j/2\Pi)ux}$, where x represents the independent variable and u represents the transformed variable. From Eq. (6), it is obvious that the ordinary Fourier transform is just a special case of the FRT, when α chosen as 1.

Even though Eq. (6), is a highly simplified representation of the FRT, in practice it is a difficult form to implement. This is specifically