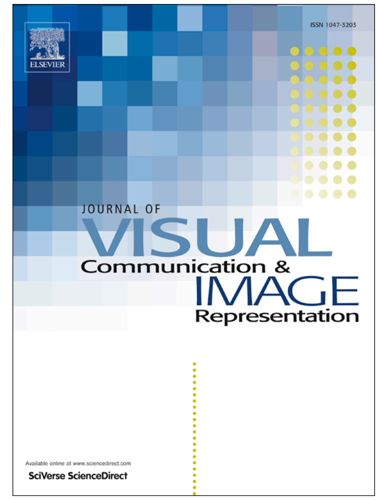

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Rician denosing and deblurring using sparse representation prior and nonconvex total variation

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Abstract

We propose a sparse representation based model to restore an image corrupted by blurring and Rician noise. Our model is composed of a nonconvex data-fidelity term and two regularization terms involving a sparse representation prior and a nonconvex total variation. The sparse representation prior, using image patches, provides restored images with well-preserved repeated patterns and small details, whereas the nonconvex total variation enables the preservation of edges. Moreover, the regularization terms are mutually complementary in removing artifacts. To realize our nonconvex model, we adopt the penalty method and the alternating minimization method. The K-SVD algorithm is utilized for learning dictionaries. Numerical experiments demonstrate that the proposed model is superior to state-of-the-art models, in terms of visual quality and certain image quality measurements.

Keywords: Rician denoising, deblurring, sparse representation, dictionary learning, nonconvex total variation, penalty method, alternating minimization method

1. Introduction

Image deblurring is a basic problem in image processing. Traditionally, image deblurring problems have been considered in the presence of Gaussian noise or impulsive noise [1, 2, 3]. However, real world images can be polluted by more complicated types of noise during the process of image acquisition. For instance, magnetic resonance (MR) images are obtained from the data in the Fourier frequency domain. In the frequency domain, real and imaginary data are polluted by independent zero-mean additive Gaussian noise with the same variance. Since the discrete Fourier transform is a unitary operator, the real and imaginary components still have the characteristic of Gaussian noise. Let us consider the domain of image defined as $\Omega = \{(i_x, i_y) : \ i_x \in \{1, 2, \cdots, M\}, i_y \in \{1, 2, \cdots, N\}\}$. Denote $\mathbf{S}$ by the acquired MR image that is given as follows:

$$\mathbf{S} = \mathbf{S}_R + i\mathbf{S}_I = \mathbf{u} + \eta_1 + i\eta_2,$$

where $\mathbf{u} : \Omega \to \mathbb{R}$ is a true amplitude image so that $\mathbf{u} \in \mathbb{R}^{M\times N}$, and η_1, η_2 are independent zero mean Gaussian noise with standard deviation σ. Indeed, the image $\mathbf{u}$ can be chosen to be real through a rotation of the quadrature detector. Then a measured magnitude MR image $\mathbf{f} \in \mathbb{R}^{M\times N}$ can be given by the following degradation model [4]:

$$\mathbf{f}_s = \sqrt{((\mathbf{Au})_s + (\eta_1)_s)^2 + (\eta_2)_s{}^2}, \tag{1}$$

where $s = (i_x, i_y)$, $\mathbf{a}_s$ means the element of $\mathbf{a}$ at s for given matrix $\mathbf{a}$, and $\mathbf{A}$ is a known blurring operator defined as $\mathbf{Au} = \mathcal{A}*\mathbf{u}$, where $\mathcal{A}$ is a blurring kernel and $*$ denotes the convolution. Since η_1 and η_2 are uncorrelated, the image $\mathbf{f}$ contains noise following a Rician distribution with probability density function

$$P(r\,|\,v, \sigma) = \frac{r}{\sigma^2}\exp\left(-\frac{r^2+v^2}{2\sigma^2} I_0\left(\frac{rv}{\sigma^2}\right)\right),$$

where r is a random variable, $v \geq 0$ is a noncentrality parameter that is the distance between the reference point and the center of the bivariate distribution, and $\sigma > 0$ is a scale parameter. Here I_0 is the zeroth order modified Bessel function of the first kind. In this work, we consider the restoration of MR magnitude images degraded by blurring and Rician noise.

Several variational models have been proposed to recover a true image from an observed image corrupted by blurring and Rician noise. Basu et al. [5] derived a log Rician likelihood

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