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Image Denoising Using Weighted Nuclear Norm Minimization with Multiple Strategies

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ABSTRACT

Low rank methods have shown to provide excellent denoising performance, of which weighted nuclear norm minimization (WNNM) is particularly effective. It assigns different weights to different singular values. However, it has limitations in three aspects, namely, no consideration of the noise effect on the similarity measure, a fixed feedback proportion of method noise, and an inflexible number of iterations for each image. In this paper, a general denoising framework based on WNNM is proposed that offers three strategies to mitigate the above drawbacks. The first strategy is to perform a coarse prefiltering on noisy patches before patch matching. The second is to adaptively feed different percentages of method noise back according to the additive noise levels. And the last strategy is to apply a stopping criterion based on Pearson's correlation coefficient during iteration. Experimental results demonstrate the efficiency of the proposed technique.

Index Terms— Image denoising, low rank, prefiltering, adaptive feedback, stopping criterion

1. INTRODUCTION

Image denoising is one of the most important problems in image processing. The goal is to recover important information of the original image from the corrupted one. This problem is typically written as an inverse problem: given Y, find X that is a smooth approximation of Y in some sense. As far as image denoising is concerned, this problem can be further expressed as $Y = X + N$, where X is a clean image and N is commonly assumed to be additive white Gaussian noise with mean 0 and standard deviation σ.

In earlier work, the image denoising is always assumed to be smooth or sparse under some prior knowledge, such as gradient. A classical model is the total variation (TV) model proposed by Rudin, Osher and Fatemi [1]. It can effectively suppress the noise in an image and preserve the edges of image. However, the recovered image usually suffers from the staircase effect.

Recently, patch-based image denoising with a non-local principle has led to several state-of-the-art algorithms [2-7]. These algorithms exploit the self-similarity of natural images as the prior knowledge. Among them, the block-matching and 3D filtering (BM3D) [3] method has become the benchmark for denoising algorithms. In Rajwade et al [6], the denoising technique using the higher order singular value decomposition (HOSVD) could learn image bases. More recently, another prior-named low rank has also been adopted for image denoising, such as spatially adaptive iterative singular value thresholding (SAIST) [8], low rank regularized collaborative filtering (LRCF) [9] and weighted nuclear norm minimization (WNNM) [10]. This is based on the fact that the matrix formed by stacking non-local similar patches from a noisy image will satisfy the low rank criterion. These algorithms using low rank models can produce outstanding denoising results. Of these, WNNM is particularly effective.

1.1 Motivation

Despite the merits of WNNM, the algorithm has its limitations.

(1) Firstly, it performs block matching to group similar patches on the noisy image. It does not account for the noise effect on the similarity measure. The block matching in this case may result in the deviation of true results.

(2) Secondly, in order to recover some image information contained in the method noise, WNNM adds a proportion of method noise back to the next denoised version in each iteration step. The method noise here, which is also called the residual image, is defined as the difference between the original (not necessarily noisy) image and its denoised version [2, 11-13]. However, WNNM fixes the feedback percentage at 10% regardless of noise levels.