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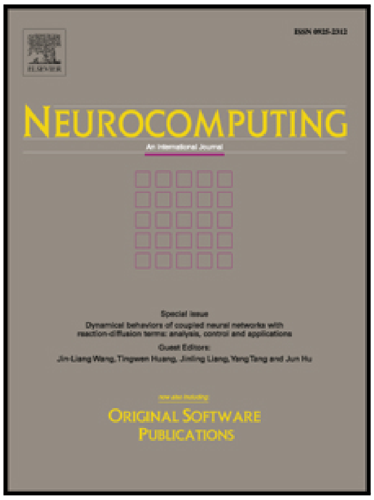

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Enhanced Residual Noise Estimation of Low Rank Approximation for Image Denoising

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Abstract

Recently, the application of rank minimization to image denoising has shown remarkable denoising results. However, due to iterative nature of low rank optimization, the estimation of noise for next iteration is an essential requirement after each iteration. In the existing approaches, the noise is estimated at the level of patches using l_2 norm based comparison of the observed image and its denoised version. Because of l_2 norm comparison, these patch-wise noise estimates may be affected in the presence of moderate and severe levels of noise. Also, the patch-wise noise estimates are inferred without considering the geometric details of a given image. Moreover, the number of iterations is pre-specified, heuristically, depending on the known initial noise in the image which limits the applicability of the existing algorithms for practical situation where the noise level is not a priori. In this paper, we attempt to address these limitations by introducing the notion of *residual noise* for iterative rank minimization. The estimation of residual noise also involves image geometry and statistical characteristics along with patch-wise comparison. In addition to more reliable noise estimation, the residual noise can also be employed as an effective stopping criterion for iterative denoising process. Furthermore, the residual noise estimation is a key factor for computation of thresholding weights, which in turn, yield a more reliable truncated singular value decomposition (SVD) for iterative rank minimization algorithms. Based on more precise truncated SVD, we propose to preserve geometric features like edges and texture in the presence of severe noise. Experimental results show that the proposed method provides better or equivalent results as compared to various state-of-the-art denoising algorithms.

Keywords: Low rank minimization, nuclear norm, singular value decomposition, filtered noise, residual noise, denoising.

1. Introduction

Patch based image denoising in conjunction with the notion of non-locality has led to several state-of-the-art algorithms [1–5]. Prior to these approaches, various neighborhood filtering techniques [6–20] have been employed which are based on variational and PDE based formulations. Despite their pioneering contribution, these approaches are less effective as compared to the above mentioned state-of-the-art algorithms.

The improved performance of the algorithms [1–5] relies on exploiting certain prior knowledge like image redundancy and sparse representation of images in suitable transform domains. These priors are found to be generally valid in case of natural images and greatly improve the denoising results. For instance, the algorithms based on image redundancy prior such as [1, 21, 22] exploit the redundant non-local similar patches over an image to estimate image intensity at each pixel location. It has also been observed that natural images admit sparse decomposition in certain suitable transform domain depending upon the geometric features of the given images. The sparse representation then may lead to enhanced results in various computer vision applications, particularly, in case of image denoising. BM3D [2], for example, performs collaborative filtering on 3D groups of similar non-local patches using pre-designed dictionary (like Haar or DCT transform) to achieve enhanced sparse representation. In contrast to BM3D, another state-of-the-art algorithm LSSC [4] avoids pre-designed dictionary to achieve enhanced sparsity. For sparse representation, LSSC extends dictionary learning approach [3] by exploiting $L_{1,2}$ grouped sparsity regularization to obtain a denoised image.

In addition to sparsity and redundancy priors, a low rank assumption has been effectively employed for various computer vision applications such as image segmentation, face recognition, robust subspace clustering [23–25], and particularly, image denoising [26–30]. According to low rank prior, a matrix constructed by stacking non-local similar patches from a given noisy image resides in a low dimensional subspace of a high dimensional space satisfying the low rank criterion. Dong *et al.* [26] introduced an iterative soft thresholding scheme (SAIST) using $L_{1,2}$ grouped sparsity regularization to penalize the singular values of the low rank matrices. More recently, Gu *et al.* [28] have further explored the low rank prior using weighted nuclear norm minimization (WNNM). This algorithm exploits the significance of the singular values and treats them differently according to their respective magnitudes. Also, Guo *et al.* [29] employed low rank approximation for image denoising. However, in contrast to iterative scheme of WNNM and SAIST, they adopted two step scheme as used in BM3D and LPG-PCA [31] algorithms. These rank minimization algorithms [26, 28, 29] have produced outstanding denoising results

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