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# A Review of an Efficient SVD-Based Method for Image Denoising

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***Abstract*** *– Image denoising could be a well explored topic within the field of image process. Within the past many decades, the progress made in image denoising has benefited from the improved modeling of natural pictures. a picture could be a price, thousand words & during this digital age, pictures are everyplace. Most of the digital pictures contain some kind of noise. Purpose of denoising is to reconstruct the initial image from its abuzz observation as accurately as possible. The necessary property of a good image denoising model is that it ought to fully remove noise as way as possible. during this paper, we tend to study of propose methodology a computationally easy denoising algorithmic rule using the nonlocal self-similarity and therefore the low-rank approximation (LRA).*

***Keywords****: Back projection, image denoising, low-rank approximation (LRA), patch grouping, self-similarity, singular value decomposition (SVD).*

## I. Introduction

Denoising is a fundamental and widely studied problem in image processing. Various denoising methods have been proposed following different disciplines such as statistics, variation theory, etc. Most of these methods exploit the local correlation of image pixels. Recently, the introduction of NLM opens the floodgate to the exploitation of nonlocal similarities inherent in natural images for denoising and other applications [1], [2]. The NLM estimates each pixel by the weighted average of many pixels in the image, and the weights are respectively evaluated according to pair-wise similarity between two patches. The advantage of NLM is that it greatly reduces the interference of noise and well preserves the details such as edges and textures in the denoised image.

Digital pictures play a very important in analysis and technology. It's the most important part within the field of medical science like ultrasound imaging, X-ray imaging, laptop tomography and MRI. a really giant portion of digital image processing includes image restoration. Image restoration could be a technique of removal or reduction of degradation that are incurred throughout the image capturing. Degradation comes from blurring also as noise because of the electronic and photometrical sources. Generally, denoising algorithms may be roughly classified into 3 categories: spatial domain strategies, transform domain strategies and hybrid strategies. Throughout acquisition and transmission, pictures are inevitably contaminated by noise. As a necessary and important step to enhance the accuracy of the potential resultant process, image denoising is very desirable for various applications, like visual improvement, feature extraction and object recognition.

Digital pictures play a very important role each in lifestyle applications like satellite TV, magnetic resonance imaging, pc tomography likewise as in areas of analysis and technology like geographical data systems and astronomy. Information sets collected by image sensors are typically contaminated by noise. Imperfect instruments, issues with the information acquisition method, and interfering natural phenomena will all degrade the information of interest. Moreover, noise may be introduced by transmission errors and compression. Thus, denoising is usually a necessary and also the first step to be taken before the pictures information is analyzed. It's necessary to use an efficient denoising technique to compensate for such information corruption. Image denoising still remains a challenge for researchers as a result of noise removal introduces artifacts and causes blurring of the pictures. The sparsity of signals and pictures during a sure transform domain or dictionary has been heavily exploited in signal and image process. it's acknowledge that natural signals and pictures have an essentially sparse representation (few important non-zero coefficients) in analytical transform domains like discrete cosine transform (DCT) and wavelets.

## II. Literature Survey

Qiang Guo et al. [1] "An Efficient SVD-Based Method for Image Denoising", In this paper, we have presented a simple and efficient method for image denoising, which takes advantage of the nonlocal redundancy and the LRA to attenuate noise. The nonlocal redundancy is implicitly used by the block-matching technique to construct low-rank group matrices. After factorizing by SVD, each group matrix is efficiently approximated by preserving only a few largest singular values and corresponding singular vectors. This is due to the optimal energy compaction property of SVD. In fact, the small singular values have little effect on the approximation of the group matrix when it has a low-rank structure. The experimental results demonstrate the advantages of the proposed method in comparison with current state-of the-art denoising methods. The computational complexity of the proposed algorithm is lower than that of most of the existing state-of-the-art denoising algorithms, but higher than BM3D. The fixed transform used by BM3D is less complex than SVD, whereas it is less adapted to edges and textures. The main computational cost of our algorithm is the calculation of SVD for each patch group matrix. As each group matrix could potentially be processed independently in parallel, our method is suitable for parallel processing. Therefore, in practice, we can use a parallel implementation to speed it up, which will make it feasible for real-time or near real-time image denoising. In addition, while developed for grayscale images, our method can be extended to shape-adaptive color image and video denoising by taking into account the shape-adaptive patches and the temporal redundancy across color components and frames. This further work will be studied in the future.

Florian Luisier et al. [2] "SURE-LET for Orthonormal Wavelet-Domain Video Denoising", In this letter, we have presented a relatively easy and however very efficient orthonormal wavelet-domain video denoising algorithmic rule. Because of a correct selective block-matching procedure, the result of motion compensation on the noise statistics became negligible, and an adapted multiframe interscale SURE-LET thresholding might be applied. The projected algorithmic rule has been shown to favorably compare with most progressive redundant wavelet-based approaches, whereas having a lighter computational load. However, it's necessary to increase the shift-invariance of the projected resolution to achieve a similar level of performance because the best video denoising algorithms obtainable.

Hossein Talebi et al. [3] "How to SAIF-ly Boost Denoising Performance", in this paper presented a framework for improved denoising by data-dependent kernels. Given any spatial domain filter, we can boost its performance to near state-of-the-art by employing optimized iteration methods. This iterative filtering is implemented patch-wise. Armed with diffusion and boosting as two complementary iteration techniques, each patch is filtered by the optimum local filter. More specifically, by exploiting the best iteration number and method which minimizes MSE in each patch, SAIF is capable of automatically adjusting the local smoothing strength according to local SNR. The experimental results demonstrate that the proposed approach improves the performance of kernel based filtering methods in terms of both PSNR (MSE) and subjective visual quality.

Ling Shao et al. [4] "From Heuristic Optimization to Dictionary Learning: A Review and Comprehensive Comparison of Image Denoising Algorithms", In this paper, we reviewed and compared representative denoising methods both qualitatively and quantitatively. These methods have been divided into three categories: spatial domain, transform domain, and dictionary learning based. Extensive experiments were conducted to evaluate the performance of all the algorithms. Through analytical comparison, it was found that image representations with over complete basis functions improve the performance within each category. In spatial filters, KSPR improves kernel regression based methods in high noise levels. In the transform domain, over complete wavelets are used in BLS-GSM to overcome the shortcomings of critically sampled wavelets. In dictionary learning based algorithms, it has been proved that the redundant dictionary based K-SVD outperforms the DCT based K-SVD [42]. In general, over complete basis functions are more adaptive to image contents, which can bring better denoising results. The major disadvantage of over complete representations is that they usually result in computational burden. Another interesting trend observed in these results is the importance of nonlocal grouping. In each category, the performance of the methods with nonlocal grouping is significantly better than that of the methods without nonlocal grouping. For instance, NLM outperforms TF, BM3D surpasses BLS-GSM, and LSSC enahnces K-SVD. In addition, adaptive basis functions in image representations contribute better to edge-preserving, which has been proved in our evaluation that dictionary learning based methods generally produce better visual results. Moreover, multiresolution structures in the transform domain benefit the edge/detail preserving.

Charles-Alban Deledalle et al. [5] "Non-Local Methods with Shape-Adaptive Patches (NLM-SAP)", patch effect arising in the NL-Means procedure and responsible of the noisy halos created around high contrasted edges. The proposed solution consists in substituting the square patches of fixed size by spatially adaptive patch shapes. A fast implementation of NL-Means, based on FFT calculations, has been proposed in this context to handle any kind of patch shape with arbitrary scale. Thanks to this acceleration, different estimates are obtained by using different patch shapes, typically one isotropic patch shape and four edge oriented patch shapes, all of them with three different scales. We have extended SURE-based approaches to aggregate properly these different shape-based estimates in a spatially adaptive way. To get an efficient locally adaptive filter, we have shown that the SURE-based risk maps require to be regularized and that anisotropic diffusion can be used to this purpose. Simulations have shown that exponentially weighted aggregation based on the regularized risk maps of the different shape-based estimates could lead to both numerical and visual improvements (the noise halo is suppressed around edges). Our method out-performs all the NL-Means improvements we have considered in our comparisons but is still out- performed by BM3D in terms of PSNR and SSIM.

# III. Method

## *III.1. Singular Value Decomposition (SVD)*

Singular value decomposition (SVD) first groups' image patches by a classification algorithm to achieve many groups of similar patches. Then each group of similar patches is estimated by the low-rank approximation in SVD domain. The denoised image is finally obtained by aggregating all processed patches. The SVD is a very suitable tool for estimating each group because it provides the optimal energy compaction in the least square sense. The main motivation to use SVD in this method is that it provide the optimal energy compaction in that it provides the optimal energy compaction in the least square sense, which implies that the signal noise can be better distinguished in SVD domain.Fig.1 shows the concept of SVD method. The patch grouping step identifies similar image patches by the Euclidean distance based similarity metric. Once the similar patches are identified, they can be estimated by the low-rank approximation in the SVD-based denoising step. In the aggregation step, all processed patches are aggregated to form the denoised image. The back projection step uses the residual image to further improve the denoised result.

For ease of presentation, let A denote a noisy image defined by:

$$A = P + E$$

where P is the noise-free image, and E represents additive white Gaussian noise (AWGN) with standard deviation $\tau$ which, in practice, can usually be estimated by various methods such as median absolute deviation (MAD), SVD-based estimation algorithm and block-based ones.

SVD has two stages: the first stage produces an initial estimation of the image x, and the second stage further improves the result of the first stage. Different from them, this method adopts the low-rank approximation to estimate image patches and uses the back projection to avoid loss of detail information of the image. Each stage contains three steps: patch grouping, SVD-based denoising and aggregation. In the first stage, the noisy image y is firstly divided into M overlapping patches. Next, each similar patch group is denoised by the low-rank approximation in SVD domain. Thirdly, the denoised image x0 is achieved by aggregating all denoised patches. In the second stage, the final denoised image is obtained by applying the processing steps described above on the image y produced by the back projection process.

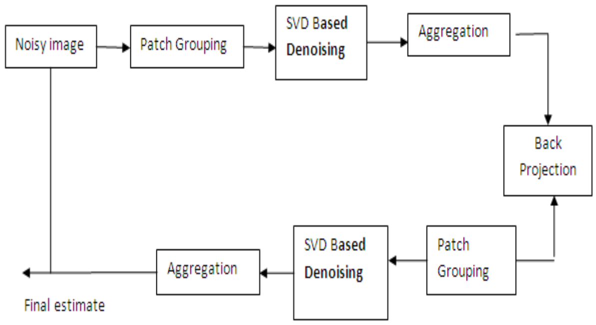


Fig.1 Block diagram of SVD denoising

# IV. Abbreviation and Acronyms

This paper has reviewed the in the main latest analysis trends and [proposed the image denoising techniques is used. Some analysis papers were mentioned, all specializing in different aspects & techniques of image denoising. the planned technique will effectively reduce noise and be competitive with this state-of-the-art denoising algorithms in terms of each quantitative metrics and subjective visual quality.

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