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Denoising of an Image with SVD-Based Method

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Abstract

Nonlocal self-similarity of images has attracted considerable interest in the field of image processing and led to several state-of-the-art image denoising algorithms, such asBM3D, LPG-PCA, PLOW and SAIST. In this paper, we propose a computationally simple denoising algorithm by using the nonlocal self-similarity and the low-rank approximation. The proposed method consists of three basic steps. Firstly, our method classifies similar image patches by the block matching technique to form the similar patch groups, which results in the similar patch groups to be low-rank. Next, each group of similar patches is factorized by singular value decomposition (SVD) and estimated by taking only a few largest singular values and corresponding singular vectors. Lastly, an initial denoised image is generated by aggregating all processed patches. For low-rank matrices,SVD can provide the optimal energy compaction in the least square sense.

The proposed method exploits the optimal energy compaction property of SVD to lead a low-rank approximation of similar patch groups. Unlike other SVD-based methods, the low-rank approximation in SVD domain avoids learning the local basis for representing image patches which usually is computationally expensive. Experimental results demonstrate that the proposed method can effectively reduce noise and be competitive with the current state-of-the-art denoising algorithms in terms of both quantitative metrics and subjective visual quality.

INTRODUCTION

During acquisition and transmission, images are inevitably contaminated by noise. As an essential and important step to improve the accuracy of the possible subsequent processing, image denoising is highly desirable for numerous applications, such as visual enhancement, feature extraction and object recognition.

The purpose of denoising is to reconstruct the original image from its noisy observation as accurately as possible, while preserving important detail features such as edges and textures in the denoised image. To achieve this goal, over the past several decades, image denoising has been extensively studied in the signal processing community, and numerous denoising techniques have been proposed in the literature. Generally, denoising algorithms can be roughly classified into three categories: spatial domain methods, transform domain methods and hybrid methods. The first class utilizes the spatial correlation of pixels to smooth the noisy image, the second one exploits the sparsity of representation coefficients of the signal to distinguish the signal and noise, and the third one takes advantage of spatial correlation and sparse representation to suppress noise.

PROPOSED METHOD:

Based on the analysis of SVD in Section II, we propose an efficient method to estimate the noise-free image by combining patch grouping with the low-rank approximation of SVD(abbreviated as LRA-SVD), which leads to an improvement of denoising performance. The main motivation to use SVD in our method is that it provides the optimal energy compaction in the least square sense, which implies that the signal

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and noise can be better distinguished in SVD domain. Fig. 1 illustrates block diagram of the proposed approach. Concretely, 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 **Y** denote a noisy image defined by

$$\mathbf{Y} = \mathbf{X} + \mathbf{E} \qquad (10)$$

where **X** is the noise-free image, and **E** represents additivewhite Gaussian noise (AWGN) with standard deviationτ which, in practice, can usually be estimated by variousmethods such as median absolute deviation (MAD) ,SVDbasedestimation algorithm and block-based ones, .In this paper, we use a vectorized version of the model, i.e.

$$\mathbf{y} = \mathbf{x} + \mathbf{e}. \qquad (11)$$

Given a noisy observation **y**, our aim is to estimate **x** asaccurately as possible.As similarly done in BM3D and LPG-PCA, the proposedmethod also has two stages: the first stage produces an initialestimation of the image **x**, and the second stage furtherimproves the result of the first stage. Different from them,our method adopts the low-rank approximation to estimateimage patches and uses the back projection to avoid loss ofdetail information of the image. Each stage contains threesteps: patch grouping, SVD-based denoising and aggregation.In the first stage, the noisy image **y** is firstly divided into$M$ overlapping patches denoted by $\{\mathbf{y}i\}Mi$=1, where $\mathbf{y}i$is a vectorized format of the i-th image patch. For each patch $\mathbf{y}j$,its similar patch group is formed by searching similar patchesfrom $\{\mathbf{y}i\}Mi$=1. Next, each similar patch group is denoisedby the low-rank approximation in SVD domain. Thirdly, thedenoised image b$\mathbf{x}$0 is achieved by aggregating all denoisedpatches. In the second stage, the final denoised image isobtained by applying the processing steps described above onthe image e$\mathbf{y}$produced by the back projection process. In therest of this section, the procedures of our proposed methodwill be described in detail.

Patch Grouping:

Grouping similar patches, as a classification problem, isan important and fundamental issue in image and videoprocessing with a wide range of applications. While thereexist many classification algorithms available in the literature,e.g., block matching, *K*-means clustering, nearest neighborclustering and others [40], we exploit the block matchingmethod for image patch grouping due to its simplicity.For each given reference patch **y***j*with size$\sqrt{m}\times\sqrt{m}$ the block matching method finds its similar patches from $\{y_i\}_i^M=1$by a similarity metric. In [22], the Euclidean distance fromthe transform coefficients is used to identify the similar squarepatches. A shape-adaptive version of this similarity metric ispresented in [23], whereas it leads to a high computationalcost. The simplest measure of similarity between two patches

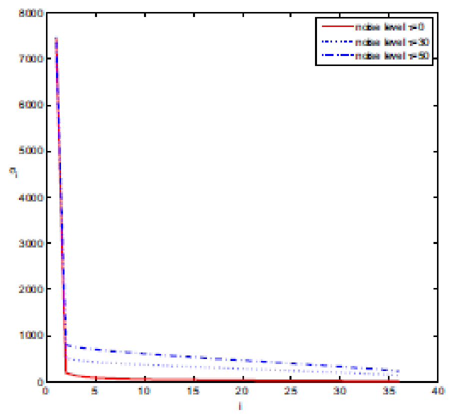

Fig. 2. Singular values of group matrices of *Lena* image with different noiselevels.

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is the Euclidean distance directly in the spatial domain. Thuswe employ the spatial Euclidean distance as our similaritymetric, which is defined by

$$S(\mathbf{y}_j, \mathbf{y}_c) = \|\mathbf{y}_j - \mathbf{y}_c\|_2^2 \quad (12)$$

where‖ • ‖ 2 denotes the Euclidean distance and $\mathbf{y}c$is acandidate patch. The smaller $S(\mathbf{y}j, \mathbf{y}c)$ is, the more similar$\mathbf{y}j$and $\mathbf{y}c$are. The reference patch $\mathbf{y}j$and its L-most similarpatches denoted by $\{\mathbf{y}c,i\}^L i$ =1, are chosen to construct a groupmatrix by using each similar patch as a column of the groupmatrix, and its corresponding group matrix $\mathbf{P}j$is formed by

$$\mathbf{P}_j = [\mathbf{y}_j, \mathbf{y}_{c,1}, \ldots, \mathbf{y}_{c,L}]. \quad (13)$$

Due to $\mathbf{P}j$being made up of the noisy patches, it can berepresented as

$$\mathbf{P}_j = \mathbf{Q}_j + \mathbf{N}_j \quad (14)$$

where$\mathbf{Q}j$and $\mathbf{N}j$denote the noise-free group matrix and thenoise matrix, respectively

In general, the number L of similar patches in the groupmatrix cannot be too small. Too small L leads to too fewpatches within each group matrix, which makes the SVDbaseddenosing less robust. On the contrary, too large one leadsto dissimilar patches being grouped together, which resultsi√n an incorrect estimation of $\mathbf{P}j$. Similarly, the patch size$\sqrt{m}\times\sqrt{m}$ also has an impact on the performance of ourmethod.

SVD-Based Denoising:

For simplicity of discription, we will use $\mathbf{Q}$ and $\mathbf{P}$ insteadof $\mathbf{Q}j$and $\mathbf{P}j$by a slight abuse of notation. Now our taskis to estimate the noise-free group matrix $\mathbf{Q}$ from its noisyversion $\mathbf{P}$ as accurately as possible. Ideally, the estimate $\mathbf{Q}$should satisfy

$$\|\mathbf{P} - \widehat{\mathbf{Q}}\|_F^2 = \tau^2 \quad (15)$$

where‖ • ‖ F is the Frobenius norm1 and τ is the standard deviation of noise.

The similarity between patches within the noise-free image $\mathbf{x}$ leads to a high correlation between them, which means that $\mathbf{Q}$ is a low-rank matrix. Fig. 2 illustrates the low-rank property of $\mathbf{Q}$ by displaying the singular values of group matrices of *Lena* image with different noise levels, where each point is the average i-th singular value over all group matrices. The estimate of $\mathbf{Q}$ can be obtained by the low-rank approximation in the least square sense. Therefore, we can estimate $\mathbf{Q}$ from $\mathbf{P}$ by solving the following optimization problem

$$\widehat{\mathbf{Q}} = \arg\min_{\mathbf{Z}} \|\mathbf{P} - \mathbf{Z}\|_F^2 \quad s.t. \quad \mathrm{rank}(\mathbf{Z}) = k \quad (16)$$

where rank(•) denotes the rank of matrix $\mathbf{Z}$.In SVD domain, $\mathbf{P}$ can be represented as

$$\mathbf{P} = \mathbf{U\Sigma V}^T. \quad (17)$$

Let

$$\mathbf{P}_k = \mathbf{U\Sigma}_k\mathbf{V}^T \quad (18)$$

where$\mathbf{\Sigma}k$is obtained from the matrix $\mathbf{\Sigma}$ by setting thediagonal elements to zeros but the first k singular values, i.e.

$$\mathbf{\Sigma}_k = \mathrm{diag}(\sigma_1, \ldots, \sigma_k, 0, \ldots, 0). \quad (19)$$

$\mathbf{P}k$is the solution of (16), which is a classical result given bythe Eckart-Young-Mirsky Theorem.*Theorem 1 (Eckart-Young-Mirsky):* For any real matrix $\mathbf{P}$,if the matrix $\mathbf{Q}$ is of rank k, then

$$\|\mathbf{P} - \mathbf{Q}\|_F^2 \geq \sum_{i=k+1}^{n} \sigma_i^2 \quad (20)$$

whereσi(i= 1,……. n) are the singular values of $\mathbf{P}$, andequality is attained when $\mathbf{Q} = \mathbf{P}_k$is defiend by (18).This theorem shows that $\mathbf{P}k$is the optimal solution for (16)in the Frobenius norms sense. Thus, we have

$$\widehat{\mathbf{Q}} = \mathbf{P}_k. \quad (21)$$

The key issue for this method is to determine the value of k.By comparing (15) with (20), we can find that $\mathbf{P}k$is

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the idealestimate of **P** whenΣi^n=k+1 $\sigma^2_i$is equal to τ^2. Therefore, $k$can be determined by the following criterion

$$\sum_{i=k}^{n} \sigma_i^2 > \tau^2 \geq \sum_{i=k+1}^{n} \sigma_i^2. \qquad (22)$$

Aggregation:

Until now, we have estimated each group matrix by applyingthe low-rank approximationdefined by (21). Then the denoisedpatches can be obtained by rearranging column vectors of eachdenoised group matrix. As a result of taking the L nearestneighbors of each patch to construct a group matrix, a singlepatch might belong to several groups, and multiple estimatesof this patch can be obtained. Thus we aggregate differentestimates of this patch to obtain its denoised version by thefollowing averaging process.

$$\widehat{\mathbf{x}}_i = \frac{1}{n}\sum_{j=1}^{n} \widehat{\mathbf{x}}_{i,j} \qquad (23)$$

whereb**x**$i$is the denoised version of a patch **y**i, and b**x**$i;j$(j =1, . . . , n) denote n different estimates of **y**i.The next step is to synthesize the denoised image from thedenoised patches. Since the patches are sampled with overlappingregions for avoiding block artifacts at the boundariesof patches, multiple estimates are obtained for each pixel.Thus these estimates of each pixel in the image need tobe aggregated to reconstruct the final denoised image. Thecommon method of combining such multiple estimates isto perform a weighted averaging of them. Meanwhile, theweighted averaging procedure can suppress noise further. Thesimplest form of aggregation is the uniformly weighted averagingwhich assigns the same weight to all estimates. However,the uniform weights will lead to an over-smoothened result. Ingeneral, the adaptive weights derived from various biased andunbiased estimators, such as variance-based weights, SUREbasedweights and exponential weights [10], can lead to betterresults. Different from these adaptive weights, in this paper,we exploit the weights depending on the rank k of each groupmatrix due to its simplicity. For the j-th group matrix b**Q**j, ourweight is defined by

$$w_j = \begin{cases} 1 - \frac{k}{L+1}, & k < L+1, \\ \frac{1}{L+1}, & k = L+1. \end{cases} \qquad (24)$$

If $k < L + 1$, it means that patches in the group matrixare linearly correlated. The higher the degree of correlation ofpatches is, the smaller the rank k of the group matrix is. Theestimate of patches yielded from the low-rank approximation isbetter. Thus, this estimate needs to be assigned a high weight.If $k = L + 1$, there exists no correlation among patches. Thesimplest uniform weight is used. Based on the weights definedin (24), the denoised estimate for the i-th pixel of the imagecan be expressed as

$$\hat{x}_i = \frac{1}{W}\sum_{j\in\Gamma(x_i)} w_j \hat{x}_{i,j} \qquad (25)$$

whereWis a normalizing factor defined by

$$W = \sum_j w_j, \qquad (26)$$

T(x_i) denotes the index set of all similar group matrices containing the pixel xi, which described as

$$\Gamma(x_i) = \{j | x_i \in \mathbf{Q}_j, j = 1, \ldots, C\}, \qquad (27)$$

and$x_{i;j}$denotes the denoised estimate of the i-th pixel in the$j$-th similar group matrix **Q**j. Once all pixels are estimated by(25), the final denoised image can be obtained by reshapingthe estimates of all pixels.

Back Projection

Although most of noise can be removed by using thedenoising procedures described before, there still exists a smallamount of noise residual in the denoised image. The noiseresidual stems from the fact that noise in the original noisyimage affects the accuracy of the patch grouping, which leadsto an inaccurate group. The

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grouping errors in turn affect theSVD-based denoising. In addition, there exists another reasonfor noise residual. Ideally, based on the discussion in SectionIII-B, the optimal estimate **Q** satisfies.

$$\|\mathbf{P}-\widehat{\mathbf{Q}}\|_F^2=\|\mathbf{P}-\mathbf{Q}\|_F^2 \implies \|\mathbf{P}-\widehat{\mathbf{Q}}\|_F^2=\|\mathbf{N}\|_F^2 \implies \sum_{i=k+1}^{n}\sigma_i^2=\tau^2. \tag{28}$$

Unfortunately, the left side of (28) is not usually equal to theright side. In most cases, it is that $\tau^2 > \Sigma_i{}^n = k+1\alpha_i^2$ Therefore,we need to further improve the denoising performance of our method.

The commonly used way to further improve the performanceof a denoising method, as used by K-LLD [43] andSAIST, is to develop an iterative version for the basic denoisingmethod. While the iterative strategy for image denoisinghas been widely used in the literature, it has a very high computational cost which limits the scope of applications. Analternative way exploited by BM3D and LPG-PCA is the twostageapproach, in which the basic estimate of the noisy imageyielded by the denoising method is used as a reference imageto perform improved grouping and parameter estimation.

In this paper, unlike the iteration-based or the referencebasedstrategies, we make use of the two-stage strategy witha back projection step to further suppress the noise residual.Back projection is an efficient method that uses the residualimage to improve the denoised result [44], [45]. In fact, the useof the residuals in improving estimates can date at least backto John Tukey's classic book [46], in which this idea is termed*twicing*. This concept is also known by several names, such asBregman iterations, *l*2-boosting, and biased diffusion. A recentpaper [47] provides a good overview of these methods. Thebasic idea of back projection is to generate a new noisy imagey adding filtered noise back to the denoised image, i.e.

$$\widetilde{\mathbf{y}}=\widehat{\mathbf{x}}_0+\delta(\mathbf{y}-\widehat{\mathbf{x}}_0) \tag{29}$$

where$\delta \in (0, 1)$ is a constant projection parameter and b**x**0is the denoised result produced by the first stage. Note thatwhen $\delta \rightarrow 0$, e**y**→ b**x**0. On the contrary, if $\delta \rightarrow 1$, e**y**→ **y**.For simplicity, in our experiments, we set $\delta = 0.5$, which is atrade-off between 1 and 0.Now we can achieve an improved result of b**x**0 by denoisinge**y**with the proposed three processing steps in previoussubsections, i.e., *patch grouping*, *SVD-based denoising*, and*aggregation*. It is necessary to point out that the noise varianceof e**y**, denoted as eτ2, needs to be updated in the SVD-baseddenoising step. We employ the estimator presented in todetermine eτ2, which is written as

$$\widetilde{\tau}=\gamma\sqrt{\tau^2-\|\mathbf{y}-\widehat{\mathbf{x}}_0\|_F^2} \tag{30}$$

whereγ is a scaling factor

PROPOSED ALGORITHM:

To summarize, the complete procedure of our proposedmethod is algorithmically described in the following Algorithm1.

Algorithm 1 The proposed denoising algorithm

Input: Noisy image $\mathbf{y}$

Output: Denoised image $\widehat{\mathbf{x}}$

1: $\tau \leftarrow$ Estimate noise standard deviation by computing the median absolute deviation (MAD) of the finest wavelet coefficients as described in [36];
2: $\{\mathbf{P}_j\}_{j=1}^{C} \leftarrow$ Group image patches with the similarity metric defined by Eq. (12) and form group matrices;
3: **for each** $j \in [1, C]$ **do**
4: $\widehat{\mathbf{Q}}_j \leftarrow$ Calculate the low-rank approximation of $\mathbf{P}_j$ via Eq. (21);
5: $w_j \leftarrow$ Compute the weight for $\widehat{\mathbf{Q}}_j$ via Eq. (24);
6: **end for**
7: $\widehat{\mathbf{x}}_i \leftarrow$ For each patch existing multiple different estimates, aggregate its estimates via Eq. (23).
8: $\widehat{\mathbf{x}}_0 \leftarrow$ Aggregate all $\widehat{\mathbf{Q}}_j$ via Eq. (25);
9: $\widetilde{\tau} \leftarrow$ Update the noise standard deviation τ via Eq. (30);
10: $\widetilde{\mathbf{y}} \leftarrow$ Generate a new noisy image via the back projection described by Eq. (29);
11: $\widehat{\mathbf{x}} \leftarrow$ Obtain the final denoised image by performing *Step 2* to *Step 8* for $\widetilde{\mathbf{y}}$.

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BLOCK DIAGRAM:

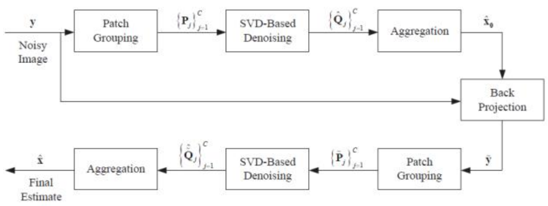

Fig. 1. Block diagram of the proposed denoising algorithm.

Let **X** be a grayscale image. The basic principle of linearimage representation is that the signal of interest can bedecomposed into a weighted sum of a given representationbasis. Thus, **X** can be represented as

$$\mathbf{X} = \sum_{i=1}^{N} a_i \phi_i \qquad (1)$$

where $ai(i= 1, . . . ,N)$ are the representation coefficients ofthe image **X** in term of the basis functions $\phi i(i= 1, . . . ,N)$.ϕican either be chosen as a prespecified basis, such as, curvelet,contourlet,shearlet and otherdirectional basis, or designed by adapting its content to fit agiven set of images. In general, an adaptive basis has betterperformance than the prespecified one.In [20], Aharon*et al*. proposed a learning method to achievea set of adaptive basis (also called dictionary). This methodextracts all the$\sqrt{m} \times \sqrt{m}$ patches from the image **X** toform a data matrix **S** = (**s**1, **s**2, . . . , **s***n*) ∈ *Rm_n*, where*m* is the number of pixels in each patch, **s***i*(*i*= 1, . . . , *n*)are image patches ordered as columns of **S** and *n* is thenumber of patches. Then the dictionary is learned by solvingthe following optimization problem

$$\min_{\mathbf{\Phi},\mathbf{A}} \sum_{i=1}^{n} \|\mathbf{s}_i - \mathbf{\Phi}\mathbf{a}_i\|_2^2 \quad s.t. \quad \|\mathbf{a}_i\|_0 \leq \beta \qquad (2)$$

where $\mathbf{\Phi} \in R^{M\times P}$is the dictionary of *p* column atoms,**A** = (**a**1, **a**2, . . . , **a***n*) ∈ $\mathbf{R}^{P\times N}$is a matrix of coefficients,β indicates the desired sparsity level of the solution, and thenotation // **a***i*// 0 stands for the count of the nonzero entries in**a***i*. Based on the learned dictionary **Φ**, **S** can be representedas

$$\mathbf{S} = \mathbf{\Phi}\mathbf{A}. \qquad (3)$$

Another method for image representation with adaptivebasis selection is principle component analysis (PCA) [32],which determines the basis from the covariance statistics ofthe data matrix **S**. The principal components transform of **S**is calculated as

$$\mathbf{A} = \mathbf{\Phi}^T(\mathbf{S} - E(\mathbf{S})) \qquad (4)$$

with**Φ** defined by

$$\mathbf{\Omega_S} = \mathbf{\Phi}\mathbf{\Lambda}\mathbf{\Phi}^T \qquad (5)$$

where*E*(**S**) is the matrix of mean vectors, **ΩS** is thecovariance matrix of **S**, **Φ** is the eigenvector matrix, and **Λ** = diag(λ1, . . . , λm) is the diagonal eigenvalue matrix with

$$\lambda_1 \geq \lambda_2 \geq, \ldots, \geq \lambda_m. \qquad (6)$$

It can easily be derived that the covariance matrix **ΩA** of thematrix **A** equals to

$$\mathbf{\Omega_A} = \mathbf{\Phi}^T\mathbf{\Omega_S}\mathbf{\Phi} = \mathbf{\Lambda} \qquad (7)$$

which implies that the entries of **A** are uncorrelated. Thisproperty of PCA can be used to distinguish between the signal and noise. It is because the energy of noise is generally spreadover the whole transform coefficients, while the energy of asignal is concentrated on a small amount of coefficients.One major shortcoming of the adaptive dictionary and PCAis that they impose a very high computational burden. Analternative method for adaptive basis selection is the singularvalue decomposition (SVD). The SVD of the data matrix **S** isa decomposition of the form

$$\mathbf{S} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T = \sum_{i=1}^{n} \sigma_i \mathbf{u}_i \mathbf{v}_i^T \qquad (8)$$

where**U** = (**u**1, . . . , **u***n*) ∈ *Rm_n*and **V** = (**v**1, . . . , **v***n*) ∈*Rn_n*are matrices with orthonormal columns, **U***T***U** =**V***T***V** = **I**, and where the diagonal matrix **Σ** =diag(σ1, . . . , σn) has nonnegative diagonal elements appearingin nonincreasing order such that

$$\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_n \geq 0. \qquad (9)$$

The diagonal entries $\sigma i$of $\mathbf{\Sigma}$ are called the singular valuesof **S**, while the vectors **u***i*and **v***i* are the left and rightsingular vectors of **S**, respectively. The product **u***i***v***Ti*in (8)can be considered as an adaptive basis, and σias representationcoefficient.In fact, SVD and PCA are intimately related. PCA can beperformed by calculating the SVD of the data matrix $p1N$**s***t*(Refer to [35] for more details). In addition, if a matrix is lowrank,we can easily estimate it from its noisy version by thelow-rank approximation in SVD domain. Thus, we propose anew denoising method by using SVD instead of PCA in thefollowing section, which has a low computational complexity.

EXPERIMENTAL RESULTS:

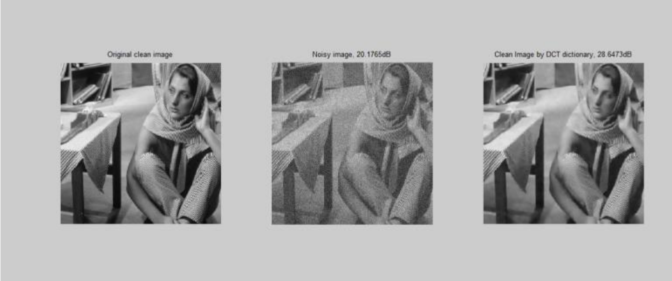

Fig: original, noisy, filtered images

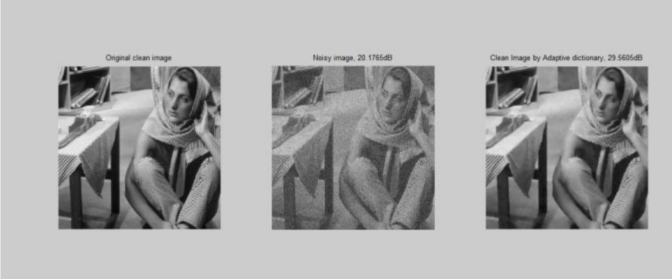

Fig: original, noisy, filtered images

To demonstrate the efficacy of the proposed denoisingalgorithm, in this section, we give our experimental resultsconcerning simulations that have been conducted on tennatural grayscale images with size 512 × 512. These imageshave been commonly used to validate many state-of-the-artdenoising methods. The noisy images are generated by addingzero mean white Gaussian noise with different levels to the testimages. The noise level τ is from 10 to 50, and the intensity value for each pixel of the images ranges from 0 to 255.

Evaluation Criteria:

Two objective criteria, namely peak signal-to-noise ratio(PSNR) and feature-similarity (FSIM) index [48], are adoptedto provide quantitative quality evaluations of the denoisingresults. PSNR is the mostly widely used quality measure inthe literature, even though it is often inconsistent with humaneye perception. FSIM measures the similarity between twoimages by combining the phase congruency feature and thegradient magnitude feature, which is based on the fact thathuman visual system (HVS) understands an image mainlyaccording to its low-level features. The aforementioned criteriacan comprehensively reflect the performance of the denoisingmethods.

CONCLUSION:

In this paper, we have presented a simple and efficientmethod for image denoising, which takes advantage of thenonlocal redundancy and the low-rank approximation to attenuatenoise. The nonlocal redundancy is implicitly used bythe block matching technique to construct low-rank groupmatrices. After factorizing by SVD, each group matrix isefficiently approximated by preserving only a few largestsingular values and corresponding singular vectors. This isdue to the optimal energy compaction property of SVD.In fact, the small singular values have little effect on theapproximation of the group matrix when it has a low-rankstructure. Experimental results demonstrate the advantages ofthe proposed method in comparison with current state-of-theartdenoising methods.The computational complexity of the proposed algorithmis lower than most of existing state-of-the-art denoising algorithmsbut higher than BM3D. The fixed transform usedby BM3D is less complex than SVD, whereas it is lessadapted to edges and textures. The main computational costof our algorithm is the calculation of SVD for each patch group matrix. As each group matrix could potentially beprocessed independently in parallel, our method is suitablefor parallel processing. Therefore, in practice, we can use aparallel implementation to speed it up, which will make itfeasible for real-time or near real-time image denoising. Inaddition, while developed for grayscale images, our methodcan be extended for shape-adaptive color image and videodenoising by taking into account the shape-adaptive patchesand the temporal redundancy across color components andframes. This further work will be studied in the future.

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