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A Novel Image Denoising By Targeted External Databases

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Abstract----
In recent years, over complete dictionaries combined with sparse learning techniques became extremely popular in computer vision. While their usefulness is undeniable, the improvement they provide in specific tasks of computer vision is still poorly understood.

The aim of the present work is to demonstrate that for the task of image denoising; nearly state-of-the-art results can be achieved using orthogonal dictionaries only, provided that they are learned directly from the noisy image. To this end, we introduce three patch based denoising algorithms which perform hard thresholding on the coefficients of the patches in image-specific orthogonal dictionaries.

The algorithms differ by the methodology of learning the dictionary: local PCA, hierarchical PCA and global PCA. We carry out a comprehensive empirical evaluation of the performance of these algorithms in terms of accuracy and running times. The results reveal that, despite its simplicity, PCA-based denoising appears to be competitive with the state-of-the-art denoising algorithms, especially for large images and moderate signal-to-noise ratios.

Key Wards: local PCA; state-of-the-art denoising algorithms; moderate signal-to-noise ratios

1. INTRODUCTION

Patch-based image denoising algorithms [1, 2, 3, 4, 5] refer to a class of recently developed denoising methods based on the concept o patch similarity. For a P n _ p n patch q 2 Rn of the noisy image, a patch-based algorithm finds a set of similar patches p1; : : : ; pk 2 Rn, and applies some linear (or non-linear) function ' to obtain an estimated (denoised) patched as

Bp = '(q; p1; : : : ; pk): (1)

For example, in non-local means, ' is a weighted averaging function [1], whereas in BM3D, ' is a transform-shrinkage operation [2].

In applying patch-based denoising algorithms, finding similar patches p1; : : : ; pk is the key. Typically, there are two sources of these patches: the noisy image itself and an external database. Finding similar patches from the noisy image itself is more popular because patches tend to recur within the image [6, 7]. However, this approach has limited performance, especially for rare patches [8]. Another source of obtaining similar patches is to use external databases [9, 10, 11, 12], which in theory can achieve the minimum mean squared estimation error [13]. However, most of the existing external denoising algorithms use generic databases, in the sense that no prior knowledge about the scene is used. This raises a natural question: are there situations under which targeted databases can be utilized to improve the denoising quality? In fact, building targeted databases is plausible in many scenarios.

As will be illustrated in later parts of this paper, targeted databases can be built for text images (e.g., newspapers and documents), human faces (under certain conditions), and images captured by multi-view camera systems. Other possible scenarios include: Contact author: E. Luo, e-mail: eluo@ucsd.edu. The work of E. Luo and T. Q. Nguyen is supported, in part, by a NSF grant CCF-1065305. The work of S. H. Chan is supported, in part, by a Croucher Foundation post-doctoral research fellowship. images of licence plates, medical CT and MRI images, and images of landmarks.

Assuming that the targeted databases are given, one fundamental question is: what is the corresponding denoising algorithm? Or in other

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words, is it possible to design a computationally efficient denoising procedure that can maximally utilize the databases? The goal of this paper is to provide an answer to this question by showing that for the above mentioned applications, an algorithm can be designed and its performance is better than several existing methods.

1.1. Related Work

The focus of this paper is about denoising algorithms using external databases. In general, there are two directions in the literature that are relevant to our work.

The first approach is to modify existing algorithms to handle external databases by brute-force extensions. For example, one can modify existing single image denoising algorithms, e.g., [1, 2, 3, 14], so that they search similar patches from an external database. Similarly one can treat a database as "videos" for multi-image denoising algorithms, e.g., [15, 16, 17, 18]. However, both approaches are heuristic in which there is no theoretical guarantee on the performance.

The other approach is to learn the prior of the database and denoise the image using a maximum a posteriori (MAP) estimation method, e.g., [4, 9, 19, 20, 21]. While some of these methods have
performance guarantee, a large number of samples are needed for training the priors which are not always available in practice.

1.2. Contributions

1.3.

In contrast to the existing methods, the proposed algorithm requires only a few targeted images in the database. Moreover, the proposed algorithm offers two new insights into the denoising problem.

First, we show that when designing a linear denoising filter, the basis matrix can be learned by solving a convex optimization involving group sparsity, and the solution is the classical eigen decomposition.

This provides justifications of many well-known denoising algorithms in which PCA is used as a learning step. Second, we show that when estimating the spectral components of the denoising filter, a localized prior can be used and the denoising quality is improved by minimizing the associated Bayesian mean squared error.

The rest of the paper is organized as follows. In Section 2 we present the problem setup and the proposed algorithm. Experimental results are shown in Section 3, and a concluding remark is given in Section 4. Technical details of this paper will be presented in a follow-up journal paper.

Patch based Global PCA (PGPCA):

We create an orthogonal basis adapted to the target image by performing a PCA on the whole collection of patches extracted from the noisy image.

Patch based Hierarchical
PCA (PHPCA):

We use quad trees with iterative partitions, i.e. we recursively divide the image into four rectangles and proceed to the PCA to the level k of partitioning. At each step a few (usually one) axes are added to the bases and the remaining patches are projected onto the orthogonal supplement of the current orthogonal sub-basis.

Patch based Local PCA (PLPCA):

We use dynamic localization to build the axes. This strategy relies on a sliding window of size WS _WS in which the patches are selected to proceed to a local PCA.

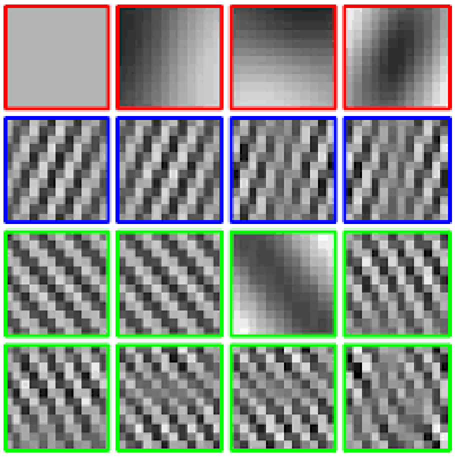

Figure:1 An image (House), its 16 first axes and 16 last axes obtained by a PCA over all the patches of the image.

2. PROPOSED METHOD

We first provide a brief review of the classical optimal denoisin filter design problem and highlight its limitations. Then, we describe the proposed method and discuss its relation to existing methods.

2.1. Optimal Denoising Filter

We consider the denoising task as an optimal filter design problem for its simplicity and analytic tractability [22, 23, 24]. Given a clean patch p 2 Rn, we model the observed noisy patch as q = p + n, where n is a vector of i.i.d. Gaussian noise of zero mean and variance _2. The optimal denoising filter problem is to find a linear

operator A 2 Rn_n such that an estimate bp can be obtained by
bp= Aq. Here, we assume that

A is symmetric, or otherwise the Sinkhorn-Knopp iteration [25] can be used to symmetrize A. Since A is symmetric, it is valid to apply the eigen-decomposition,

A = U_UT , to obtain the eigenvectors U = [u1; : : : ;un] 2 Rn_n and the Eigen values _ = diag f_1; : : : ; _ng 2 Rn_n.

Therefore, the filter design problem becomes the question of finding U and _ so that the linear estimated value.

Figure2: Denoising text images: Visual comparison and objective comparison (PSNR and SSIM in the parenthesis). Prefix "i" stands for internal denoising (i.e., single image denoising), and prefix "e" stands for external denoising (i.e., using external databases).

3. EXPERIMENTAL RESULTS

3.1. Experiment Settings

In this section we evaluate the performance of the proposed method by comparing to several existing algorithms. The methods we considered in the comparison include BM3D[2], BM3D-PCA[3], LPG-PCA[5], NLM[1] and EPLL[4].

Except for EPLL, all other four methods are re-implemented so that patches can be searched over multiple images. As for NLM, instead of using all patches in the database, we consider only the best k patches following [27].

For EPLL, we consider both the default patch prior learned from a generic database, and a new prior learned from our targeted database by running the same EM algorithm. To emphasize the difference between the original algorithms (which are single image denoising algorithms) and the corresponding new implementations for external databases, we denote "i" (internal) for the single image denoising algorithms, and "e" (external) for the corresponding extension for external databases.

3.2. Denoising Text and Documents

Our first experiment considers denoising a noisy text image (size 161_145) using a collection of 9 arbitrarily chosen text images containing texts of the same font sizes. The purpose of the experiment is to simulate the case where we want to denoise a noisy document with the help of other similar but non-identical texts.

Figure 1 shows the results of the experiment. We observe that among all the methods, our proposed method yields the highest PSNR and SSIM values. Our PSNR is 6dB better than the benchmark BM3D (internal) algorithm.

3.3. Denoising Multiview Images

The second experiment considers the scenario of capturing images using a multi view camera system where one of the views is corrupted. We add i.i.d. Gaussian noise to one of the five multi view images, and use the rest of the images to denoise.

Figure 2 illustrates the denoising results of the "Barn" and "Cone" multi view datasets, which indicate that our proposed method yields much better PSNR than BM3D. In Figure 3 we plot and compare the PSNR values over a range of noise levels. The proposed method is consistently better than its counterparts.

Figure 3: Multiview image denoising using the proposed method and internal BM3D. [Top] "Barn"; [Bottom] "Cone".

4. CONCLUSION

Classical image denoising methods based on single noisy input and generic databases are approaching their performance limits. We envision that future image denoising should be target-oriented, i.e., for specific objects to be denoised, only similar images should be used for training. To address this new paradigm shift in image denoising, we present algorithms and corresponding simulations of using targeted databases for optimal linear denoising filter design. Our proposed method based on group sparsity and localized priors, showed robustness and performance superiority over a wide range of existing algorithms. Future work includes detailed sensitivity analysis of the algorithm.

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