Optimisation of Image Denoising: Case Study

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Abstract

Within each category, several representative algorithms are selected for evaluation and comparison. The experimental results are discussed and analyzed to determine the overall advantages and disadvantages of each category. In general, the nonlocal methods within each category produce better denoising results than local ones. And, methods based on overcomplete representations using learned dictionaries perform better than others. This paper presents an image denoising algorithm that uses principal component analysis (PCA) in conjunction with the non-local means image denoising. Image neighborhood vectors used in the non-local means algorithm are first projected onto a lower-dimensional subspace using PCA. Consequently, neighborhood similarity weights for denoising are computed using distances in this subspace rather than the full space.

Keywords: Image Denoising, Filters, Evaluation, Spatial Domain, Transform Domain.

1. INTRODUCTION

IMAGE denoising is an important research area serving as the actual foundation for many applications such as object recognition, digital entertainment, and remote sensing imaging. As the number of image sensors per unit area increases, camera devices tend to be more sensitive to noise. Denoising techniques have become a critical step for improving the final visual quality of images [1]. Denoising is the process of reconstructing the original image by removing unwanted noise from a corrupted image. It is designed to suppress the noise while preserving as many image structures and details as possible. The main challenge is to design noise reduction filters that provide a compromise. This modification to the non-local means algorithm results in improved accuracy and computational performance. We present an analysis of the proposed method’s accuracy as a function of the dimensionality of the projection subspace and demonstrate that denoising accuracy peaks at a relatively low number of dimensions. Data-driven descriptions of structure are becoming increasingly important in image processing applications such as denoising, regularization and segmentation. One strategy is to use collections of nearby pixels, i.e. image neighborhoods, as a feature vector for representing local structure. Image neighborhoods are rich enough to capture the local structures of real images, but do not impose an explicit model. This representation has been used as a basis for image denoising [1,2] and for texture image segmentation [5]. For both denoising and segmentation, it has been demonstrated that the accuracy of this strategy is on the same level as state-of-the-art methods in general and exceeds them in particular types of images such as those that have significant texture patterns. The drawback is the relatively high computational cost. Hence, the computation of similarities between feature vectors incurs a large computational cost. In this paper, we propose to project the image neighborhood vectors to a lower-dimensional space by principal component analysis (PCA).

2. METHODS OF DENOISING

2.1 Spatial Domain Methods

Spatial domain filters exploit spatial correlations in images. In this paper, the spatial filters are classified into two categories: local and nonlocal filters. A filter is local if the candidate selection process used for filtering is restricted by the spatial distance. A filter is nonlocal if the candidate selection depends only on the similarity and is not restricted by the spatial distance. A Local filters Since the Gaussian filter [5] was applied to image denoising, many local filters have been proposed to improve it and provide better edge-preserve ability. The anisotropic filter [6] was designed to avoid the blurring effect of Gaussian by smoothing the image only in the direction which is orthogonal to the gradient direction. The method in [7] utilizes the total variation minimization technique to smooth the homogenous regions of the image but not its edges. Similarly, for better edge-preserving, the Smallest univalue segment assimilating Nucleus (SUSAN) filter can average all pixels in the local neighborhood which are from the same spatial region as the central pixel. In contrast to the above parametric methods, SKR [11] adapts and expands the kernel regression idea to be more nonparametric and semi-parametric. They are summarized below: TF Similar to the idea of early local filters [5,8], a weighted averaging scheme
is adopted to perform image denoising in the trained filter [8]. The difference is that the trained filter adopts the nonparametric process in which the weights are obtained from the off-line training on a large number of images. In the training step, the classification process ensures best adaptation for local image patterns by changing fixed kernel coefficients into trained coefficients. The classification is based on Adaptive Dynamic Range Coding (ADRC), in which image patterns are encoded as class indexes. In the filtering process, the same classification is applied to each input noisy aperture, and accordingly filter coefficients are obtained from a Look-Up Table (LUT) stored in the previous training process. The advantage of the trained filter is that the training process is off-line and the LUT only has to be trained once. Thus, the filtering process is so efficient that it can be used in real-time denoising applications. The framework is also applicable to other image enhancement tasks, for example, coding artifact reduction. Moreover, it improves the adaptivity of the local neighborhood filtering by exploring the sparsity in the dataset, which is similar to the learning-based denoising methods. The disadvantage of this method is that ADRC is very vulnerable to severe image degradations (e.g. high noise levels), and same ADRC codes sometimes cannot properly represent same patch textures.

### 3. IMPLICATION OF IMAGES

Discussions on dictionary learning based methods: over complete dictionaries learned from clean or noisy image patches provide adaptive representations for image denoising. Earlier sparse coding based methods (e.g., K-SVD) search for the optimal decomposition of a patch in the whole dictionary while updating the dictionary with the information from the input. Though most of them [2] managed to achieve satisfactory denoising results, they have a disadvantage that similar patches might have very different sparse decompositions [2]. LSSC improves this situation by applying clustering in sparse decompositions. However, its performance largely depends on the initial dictionary trained offline on high quality images and the nonlocal grouping results. Later, CSR uses a similar framework but reduces the computational complexity significantly.

### 4. PERFORMANCE COMPARISON OF REPRESENTATIVE

#### 4.1 Image Denoising Methods

A. The Image Database

1) Source Image Content: The image database was derived from a set of source images that reflects adequate diversity in complexity of image content. These images include pictures of human faces, natural scenes, and man-made objects. Most of them are extensively used by researchers in the field of image denoising. The first dataset (200 images) we use is the Berkeley segmentation dataset

\[
A = \arg \min_A \frac{1}{2} \|v - DA\|_2^2 + \lambda_1 \|A\|_1 + \lambda_2 \sum_{k=1}^{K} \sum_{i \in C_k} \|\alpha_i - \beta_k\|_1
\]

where A is the sparse matrix, _ denotes sparse coefficients for the centroid vectors, v is the noisy image, and D is the learned redundant dictionary. K is the number of the clusters, and Ck is the number of elements in each cluster.

### 5. CONCLUSIONS

It is clear from the comparison in this paper that all three categories are important denoising techniques for various applications. In applications that require high efficiency,
some of the local spatial filters or transform domain filters are more appropriate, because nonlocal spatial filters lead to high searching complexity. If the memory and complexity were not a major concern for the users, dictionary learning based methods would be more applicable because the online training and iterations are not practical in real time systems but they significantly boost the performance. Moreover, algorithms contain multi resolution structures tend to be more efficient than single resolution ones.

6. REFERENCES


