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Hybrid Approach for Image Restoration

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Abstract: Local and Nonlocal image representations have shown great potential in low-level vision tasks leading to several state-of-the-art image restoration techniques. Both of these representations have their own advantages. The work towards combining these two representations seems to be minimal. The paper tries to contribute to the area of unification of these two representations. Ahybrid approach for image restoration has been proposed in this paper that combines both of these representatins. The main idea behind this approach is singular value decomposition (SVD), a bilateral variance estimation perspective. SVD of similar patches has the property of pooling both local and non-local information for estimating signal variances. This, in-turn, has led to the development of new class of image restoration algorithms. For noisy data, the algorithm makes use of iterative regularization concept; for incomplete data, it makes use of deterministic annealing-based solution along with dictionary learning. The performance of this hybrid approach will have the results that can be compared favorably with other leading image restoration algorithms.

Index Terms: Deterministic annealing, iterative regularization, singular value thresholding, singular value decomposition, image denoising, image completion, patch clustering.

I. INTRODUCTION

In recent years, images and videos have become integral parts of our lives. Applications now range from the casual documentation of events and visual communication to the more serious surveillance and medical fields. This has led to an ever-increasing demand for accurate and visually pleasing images. Such images are prone to different types of degradations. Image restoration is the field that has been flourished to provide solutions to obtain the accurate images.It is the field emerged out of the combination of three important areas: image processing, computer vision and computational imaging. Image restoration is the process of undoing the defects which degrade an image and tries to rebuild the original image to a maximum extent. Natural images, when displayed, have gone through some sort of degradations during display mode, acquisition mode or processing mode. The reasons for these degradations are sensor noise, blur due to camera misfocus, relative object-camera motion, random atmospheric turbulence, etc,. Depending on the type of degradation, image restoration has following derivatives as its kinds: Image denoising, image inpainting, image interpolation, image deconvolution, etc,. An image (Latin: imago) is an artifact, for example a two-dimensional picture, that has a similar appearance to some subject—usually a physical object or a person. Mathematically image can be defined as a two dimensional light intensity function, f(x,y), where the value of 'f' at a spatial location (x, y) is the intensity of the image at that point. There are two ways by which an image can be represented: local and nonlocal image representations. In local representation, a pixel is based on its spatial neighborhood pixels. In nonlocal representation, a pixel is based on k-Nearest Neighbor image patch. Under the context of image modeling, it has been argued that both local and nonlocal variations are the two sides of the same coin and it is necessary to strike a good balance between them.

The key concept that unifies these two strategies are the Singular value Decomposition (SVD) from the bilateral variance estimation perspective. It will be shown for a data matrix consisting of similar patches, left-multiplying and right-multiplying matrices of SVD jointly characterize the local variation in the row space and nonlocal variation in the column space respectively. Apart from this, SVD has the property of excellent energy compaction. Two other strategies that the paper uses are iterative regularization and deterministic annealing. These two are the strategies of obtaining spatial adaptation. The basic idea of iterative regularization is to add the filtered noise back to denoised image such that only strong signals survive thresholding. This decreases noise variance monotonically. The main idea of deterministic annealing is to start with the large threshold and to decrease the threshold progressively based on some annealing schedule which helps to overcome different types of saddle points.

The rest of the paper is organized as follows: In Sec. II, works related to the paper are described briefly. In Sec. III, hybrid approach algorithm has been developed borrowing the ideas of iterative regularization and deterministic annealing. In Sec. IV, performance metrics that have been considered for performance comparison with other algorithms are described briefly. In Sec.V, some concluding remarks are mentioned.

II. RELATED WORKS

In [1], a novel image denoising strategy based on an enhanced sparse representation in transform domain is proposed. The enhancement of the sparsity is achieved by grouping similar 2D image fragments (e.g. blocks) into 3D data arrays which has been called "groups". Collaborative filtering is a special procedure developed to deal with these 3D groups. It is realized using the three successive steps: 3D transformation of a group, shrinkage of the

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transform spectrum, and inverse 3D transformation. The result is a 3D estimate that consists of the jointly filtered grouped image blocks. By attenuating the noise, the collaborative filtering reveals even the finest details shared by grouped blocks and at the same time it preserves the essential unique features of each individual block. The filtered blocks are then returned to their original positions. Because these blocks are overlapping for each pixel we obtain many different estimates which need to be combined. Aggregation is a particular averaging procedure which is exploited to take advantage of this redundancy. A significant improvement is obtained by a specially developed collaborative Wiener filtering. The drawback of the system is collaborative filtering essentially differs from other filters because the model induced by hard-thresholding has low complexity only in relation to the group as a whole. For the block-wise estimates and for the overall image, the model can instead be highly complex and redundant as each block can enter in many groups and thus can participate in many collaborative estimates.

In [2], the author unifies two different approaches to image restoration: On the one hand, learning a basis set (dictionary) adapted to sparse signal descriptions has proven to be very effective in image reconstruction and classification tasks. On the other hand, explicitly exploiting the self-similarities of natural images has led to the successful non-local means approach to image restoration. It proposes simultaneous sparse coding as a framework for combining these two approaches in a natural manner. This is achieved by jointly decomposing groups of similar signals on subsets of the learned dictionary. Experimental results in image denoising with synthetic and real noise show that the proposed method outperforms the state of the art, making it possible to effectively restore raw images from digital cameras at a reasonable speed and memory cost. The paper has several advantages such as speed and low memory cost but it also has an important limitation that it is applicable for only uniform noise models in the reconstruction process.

In [3], a patch-based, locally adaptive denoising method based on clustering the given noisy image into regions of similar geometric structure is proposed called K-LLD (K-Locally Learned Dictionaries). In order to effectively perform such clustering, the local weight functions derived from steering kernel regression. These weights are exceedingly informative and robust in conveying reliable local structural information about the image even in the presence of significant amounts of noise. Next, each region (or cluster) is modeled—which may not be spatially contiguous—by "learning" a best basis describing the patches within that cluster using principal components analysis. This learned basis (or "dictionary") is then employed to optimally estimate the underlying pixel values using a kernel regression framework. The paper also introduces a novel mechanism for optimally choosing the local patch size for each cluster using Stein's unbiased risk estimator (SURE).For optimal performance, it is necessary to tune a few parameters of the framework. This is indeed undesirable. Although the method is not very sensitive to the number of clusters when it lies within a particular range, it may be useful to use variants of K-Means that converge to the optimal number of clusters automatically. All these factors influence the output of the method.

In [4], the author proposes an approach that unifies local and nonlocal image models. Local and nonlocal image models have supplied complementary views toward the regularity in natural images -the former attempts to construct or learn a dictionary of basic functions that promotes the sparsity; while the latter connects the sparsity with the self-similarity of the image source by clustering. It presents a variation framework for unifying the above two views and propose a new denoising algorithm built upon clustering-based sparse representation (CSR). Inspired by the success of l1-optimization, they have formulated a double-header l1-optimization problem where the regularization involves both dictionary learning and structural structuring. A surrogate-function based iterative shrinkage solution has been developed to solve the double-header l1-optimization problem and a probabilistic interpretation of CSR model is also included. The algorithm has produced improved results only for the class of regular texture images.

In [5], a novel MRF framework which is called Non-Local Range Markov Random Field (NLRMRF) is proposed and designed. The local spatial range of clique in traditional MRF is extended to the non-local range which is defined over the local patch and also its similar patches in a non-local window. Then the traditional local spatial filter is extended to the non-local range filter that convolves an image over the non-local ranges of pixels. In this framework, a gradient-based discriminative learning method to learn the potential functions and non-local range filter bank is proposed. As the gradients of loss function with respect to model parameters are explicitly computed, efficient gradient-based optimization methods are utilized to train the model. The methodology proposed in this paper suits for binary images and gray scale images only. It does not support color image.

In [6], a novel algorithm to approximate the matrix with minimum nuclear norm among all matrices obeying a set of convex constraints is introduced. This problem may be understood as the convex relaxation of a rank minimization problem, and arises in many important applications as in the task of recovering a large matrix from a small subset of its entries. It develops a simple first-order and easy-to-implement algorithm that is extremely efficient at addressing problems in which the optimal solution has low rank. The algorithm is iterative and produces a sequence of matrices and at each step, mainly performs a soft-thresholding operation on the singular values of the matrix. There are two remarkable features making this attractive for low-rank matrix completion problems. The first is that the soft-thresholding operation is applied to a sparse matrix; the second is that the rank of each iterate is empirically nondecreasing. Both these facts allow the algorithm to make use of very

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minimal storage space and keep the computational cost of each iteration low.

In [7],an expectation-maximization (EM) algorithm for image inpainting based on a penalized likelihood formulated using linear sparse representations is introduced. Taking advantage of the sparsity of representations, regularization through a prior penalty is imposed on the reconstructed coefficients. From a statistical point of view, the inpainting can be viewed as an estimation problem with missing data. The EM framework is a general iterative algorithm. The EM framework gives a principled way to establish formally the idea that missing samples can be recovered based on sparse representations. Furthermore, owing to its well known theoretical properties, the EM algorithm allows to investigate the convergence behavior of the inpainting algorithm.

In [8], Deterministic annealing approach to clustering and its extensions has been demonstrated with substantial performance improvement over standard supervised and unsupervised learning methods in a variety of important applications including compression, estimation, pattern recognition and classification, and statistical regression. The method offers three important features: 1) the ability to avoid many poor local optima; 2) applicability to many different structures/architectures; and 3) the ability to minimize the right cost function even when its gradients vanish almost everywhere, as in the case of the empirical classification error. It is derived within a probabilistic framework from basic information theoretic principles (e.g., maximum entropy and random coding). The application-specific cost is minimized subject to a constraint on the randomness (Shannon entropy) of the solution, which is gradually lowered. The basic algorithm is extended by incorporating structural constraints to allow optimization of numerous popular structures including vector quantizers, decision trees, multilayer perceptrons, radial basis functions, and mixtures of experts. Experimental results show considerable performance gains over standard structure-specific and application-specific training methods.

In [9], a new iterative regularization procedure for inverse problems based on the use of Bregman distances, with particular focus on problems arising in image processing is described. The method is motivated by the problem of restoring noisy and blurry images via variation methods by using total variation regularization. The method obtains rigorous convergence results and effective stopping criteria for the general procedure. The numerical results for denoising appear to give significant improvement over standard models, and preliminary results for deblurring/denoising are very encouraging.

In [10], the image denoising problem is addressed, where zero-mean white and homogeneous Gaussian additive noise is to be removed from a given image. The approach taken is based on sparse and redundant representations over trained dictionaries. Using the K-SVD algorithm, the method obtains a dictionary that describes the image content effectively. Two training options are considered: using the corrupted image itself, or training on a corpus of high-quality image database. Since the K-SVD is limited in handling small image patches, the method extend its deployment to arbitrary image sizes by defining a global image prior that forces sparsity over patches in every location in the image. The method shows how such Bayesian treatment leads to a simple and effective denoising performance, equivalent and sometimes surpassing recently published leading alternative denoising methods.The work concentrated on small image patches, completely overlooking the global structure of the image, and the multiscale analysis that other techniques have exploited rather well. Thus, the method has the enhancement of using multiscale dictionaries.

III. ALGORITHM

In this section, algorithms for image denoising and image completion has been developed and explained briefly. As already stated, the algorithms solely rely on the concepts of iterative regularization and deterministic annealing which have been dealt in the previous sections.

ALGORITHM 1: HYBRID APPROACH FOR IMAGE DENOISING

Step1: Initialization;
Step 2: Iterate on i=1,2,3,…, iter
- Patch clustering;
- Iterative regularization;
- Noise variance update;
- Perform SVD for each noisy data matrix ;
- Threshold update;
- Singular value thresholding;
- Image update;
Step 3: Output;

A. Image Restoration from Noisy Data
Noisy data is represented as **Y = X + W**. Image restoration from noisy data involves the removal of term ‘W’retrieving only ‘X’.The steps in the algorithm, hybrid approach for image denoising, have been described below.

a. Patch Clustering
Patch clustering is the process by which the images are first divided into several patches and are clustered. The patches are clustered based on kNN for each exemplar patch. After that, each cluster gets converted into data matrices.

b. Iterative Regularization
Spatial adaptation of the noisy image is provided by iterative regularization techniques. The basic idea of iterative regularization is to add filtered noise back to the denoised image such that noise variance is estimated effectively.

c. Noise Variance Update
After iterative regularization, in which noise variance is estimated, noise variance updating is performed.

d. Threshold Update
After singular value decomposition for each noisy data matrix, threshold parameter is updated by considering local estimated variance at each position. This local

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estimated variance makes use of singular value calculated for the noisy data matrix.

f. Image Update

Image update involved making improvement over the noisy image by weighted averaging all denoised patches. This progressively leads to denoised image.

ALGORITHM 2:HYBRID APPROACH FOR IMAGE COMPLETION

Step 1: Initialization;
Step 2: Iterate on i=1,2,3,…, iter
- Patch clustering;
- Landweber Iteration;
- Perform SVD for each Data Matrix;
- Singular Value Thresholding;
- Image Update;
- Deterministic Annealing;

Step 3: Output;

B. Image Completion from Incomplete Data

Completion of the image has been achieved using the algorithm, hybrid approach for image completion. The algorithm has been described briefly below.

a. Patch Clustering

Patch clustering is the process by which the images are first divided into several patches and are clustered. The patches are clustered based on kNN for each exemplar patch. After that, each cluster gets converted into data matrices.

b. Perform SVD

Singular Value Decomposition for each data matrix is performed.

c. Singular Value Thresholding

Singular value thresholding involves computing the threshold value based on threshold value parameter. This results in reconstruction of each patch.

d. Image Update

Obtain the new reconstructed image by weighted averaging of all reconstructed patches.

e. Deterministic Annealing

The idea of deterministic annealing is to start with a large threshold and then progressively decrease the threshold value according to some annealing schedule.

IV. PERFORMANCE METRICS

The section briefly describes the various metrics that have been considered for evaluating the performance of the proposed system. They are listed below:

A. Peak Signal-to-Noise Ratio (PSNR).
B. Structural Similarity (SSIM).

A. Peak Signal-to-Noise Ratio

Peak Signal-to-noise ratio (PSNR) is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. It is the approximation to human perception of reconstruction quality. It is usually expressed in terms of the logarithmic decibel scale. PSNR measure can be easily defined based on Mean Squared Error (MSE). It is given by,

$$\text{PSNR}= 10.\ \log_{10}\left(\frac{\text{MAX}_I^2}{\text{MSE}}\right)$$

B. Structural Similarity

The structural similarity (SSIM) index is a method for measuring the similarity between two images. It is a full reference metric since it is the measure of image quality based on an initial uncompressed or distortion-free image as reference. It is calculated on various windows of an image. The SSIM measure between two windows x and y of common size N X N is given below.

$$\text{SSIM(x,y)} = \frac{\left(2\mu_x\mu_y + C_1\right)\ (2\sigma_{xy} + C_2)}{\left(\mu_x{}^2 + \mu_y{}^2 + C_1\right)(\sigma_x{}^2 + \sigma_y{}^2 + C_2)}$$

V. CONCLUSION

The proposed system tries to unify the two different strategies of image restoration namely local and non-local image representations. The combination of these two techniques helps the usage of the proposed method to restore transient images as well as invariant images contributing to the exploration of the concept of unification. Also, the proposed system has the scope for further improvement such as the optimization of the algorithm, choosing patch size and neighborhood size in a less ad-hoc fashion. There are many application areas that can benefit from the proposed system such as computational photography, low-light remote sensing, faster MRI, satellite imaging, etc,

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