Volume 3, No. 3, May-June 2012

ISSN No. 0976-5697

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

Image Deblurring Using Adaptive Sparse Domain Selection and Adaptive Regularization

D. Suresh
Department of CSE,
PSNA College of Engineering and Technology, Dindigul, India.
sureshdgll@gmail.com

Abstract: **Problem Statement:** Image restoration (IR) aims to reconstruct a high-quality image from its degraded measurement. **Approach:** As a powerful statistical image modeling technique, sparse representation has been successfully used in various image restoration applications. The contents of images can vary significantly across different images or different patches in a single image, and then, for each selected patch, one set of bases are adaptively selected to characterize the local sparse domain. Then two adaptive regularization terms are used into the sparse representation framework. First, a set of autoregressive (AR) models are adaptively selected to regularize the image local structures. Second, the image non-local self-similarity is introduced as another regularization term estimated for better image restoration performance. **Conclusion:** Iterative experiments using adaptive sparse domain selection and adaptive regularization, the proposed method achieves much better results than many state-of-the-art algorithms in terms of both PSNR and visual perception.

Key Words: Sparse representation, image restoration, deblurring, super-resolution, regularization.

I. INTRODUCTION

The image deblurring is performed to compensate for or undo defects which degrade an image. The image restoration problem can be modeled as $\mathbf{y=DHx+\upsilon}$, where x is the unknown image to be estimated, H and D are degrading operators and υ is additive noise[1]. When H and D are identities, the IR problem becomes denoising; when D is identity and H is a blurring operator, IR becomes deblurring; when D is identity and H is a set of random projections, IR becomes compressed sensing; When D is a down-sampling operator and H is a blurring operator, IR becomes (single image) super-resolution. [2]In this paper, we focus on deblurring and single image super-resolution.

To find a better solution for the ill-posed nature, prior knowledge of natural images can be used to regularize the IR problem. One of the most commonly used regularization models is the total variation (TV) model. The TV model favors the piecewise constant image structures, it tends to smooth out the fine details of an image. The success of TV regularization validates the importance of good image prior models in solving the IR problems[3]. In wavelet based image denoising, researchers have found that the sparsity of wavelet coefficients can serve as good prior. This reveals the fact that many types of signals, e.g., natural images, can be sparsely represented (or coded) using a dictionary of atoms, such as DCT or wavelet bases. That is, denote by Φ the dictionary; we have $x\approx\Phi\alpha$ and most of the coefficients in α close to zero. Recent studies showed that iteratively reweighting the l1-norm sparsity regularization term can lead to better IR results. Sparse representation has been successfully used in various image processing applications.

A critical issue in sparse representation modeling is the determination of dictionary Φ. analytically designed dictionaries, such as DCT, wavelet, curvelet and contourlets share the advantages of fast implementation[4]; however, they lack the adaptivity to image local structures. Many dictionary learning (DL) methods aim at learning a universal and over-complete dictionary to represent various image structures. However, sparse decomposition over a highly redundant dictionary is potentially unstable and tends to generate visual artifacts. In this paper we propose an adaptive sparse domain selection (ASDS) scheme for sparse representation. By learning a set of compact sub-dictionaries from high quality example image patches. The example image patches are clustered into many clusters. Since each cluster consists of many patches with similar patterns, a compact sub-dictionary can be learned for each cluster. Particularly, for simplicity we use the principal component analysis (PCA) technique to learn the sub-dictionaries. For an image patch to be coded, the best sub-dictionary that is most relevant to the given patch is selected. Since the given patch can be better represented by the adaptively selected sub-dictionary, the whole image can be more accurately reconstructed than using a universal dictionary, which will be validated by our experiments.

Apart from the sparsity regularization, other regularization terms can also be introduced to further increase the IR performance. In this paper, we propose to use the piecewise autoregressive (AR) models, which are pre-learned from the training dataset, to characterize the local image structures. For each given local patch, one or several AR models can be adaptively selected to regularize the solution space. Also we introduce a non-local (NL) self-similarity constraint served as another regularization term, which is very helpful in preserving edge sharpness and suppressing noise. Then we apply an efficient iterative shrinkage (IS) algorithm to solve the *l*1-minimization problem[5]. In addition, we adaptively estimate the image local sparsity to adjust the sparsity regularization parameters shows that the proposed ASDS-AReg approach can effectively reconstruct the image details, outperforming many state-of-the-art IR methods in terms of both PSNR and visual perception.

II. RELATED WORKS

Images can be generally coded by structural primitives, e.g., edges and line segments, and these primitives are qualitatively similar in form to simple cell receptive fields. Sparse coding or sparse representation strategy has been widely studied to solve inverse problems, partially due to the progress of $l0$-norm and $l1$-norm minimization techniques. Suppose that $\boldsymbol{x}\in\Re^{n}$ is the target signal to be coded, and $\Phi = [\varphi 1\ldots \varphi m] \in \Re^{nxm}$ is a given dictionary of atoms (i.e., code set). The sparse coding of $\boldsymbol{x}$ over Φ is to find a sparse vector $\alpha= [\alpha 1\ldots\alpha m]$ (i.e., most of the coefficients in α close to zero) such that $\boldsymbol{x}\approx\Phi\alpha$. Given a set of training image patches $\boldsymbol{S}=[\boldsymbol{s}1, \ldots, \boldsymbol{s}N] \in\Re^{nxN}$, the goal of dictionary learning (DL) is to jointly optimize the dictionary Φ and the representation coefficient matrix $\Lambda=[\alpha 1,\ldots,\alpha N]$ such that $\boldsymbol{si} \approx\Phi\, \boldsymbol{\alpha i}$ where p = 0 or 1. Various approaches like MOD and K-SVD have been proposed to alternatively optimizing Φ and Λ, leading to many state-of-the-art results in image processing.

Regularization has been used in IR for a long time to incorporate the image prior information. The autoregressive (AR) modeling has been successfully used in image compression and interpolation. Recently the AR model was used for adaptive regularization in compressive image recovery[6]. In this paper, we will propose a learning-based adaptive regularization, where the AR models are learned from high-quality training images, to increase the AR modeling accuracy. The non-local (NL) methods have led to promising results in various IR tasks, The idea of NL methods is that the patches that have similar patterns can be spatially far from each other and thus we can collect them in the whole image. In this paper, we use an NL self-similarity regularization term into our proposed IR framework.

III. SPARSE REPRESENTATION WITH ADAPTIVE SPARSE DOMAIN SELECTION

Here we propose an adaptive sparse domain selection (ASDS) scheme, which learns a series of compact sub-dictionaries and assigns adaptively each local patch a sub-dictionary as the sparse domain. With ASDS, a weighted $l1$-norm sparse representation model will be proposed for IR tasks. Suppose that $\{\Phi_k\}$, k=1, 2… K is a set of K orthonormal sub-dictionaries. Let $\boldsymbol{x}$ be an image vector, and $\mathbf{x}_i=\mathbf{R_I}\,\mathbf{x}$, I=1, 2… N, be the ith patch (size: $\sqrt{n}$ x $\sqrt{n}$) vector of $\boldsymbol{x}$, where $\mathbf{R_I}$ is a matrix extracting patch $\mathbf{x}_i$ from $\boldsymbol{x}$. For patch $\boldsymbol{x}_\mathbf{i}$, suppose that a sub-dictionary Φ_{ki} is selected for it. Then, $\boldsymbol{x}_i$ can be approximated as $\boldsymbol{x}_{i=}\ \Phi_{ki}\,\alpha_{i,}$ via sparse coding. The whole image $\boldsymbol{x}$ can be reconstructed by averaging all the reconstructed patches $\mathbf{x}_{\mathbf{i}.}$ The matrix to be inverted is a diagonal matrix, and hence the calculation is to be done in a pixel-by-pixel manner[7]. The image patches can be overlapped to better suppress noise and block artifacts. To facilitate the sparsity-based IR, we propose to learn offline the sub-dictionaries $\{\Phi k\}$, and select online from $\{\Phi k\}$ the best fitted sub-dictionary to each patch $\boldsymbol{x}_\mathbf{i}$.

A. Learning the sub-Dictionaries:

First construct a dataset of local image patches for training. To this end, we collected a set of high-quality natural images, and cropped from them a rich amount of image patches with size $\sqrt{n}$ x $\sqrt{n}$. A cropped image patch, denoted by $\boldsymbol{s}_\mathbf{i}$, will be involved in DL if its intensity variance Var($\mathbf{s}_\mathbf{i}$) is greater than a threshold Δ, i.e.,Var($\mathbf{s}_\mathbf{i}$)> Δ. This patch selection criterion is to exclude the smooth patches from training and guarantee that only the meaningful patches with a certain amount of edge structures are involved in DL. Suppose that M image patches $\boldsymbol{S}= [\boldsymbol{s}1, \boldsymbol{s}2\ldots \boldsymbol{s}M]$ are selected. We aim to learn K compact sub-dictionaries $\{\Phi k\}$ from $\boldsymbol{S}$ so that for each given local image patch, the most suitable sub-dictionary can be selected. Then cluster the dataset $\boldsymbol{S}$ into K clusters, and learn a sub-dictionary from each of the K clusters.

PCA is a classical signal de-correlation and dimensionality reduction technique that is widely used in pattern recognition and statistical signal processing. PCA has been successfully used in spatially adaptive image denoising by computing the local PCA transform of each image patch. In this paper we apply PCA to each sub-dataset $\boldsymbol{S}_\mathbf{K}$ to compute the principal components, from which the dictionary Φ_k is constructed. Denote by $\mathbf{\Omega_k}$ the co-variance matrix of dataset $\boldsymbol{S}_{\mathbf{k}.}$ By applying PCA to $\mathbf{\Omega_k}$ an orthogonal transformation matrix $\boldsymbol{P}_\mathbf{k}$ can be obtained. To make a better balance between the $l1$-norm regularization term and $l2$-norm approximation term, we only extract the first r most important eigenvectors in $\boldsymbol{P}_\mathbf{k}$ to form a dictionary Φ_r, $\Phi_r= [\boldsymbol{p}1, \boldsymbol{p}2 ,..., \boldsymbol{p}r]$.

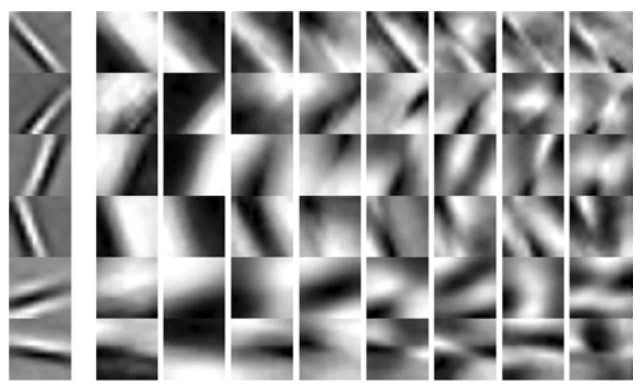

Figure. 1 Examples of learned sub-dictionaries

In Fig. 1, the left column shows the centroids of some sub-datasets after K-means clustering, and the right eight columns show the first eight atoms in the sub-dictionaries learned from the corresponding sub-datasets[8].

B. Adaptive Selection of the sub-Dictionary:

Here we assign adaptively a sub-dictionary to each local patch of $\boldsymbol{x}$, spanning the adaptive sparse domain. Since $\boldsymbol{x}$ is unknown beforehand, we need to have an initial estimation of it by taking wavelet bases as the dictionary and then with the iterated shrinkage algorithm. The centroid $\boldsymbol{\mu}_\mathbf{k}$ of each cluster is available, to determine the sub-dictionary in the subspace of. $\boldsymbol{\mu}_\mathbf{k}$ let $\boldsymbol{U} = [\mu 1,\mu 2 ,...,\mu K]$[9] be the matrix containing all the centroids. By applying SVD to the co-variance matrix of $\boldsymbol{U}$, we can obtain the PCA transformation matrix of $\boldsymbol{U}$. This process is iteratively implemented until the estimation of **x** converges.

C. Adaptively Reweighted Sparsity Regularization:

Here we propose a new method to estimate adaptively the image local sparsity, and then reweight the *l*1-norm sparsity in the ASDS scheme. The proposed adaptive reweighting method is more robust because it exploits the image nonlocal redundancy information. Based on our experimental experience, it could lead to about 0.2dB improvement in average over the reweighting method in for deblurring and super-resolution under the proposed ASDS framework.

IV. SPATIALLY ADAPTIVE REGULARIZATION

The proposed ASDS-based IR method can be further improved by introducing two types of adaptive regularization (AReg) terms. A local area in a natural image can be viewed as a stationary process, which can be well modeled by the autoregressive (AR) models. After exploit the image local correlation, we propose to use the non-local similarity constraint as a complementary AReg term to the local AR models. With the fact that there are often many repetitive image structures in natural images, the image non-local redundancies can be very helpful in image enhancement[10].

A. Training the AR Models:

Here we assume of the AR model be a square window, and the AR model aims to predict the central pixel of the window by using the neighbouring pixels. Considering that determining the best order of the AR model is not trivial, and a high order AR model may cause data over-fitting, in our experiments a 3×3 window (i.e., AR model of order 8) is used. By applying the AR model training process to each sub-dataset, we can obtain a set of AR models $\{a_1, a_2 \ldots a_k\}$ that will be used for adaptive regularization.

B. Adaptive Selection of the AR Model for Regularization:

The adaptive selection of the AR model for each patch $\boldsymbol{x}_\mathbf{i}$ is the same as the selection of sub-dictionary for $\boldsymbol{x}_\mathbf{i}$. With an estimation $\boldsymbol{x}_\mathbf{i}$, we compute its high-pass Gaussian filtering output. Denote by $\boldsymbol{x}_\mathbf{i}$, the central pixel of patch $\boldsymbol{x}_\mathbf{i}$, and by χi the vector containing the neighbouring pixels of $\boldsymbol{x}_\mathbf{i}$ within patch $\boldsymbol{x}_\mathbf{i}$. We can expect that the prediction error of xi using $\boldsymbol{x}_\mathbf{i}$, $a_\mathbf{k}$ and χi should be small.

C. Adaptive Regularization by Non-Local Similarity:

The AR model based AReg exploits the local statistics in each image patch. There may often many repetitive patterns throughout a natural image. Such non-local redundancy is very helpful to improve the quality of reconstructed images. As a complementary AReg term to AR models, a non-local similarity regularization term is introduced into the sparsity-based IR framework. For each local patch $\boldsymbol{x}_\mathbf{i}$, we search for the similar patches to it in the whole image **x.** Thus we incorporate the non-local similarity regularization term into the ASDS based sparse representation.

D. Summary of the Algorithm:

First l2-norm term is the fidelity term, guaranteeing that the solution $\mathbf{x} = \boldsymbol{\Phi\alpha}$ can well fit the observation **y** after degradation by operators **H** and **D[11]**. Second l2-norm term is the local AR model based adaptive regularization term, requiring that the estimated image is locally stationary. Third l2-norm term is the non-local similarity regularization term, which uses the non-local redundancy to enhance each local patch. Last the weighted l1-norm term is the sparsity penalty term, requiring that the estimated image should be sparse in the adaptively selected domain.

V. EXPERIMENTAL RESULTS

A. Training Datasets:

Image contents can vary a lot from image to image; it has been found that the micro-structures of images can be represented by a small number of structural primitives like edges, line segments and other elementary features. These primitives are qualitatively similar in form to simple cell receptive fields. The human visual system employs a sparse coding strategy to represent images. Therefore, using the many patches extracted from several training images which are rich in edges and textures, we are able to train the dictionaries which can represent well the natural images. To illustrate the robustness of the proposed method to the training dataset, we use two different sets of training images in the experiments, each set having 5 high quality images as shown in Fig. 2.

Figure 2 Two sets of high quality images
First column Training Dataset 1
Second column Training Dataset 2

In a clustering-based method, an important issue is the selection of the number of classes. If the number of classes is too small, the boundaries between classes will be smoothed out and thus the distinctiveness of the learned sub-dictionaries and AR models is decreased. For too large number of the classes will make the learned sub-dictionaries and AR models less representative and less reliable. Based on the above considerations to find a good number of classes, we first partition the training dataset into 200 clusters, and merge those classes that contain very few image patches (i.e., less than 300 patches) to their nearest neigh boring classes.

B. Experimental Settings:

In the experiments of deblurring, two types of blur kernels, a Gaussian kernel of standard deviation 3 and a 9×9 uniform kernel, were used to simulate blurred images. Additive

Gaussian white noises with standard deviations √2 and 2 were then added to the blurred images, respectively. We compare the proposed methods with five recently proposed image deblurring methods: the iterated wavelet shrinkage method, the constrained TV deblurring method, the spatially weighted TV deblurring method, and the l0-norm sparsity based deblurring method, and the BM3D deblurring method.

In the experiments of super-resolution, the degraded LR images were generated by first applying a truncated 7×7 Gaussian kernel of standard deviation 1.6 to the original image and then down-sampling by a factor of 3. We compare the proposed method with four state-of-the-art methods: the iterated wavelet shrinkage method, the TV-regularization based method, the Softcuts method, and the sparse representation based method.

In both of the deblurring and super-resolution experiments, 7×7 patches (for HR image) with 5-pixel-width overlap between adjacent patches were used in the proposed methods. For colour images, all the test methods were applied to the luminance component only because human visual system is more sensitive to luminance changes, and the bi-cubic interpolator was applied to the chromatic components. Here we only report the PSNR and SSIM results for the luminance component.

To examine more comprehensively the proposed approach, we give three results of the proposed method: the results by using only ASDS (denoted by ASDS), by using ASDS plus AR regularization (denoted by ASDS-AR), and by using ASDS with both AR and non-local similarity regularization (denoted by ASDS-AR-NL).

Figure 3 Comparison of deblurred images (uniform blur kernel, $\sigma_n = 2$) on Parrot by the proposed methods.

Top row: Original, Degraded, ASDS-TD1 (PSNR=30.71dB, SSIM=0.8926), ASDS-TD2 (PSNR=30.90dB, SSIM=0.8941).
Bottom row: ASDS-AR-TD1 (PSNR=30.64dB, SSIM=0.8920), ASDS-AR-TD2 (PSNR=30.79dB, SSIM=0.8933),
ASDS-AR-NL-TD1 (PSNR=30.76dB, SSIM=0.8921), ASDS-AR-NL-TD2 (PSNR=30.92dB, SSIM=0.8939).

C. Experimental Results on Single Image Super-Resolution:

In this section we present experimental results of single image super-resolution. The proposed method with the two different training datasets produces almost the same HR images. It can also be observed that the ASDS scheme can well reconstruct the image, while there are still some ringing artifacts around the reconstructed edges[12]. Such artifacts can be reduced by coupling ASDS with the AR model based regularization, and the image quality can be further improved by incorporating the non-local similarity regularization.

The visual comparisons are shown in Fig.4. The Softcuts method produces very smooth edges and fine structures, making the reconstructed image look unnatural. By sparsely coding the LR image patches with the learned LR dictionary and recovering the HR image patches with the corresponding HR dictionary, the sparsity-based method is very competitive in terms of visual quality. The proposed method shows good robustness to noise. Not only is the noise effectively suppressed, but also the image fine edges are well reconstructed[13]. This is mainly because the noise can be more effectively removed and the edges can be better preserved in the adaptive sparse domain.

Figure 4 Reconstructed HR images (scaling factor 3) of Parrot by different methods

Top row: LR image,(PSNR=28.78dB, SSIM=0.8845) and (PSNR=27.59dB, SSIM=0.8856).
Bottom row: (PSNR=27.71dB, SSIM=0.8682), (PSNR=27.98dB, SSIM=0.8665) and proposed (PSNR=30.00dB, SSIM=0.9093).

D. Discussions on the Computational Cost:

The proposed Algorithm 1 converges in 700~1000 iterations in most cases. For a 256×256 image, the proposed algorithm requires about 2~5 minutes for image deblurring and super-resolution on an Intel Core2 Duo 2.79G PC under the Matlab R2010a programming environment[13]. In addition, several accelerating techniques can be used to accelerate the convergence of the proposed algorithm. Hence, the computational cost of the proposed method can be further reduced.

VI. CONCLUSION

Hence a Proposed system employs sparse representation based Image deblurring using Adaptive Sparse Domain Selection and Adaptive Regularization. Here we adaptively selects a high quality example patches for each local patch. The Adaptive Sparse Domain Selection improves significantly the effectiveness of sparse modeling and consequently the results of image restoration. Auto regressive models are used to regularize the image local smoothness. The image non-local similarity was incorporated as another regularization term to exploit the image non-local redundancies. The experimental results based on this approach outperform many state-of-the-art methods in both PSNR and visual quality.

VII. REFERENCES

[1]. Michael Elad and Michal Aharon, "Image Denoising Via Sparse and Redundant Representations Over Learned Dictionaries" IEEE Trans. on IMAGE PROCESSING, VOL. 15, NO. 12, DECEMBER 2006

[2]. A. Marquina and S. J. Osher, "Image super-resolution by TV-regularization and Bregman iteration" J. Sci. Comput., vol. 37, pp. 367–382, 2008.

[3]. M. Elad and I. Yavneh, "A plurality of sparse representation is better than the sparsest one alone," IEEE Trans. Inf. Theory, vol. 55, no. 10, pp. 4701–4714, Oct. 2009.

[4]. Salem Saleh Al-Amri, "Restoration and Deblured Motion Blurred Images," International Journal of Multimedia, Volume 1, Issue 1, 2011, pp-03-06

[5]. J. Yang, J. Wright, Y. Ma, and T. Huang,"Image super-resolution as sparse representation of raw image patches" in Proc. IEEE Comput. Vis. Pattern Recognit., Jun. 2008, pp. 1–8.

[6]. G. Monaci and P. Vanderqheynst,"Learning structured dictionaries for image representation," in Proc. IEEE Int. Conf. Image Process., Oct. 2004, pp. 2351–2354.

[7]. R. Rubinstein, A. M. Bruckstein, and M. Elad, "Dictionaries for sparse representation modeling," Proc. IEEE, vol. 98, no. 6, pp. 1045–1057, Jun. 2010.

[8]. A. M. Bruckstein, D. L. Donoho, and M. Elad, "From sparse solutions of systems of equations to sparse modeling of signals and images," SIAM Rev., vol. 51, no. 1, pp. 34–81, Feb. 2009.

[9]. J. A. Tropp and S. J. Wright, "Computational methods for sparse solution of linear inverse problems," Proc. IEEE, vol. 98, no. 6, pp. 948–958, Jun. 2010.

[10]. M. Elad, M. A. T. Figueiredo, and Y. Ma,"On the role of sparse and redundant representations in image processing," Proc. IEEE, vol. 98, no. 6, pp. 972–982, Jun. 2010.

[11]. I. Daubechies, M. Defriese, and C. DeMol, "An iterative thresholding algorithm for linear inverse problems with a sparsity constraint," Commun. Pure Appl. Math., vol. 57, pp. 1413–1457, 2004.

[12]. L. Zhang, R. Lukac, X.Wu, and D. Zhang, "PCA-based spatially adaptive denoising of CFA images for single-sensor digital cameras," IEEE Trans. Image Process., vol. 18, no. 4, pp. 797–812, Apr. 2009.

[13]. X. Wu, X. Zhang, and J. Wang, "Model-guided adaptive recovery of compressive sensing," in Proc. Data Compression Conf., 2009, pp. 123–132.

