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Centralized Sparse Representation Non-locally For Image Restoration

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Abstract: ***Sparse representation based image restoration is an interesting and challenging field of research in image processing and it is used in many real life applications. In this paper represent the non-locally centralized sparse representation model for image restoration. Sparse coding noise is used to define the sparse code of the degraded image and unknown original image; it is also used to increase the performance of sparsity based image restoration sparse representation model shown promising results in various image restoration applications. In this paper sparse coding noise is introduced and the goal of image restoration changes the sparse coding noise. Standard sparse representation model used to solve the image restoration problem. Image restoration intends to recover high resolution image from low resolution image. Non-local means approach to image de-noising, where the prominence of self similarities is used as a prior on natural images. Sparse representation model sufficient for reconstruction of the original image.***

Keywords: Image restoration, nonlocal similarity, super resolution, sparse representation, de-blurring, de-noising

1. Introduction

High quality images reconstructing from one or many versions used for many applications such as medical imaging, remote sensing, surveillance, and entertainment etc. image restoration intends to recover high resolution image from low resolution image. Blurring is a process of reducing the bandwidth of an ideal image that results in imperfect image formation. It happens due to the relative motion between the camera and the original scene or by atmospheric turbulence and relative motion between camera and ground. Image restoration concerned with the estimation or reconstruction of uncorrupted image from a blurred or noise one.

1.1 Non Local Means Filtering

Efros and Leung shows that the self-similarities to natural images could effectively be used in texture synthesis tasks. The *non-local means* approach to image de-noising, where the prominence of self similarities is used as a prior on natural images. Two blur models were used. They are linear motion blur and uniform Out-of-focus blur. In linear motion blur, the relative motion between recording device and the scene results in several forms of motion blur that are all distinguishable. In Uniform Out-of-focus blur when camera captures the 3D image onto 2D image some parts are out of focus. These out of focus can be calculated by spatial continuous point spread function. Yusuf Abu Sa'dah discussed in image enhancement that Low pass filters blur the images which result in noise reduction, whereas high pass filters used to sharpen the images. Butterworth filter and Gaussian filter can be used to sharpen the images and also high pass filter reside in the shape of the curve.

2. Literature Survey

We start with a brief description of well-established approaches to image restoration that are relevant and related to the proposed approach. Since it is difficult to design a standard model for digital camera noise, these methods assume white Gaussian noise. Even though this generic setting slightly differs from that of real image de-noising, it has allowed the development of effective algorithms that are now widely used in digital cameras and commercial software packages. We will use the same assumption in the rest of this paper, but will demonstrate empirically that our approach is effective at restoring real images corrupted by non-Gaussian, non-uniform noise.

3. Proposed System

3.1 Proposed image de-noising algorithm

K.Dabov proposed a novel image de-noising strategy on an enhanced sparse representation in transform domain. Sparsity is achieved by grouping similar 2D image fragments into 3D data arrays called groups. Collaborative filtering procedure developed to deal with 3D groups. It involves three steps i.e. 3D transformation of group, Shrinkage of transform spectrum, inverse 3D transformation. Some of the methods used to de-noising are transform domain de-noising method, sliding window transform domain image de-noising. To apply shrinkage in local transform domain sliding window transform domain is employed. Sharp adaptive transform can achieve a very sparse representation of true signal in adaptive neighborhoods.

Collaborative filtering for image de-noising algorithm involves 2 steps:

1) Block estimate: In step one Block wise estimate is done for grouping and thresholding which follows aggregation.
2) Final estimate: In step two Block wise estimates is done for grouping and filtering which also follows aggregation.

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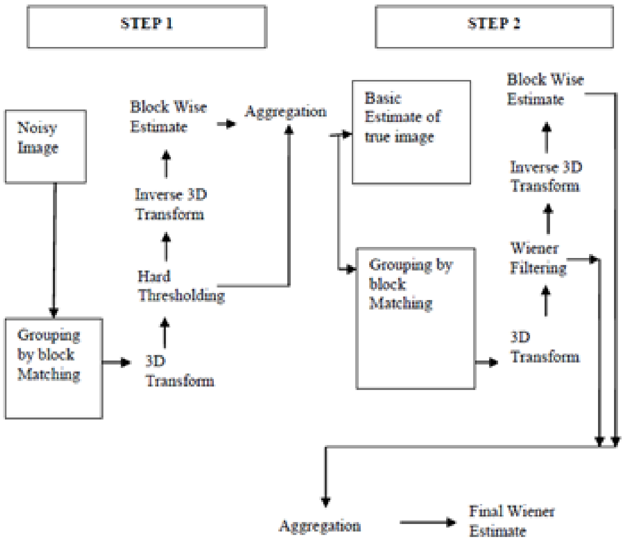

Figure 1: Flowchart of the proposed image de-noising algorithm

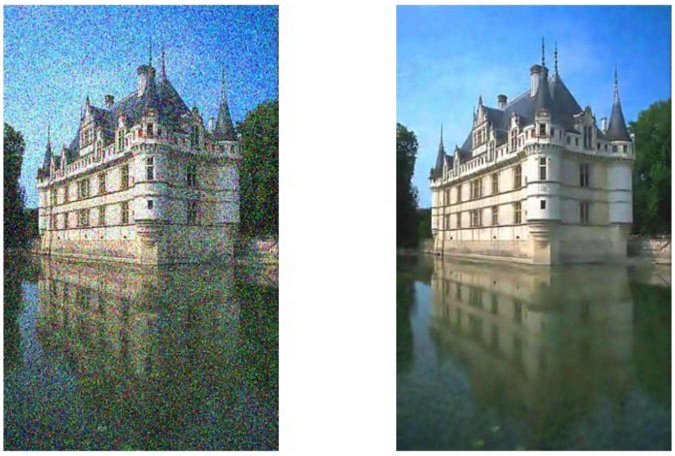

Figure. 2: Image de-noising via sparse modeling

4. Dictionary Learning for Image Analysis

A sparse representation in an over complete dictionary consisting of the samples themselves yielded semantic information. For many applications, however, rather than simply using the data themselves, it is desirable to use a compact dictionary that is obtained from the data by optimizing some task-specific objective function. This section provides an overview of approaches to learning such dictionaries, as well as their applications in image processing.

A) Image Denoising And Deblurring Techniques

Reginald L. Lagendijk and Jan Biemond describe about the basic methods and filters for the image restoration. Linear Spatially Invariant Restoration Method is basic restoration filters were used. The author described blurring function act as a convolution kernel or point spread function d (n1, n2) that does not vary spatially. It is also assumed that the statistical properties of mean and correlation function of the image and noise do not change spatially. Modeling assumption can be denoted by f(n1,n2) spatial discrete image that does not contain any blur or noise then the recorded image g(n1,n2) is shown in the equation ,

$g\,(n1, n2) = d\,(n1, n2) * (\,n1, n2) + w(n1, n2)$

Two blur models were used. They are linear motion blur and uniform Out-of-focus blur. In linear motion blur, the relative motion between recording device and the scene results in several forms of motion blur that are all distinguishable. In Uniform Out-of-focus blur when camera captures the 3D image onto 2D image some parts are out of focus. These out of focus can be calculated by spatial continuous point spread function.

Yusuf Abu Sa'dah *et.al* discussed in image enhancement that Low pass filters blur the images which result in noise reduction, whereas high pass filters used to sharpen the images. Butter worth filter and Gaussian filter can be used to sharpen the images and also high pass filter reside in the shape of the curve. Therefore any one of the high pass filters can be used to sharpen the images in restoration algorithm.

Jan Biemond et al. discusses the iterative restoration algorithms for the elimination of linear blur from images that tainted by point wise nonlinearities such as additive noise and film saturation. Regularization is projected for preventing the excessive noise magnification that is associated with ill-conditioned inverse problems such as de-blurring problem. There are various basic iterative solutions such as inverse filter solution; least squares solutions, wiener solution, constrained least squares solution, kalman filter solution. Inverse filter is a linear filter whose point spread function is the inverse of blurring function. It requires only the blur point spread function. Least Square filters are used to overcome the noise sensitivity and Weiner filter is a linear partial inverse filter which minimizes the mean-squared error with the help of chosen point spread function. Power spectrum is a measure for the average signal power per spatial frequency carried by the image that is estimated for the ideal image. Constrained least squares filter for overcoming some of the difficulties of inverse filter and of wiener filter and it also estimates power spectrum. Regularization methods associated with the names of Tikhonov and Miller. For both the non-iterative and iterative restorations based on Tikhonov-Miller regularization analyzed using Eigen vector expansions.

Michael Elad and Michal Aharon address the image de-noising problem zero-mean white and homogenous Gaussian additive noise is to be removed from given image. Based on sparse and redundant representation over trained dictionaries using K-SVD algorithm, image content dictionaries is obtained. Using corrupted image or high quality image database training is done. So far K-SVD algorithm is used to handle small image patches we extend it to handle large image patches. Sparsity of unitary wavelet coefficient was considered leading to shrinkage algorithm. One-dimensional wavelet are inappropriate for handling images, several new multi scale and directional redundant transforms are introduced including curve let, contour let, vedgelet, bandlet and steerable wavelet. Matching pursuit and basic pursuit de-noising give rise to ability to address image de-noising problem as a direct sparse decomposition technique over

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redundant dictionaries. In sparseland model Bayesian reconstruction framework is employed for local treatment on local patches to global patches. This K-SVD cannot be directly deployed on larger blocks even if provides de-noising results.

Priyam Chatterjee and Peyman Milanfar proposed K-LLD: a patch based locally adaptive de-noising method based on clustering the given noisy image into region of similar geometric structure is proposed with the use of K-LLD. To perform clustering, employ the features of local weight function derived from steering regression. Dictionary employed to estimate the underlying pixel values using a kernel regression. With the use of stein unbiased risk estimator (SURE) local patch size for each size can be chosen. Kernel regression framework uses the methods such as bilateral filter, nonlocal means and optimal spatial adaptation. De-noising can be learned with a suitable basis function that describes geometric structure of image patches. Image de-noising can be first performed by explicitly segmenting the image based on local image structure and through efficient data representation. Clustering based de-noising (K-LLD) makes use of locally learned dictionary that involves three steps:

1) Clustering: Image is clustered using the features that capture the local structure of the image data.
2) Dictionary selection: We form an optimized dictionary that adapts to the geometric structure of the image patches in each cluster.
3) Coefficient calculation: Coefficients for the linear combination of dictionary atoms are estimated with respect to the steering kernel weights.

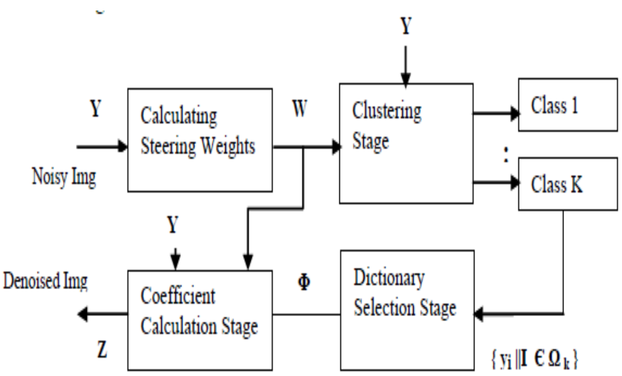

Figure 3: Block diagram of the iterative version of algorithm

B) Image De-noising

We compare the proposed method with three recently developed state-of-the-art de-noising methods, including the shape-adaptive PCA based BM3D (SAPCA-BM3D),(Which outperforms the benchmark BM3D algorithm), The learned simultaneously sparse coding (LSSC) method and the expected patch log likelihood (EPLL) based de-noising method. A set of 4 natural images commonly used in the literature of image de-noising are used for the comparison study. The PSNR results of the test methods are reported in Table 1: From Table I, we can see that the proposed NCSR.

Table 1: PSNR and FSIM results by GSR for image restoration from partial random samples at different percentages of random samples

Data percentage	*Image*			
	Barbara	*House*	*Butterfly*	*Lena*
20%	31.32/05 98	35.61/0.9594	30.31/0.9792	34.12/0.9815
30%	34.42/0.9768	37.65/0.9745	33.02/0.9888	36.38/0.9893
50%	39.12/0.9906	41.61/0.9886	37.26/0.9956	39.83/0.9956

B. Image De-blurring

We applied de-blurring methods to both the simulated blurred images and real motion blurred images. In the simulated image de-blurring two commonly used blur kernels, i.e. 9×9 uniform blur and 2D Gaussian function (non-truncated) with standard deviation 1.6, are used for simulations. Additive Gaussian noise with noise levels $\sigma n = \sqrt{2}$ is added to the blurred images. In addition, 6 typical non-blind de-blurring image experiments presented in & conducted for further test. For the real motion blurred images, we borrowed the motion blur kernel estimation method from to estimate the blur kernel and then fed the estimated blur kernel into the NCSR de-blurring method. For color images, we only apply the de-blurring operation to the luminance component. We compared the NCSR de-blurring method with four state of-the-art de-blurring methods, including the constrained TV de-blurring (denoted by FISTA) method the *l*0-sparsity based de-blurring (denoted by *l*0-SPAR) method.

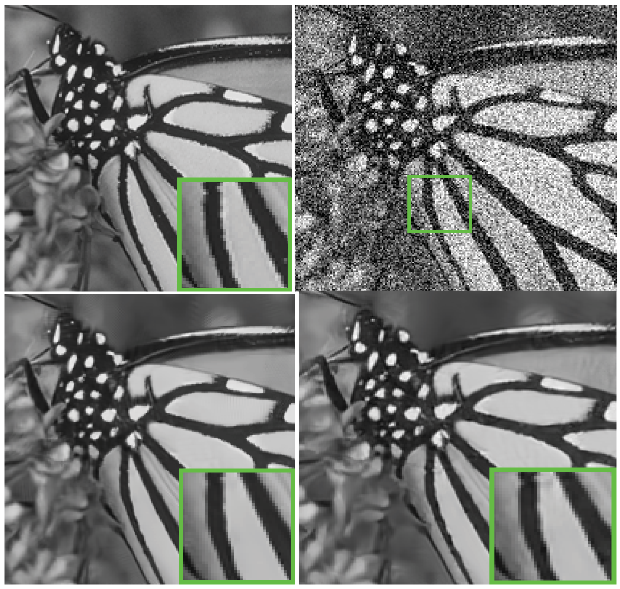

Figure 4: De-noising Performance

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Figure 5: image De-blurring

To verify the IR performance of the proposed NCSR algorithm WC conduct extensive experiments on image de-noising, de-blurring and super-resolution. The basic parameter setting of NCSR is as follows: the patch size is 7 × 7 and K = 70. For image de-noising, δ = 0.02, L = 3, and J = 3; for image de-blurring and super-resolution, δ = 2.4, L = 5, and J = 160. To evaluate the quality of the restored images, the PSNR and the recently proposed powerful perceptual quality metric FSIM are calculated.

c) Image Super-Resolution

Figure 6: image super-resolution

In image super-resolution the simulated LR image is generated by first blurring an HR image with a 7 × 7 Gaussian kernel with standard deviation 1.6, and then down sampling the blurred image by a scaling factor 3 in both horizontal and Fig. 6 Image super-resolution performance comparison on *Plant* image (scaling factor 3, σn = 0). From left to right and top to bottom: original image, LR image, the reconstructed images by TV (PSNR=31.34 dB;

FSIM=0.8909), sparsity-based (PSNR=31.55 dB; FSIM=0.8964), ASDS-Reg. (PSNR=33.44 dB; FSIM=0.9242), and the proposed NCSR (PSNR=**34.00**dB; FSIM=**0.9369**).Vertical directions. The additive Gaussian noise of standard deviation 5 is also added to the LR images, making the IR problem more challenging. Since human visual system is more sensitive to luminance changes, we only apply the IR methods to the luminance component and use the simple bi-cubic interpolator for the chromatic components. We compare the proposed NCSR approach with three recently developed image super-resolution methods, including the TV-based method , the sparse representation based method , and the ASDS-Reg. method .Since the sparsity-based method in cannot perform the resolution up scaling and de-blurring simultaneously, as suggested by the authors we apply the iterative back-projection to the output of method to remove the blur. The PSNR results of the test methods on a set of 9 natural images are reported in Table IV, from which we can conclude that the proposed NCSR approach significantly outperforms the TV and sparsity-based methods. The subjective comparison between the NCSR the NCSR approach reconstruct the best visually pleasant HR images. The reconstructed edges are much sharper than all the other three competing methods, and more image fine structures are recovered.

5. Objectives and Scope of Research

The work thesis done for this thesis is a contribution to image processing in general and to image de-noising and enhancement in particular.

First, we present and study a novel grayscale-image de-noising filter, termed BM3D filter, and present the scientific background of works that it is related to.

Second, we study various applications of the BM3D filter to other image processing problems, including:
- Video de-noising,
- de-noising of raw sensor images,
- de-noising RGB images
- Non-blind image de-blurring
- Image sharpening

By including the above applications of the BM3D, we aim to show that image de-noising is a fundamental tool in image processing, which can be applied to solve other (often more practical) image processing problems.

6. Algorithm of NCSR

The parameter λ that balances the fidelity term and the centralized sparsity term should be adaptively determined for better IR performance. In this subsection we provide a Bayesian interpretation of the NCSR model, which also provides us an explicit way to set the regularization Parameter λ. In the literature of wavelet de-noising, the Connection between *Maximum a Posterior* (MAP) estimator and sparse representation has been established, and here we extend the connection from the local sparsity to non-locally centralized sparsity. For the convenience of expression,

Let's define $\theta = \boldsymbol{\alpha} - \boldsymbol{\beta}$.

For a given $\boldsymbol{\beta}$, the MAP estimation of θ can be formulated as

$$\boldsymbol{\Theta}\, y = \text{argmax}\boldsymbol{\theta} \log P\,(\boldsymbol{\theta}\,|\boldsymbol{y})$$
$$= \text{argma}\boldsymbol{\theta}\,\{\log P\,(\boldsymbol{y}|\boldsymbol{\theta}) + \log P\,(\boldsymbol{\theta})\}.$$

Algorithm I: NCSR-Based Image Restoration

1. Initialization:

(a) Set the initial estimate as ˆ x = $\boldsymbol{y}$ for image De-noising and de-blurring, or initialize ˆ$\boldsymbol{x}$ by bi-cubic Interpolator for image super-resolution;

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(b) Set initial regularization parameter λ and δ; 2. Outer loop (dictionary learning and clustering): iterate

On $l = 1, 2. . . . L$

(a) Update the dictionaries {_*k*} via k-means and PCA;

(b) Inner loop (clustering): iterate on $j = 1, 2. . . . J$

(I) $\hat{\mathbf{x}}\ (j+1/2) = \hat{x}\ (j) + \delta \mathbf{H}T\ (\mathbf{y} - \mathbf{H}\hat{}\ x\ (j))$, where δ is
The pre-determined constant;

(II) Compute $\mathbf{v}\ (j) = [\_Tk1\mathbf{R}1\ \hat{}\ x\ (j+1/2) . . . \_TkN\ \mathbf{R}N\ \hat{\mathbf{x}}\ (j+1/2)]$, where *_ki* is the dictionary assigned to patch $\hat{}\ Xi = \mathbf{R}I\ \hat{}x\ (j+1/2)$;

(III) Compute $\boldsymbol{\alpha}\ (j+1)\ i$ using the shrinkage operator**.**

(IV) If *mod* (j, *J0*) = 0 update the parameters λi, and $\{\boldsymbol{\beta} i\}$

(V) Image estimate update: $\hat{\mathbf{x}}\ (j+1) = \_ \circ \boldsymbol{\alpha}\ (j+1)$

Algorithm II: Iterative Shrinkage Algorithm:

As discussed in Section II, we use an iterative algorithm to solve the NCSR objective function in Eqs. Each iteration, for fixed $\boldsymbol{\beta} i$ we solve the following $l1$-norm minimization problem:

$$\boldsymbol{\alpha y} = \arg\min_\alpha \left\{ \left\| \mathbf{y} - \mathbf{H}\_ \circ \alpha \right\|\_22 + \_i\_j \lambda i, j\ |\alpha i\ (j) - \boldsymbol{\beta} i\ (j)| \right\}$$

Which is convex and can be solved efficiently? In this paper we adopt the surrogate algorithm in the $(l+1)$-*th* iteration, the proposed shrinkage operator for the j th element of $\boldsymbol{\alpha} i$ is

$$\boldsymbol{\alpha}(l+1)i\ (j) = S\tau\ (\mathbf{v}(l)i, j - \boldsymbol{\beta} i\ (j)) + \boldsymbol{\beta} i\ (j)$$

Where $S\tau\ (\cdot)$ is the classic soft-thresholding operator and

$$\mathbf{v}\ (l) = KT\ (\mathbf{y} - K \circ \boldsymbol{\alpha}\ (l))/c + \boldsymbol{\alpha}(l), \text{ where } K = \mathbf{H}\_,\ KT = \_T \circ \mathbf{H}T,$$

$\tau = \lambda i, j\ /c$, and c is an auxiliary parameter guaranteeing the convexity of the surrogate function. The derivation of the above shrinkage operator follows the standard surrogate algorithm.

7. Conclusion

This paper we presented study of non- locally centralized sparse representation (NCSR) model for image restoration. Image de-noising and de-blurring had been a major problem in the image restoration methodologies. Different types of algorithms are studied for the de-blurring, de-noising of degraded images and different type of filters are also analyzed. Sparse representations have been found to provide the better results of image restoration than other representations. Therefore based on sparse representation, local and non-local methods can be used to restore the degraded version of images effectively. The sparse coding noise (SCN), which is defined as the difference between the sparse code of the degraded image and the sparse code of the unknown original image, should be minimized to improve the performance of sparsity-based image restoration. To this end, we proposed a centralized sparse constraint, which exploits the image nonlocal redundancy, to reduce the SCN. The Bayesian interpretation of the NCSR model was provided and this endows the NCSR model an iteratively reweighted implementation. By using the different sparse representation technique solves the image related problems, Such as image de-noising, de-blurring and super-Resolution. using the different NCSR approach improving the performance of image restoration. Solve various types of image restoration problems, including de-noising, de-blurring and super-resolution; validate the generality and state-of-the-art performance of the proposed NCSR algorithm. Improve the sparse representation performance by proposing a non-locally centralized sparse representation (NCSR) model.

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