



## A SHORT REVIEW ON IMAGE RESTORATION OF NOISY AND BLURRED IMAGES AND COMPARISON OF STATE OF ART ALGORITHMS

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**Abstract:** This paper analyzes most of restoration method frequently used and gives comparison of seven recent algorithms in terms of working and applicability. It compares algorithms like KSVD, BM3D, CSR, KLLD, SVD based, LPGPCA, NCSR and many other spatial domain, transform domain and dictionary based methods, iterative methods for image restoration of noisy and blurred images. It gives comparative survey of all restoration techniques which will be useful to researchers for further development in the field.

**Keywords:** KSVD; KLLD; NCSR; BM3D; CSR; SVD based; LPGPCA; Dictionary learning; Transform domain; Spatial domain; ISTA; FISTA; TWIST.

### I. INTRODUCTION

Image Restoration is process of regaining the original image from its degraded version [1]. It includes image denoising [28], deblurring, superresolution [1]. It is an ill posed problem and many researchers tried to solve it in various ways. These can be broadly classified and discussed in rest of the paper.

### II. CLASSIFICATION OF IMAGE RESTORATION TECHNIQUES

The vast work done in the area can be classified in following heads.

#### A. Local and Non local filters

Many local filters such as Gaussian filter, median filter [3], inverse filter Wiener filter[2], Least Mean Squares filter, bilateral filter [6][7], joint bilateral filter, Lee filter, etc. are used for noise reduction but as compared to them non local filter always gives better results. The nonlocal filters make use of the self-similarity of natural images in a nonlocal manner. The basic NLM was developed in[4], later many improvements to algorithm are proposed [5].

#### B. Transform Domain Techniques:

These include wavelets, BM3D, LPGPCA, and LPGSVD. Noise is spread out uniformly in wavelet domain while signal gets concentrated in few significant components. This is called as sparsity property. Using this concept different wavelet transforms can be used for image restoration. Discrete Wavelet Transform and thresholding is used to get denoised image in [8] and DWT is applied on restored image to get better quality image in [9]. Wavelet based EM algorithm for multispectral images is proposed in [10] [11]. Noise is first reduced by adaptively shrinking wavelet coefficients using alpha map [13] and entropy,

and then a new directional transform using combined wavelet functions and an adaptive Gaussian low-pass filter is composed in [12]. In [15] researchers have compared 17 methods for Image Denoising using wavelet transforms where various types of noise, transforms and thresholding are compared. It indicates vast work done by researchers in the area. With

wavelets usually five thresholding methods are used to reduce the noises that are hard thresholding, soft thresholding, VisuShrink, SureShrink, BayesShrink. [8][12][14]. Block Matching and 3-D Filtering (BM3D) based on variation of K nearest neighbor clustering and 2 stage simplification of EM based estimation of signal variance was developed [16]. Improvements [17] [18] to it are also proposed and used for image restoration. LPGPCA includes 3 steps local pixel grouping, PCA transform and inverse PCA transform [19]. LPGSVD [20] is similar technique to LPGPCA. It also has 3 steps local pixel grouping, SVD computation followed by aggregation.

#### C. Vector Quantization

Blind image restoration algorithm based on Vector Quantization was proposed by Aggelos K. Katsaggelos et.al. [21] [22] [23].

#### D. Regularization

Regularization can be iterative or direct. Regularization has a general form as

$$\text{Min} \|y - Hx\|_2^2 + \lambda \|x\|_0$$

Where  $\lambda$  is regularization parameter.

Many variations to this basic equation are developed and known as L1 norm, Lp norm, Tikhonov, L1/L12, Total Variation [24], Mumford Shah [27] [29], Sparsity [25] [30] [33] etc. Using **Sparsity** property of image many recent methods of Image Restoration [28] are developed such as KSVD [31] [32], Learned Simultaneous Sparse Coding (LSSC) [34], and Clustering-based Sparse Representation

(CSR) [35], Non locally Centralized Sparse Representation(NCSR) [1] [36], Clustering-based Denoising with locally learned dictionaries (KLLD) [38] [37]. These are explained below in short.

**E. KLLD [38]**

This algorithm applies K-means clustering to images. On these clusters PCA transform is applied and then dictionary is formed. It uses steering Kernel Regression for weight calculation [38].

**F. CSR [35]**

The steps in algorithm are K-means clustering, followed by PCA then shrinkage algorithm. In last step it uses L1 optimization as regularization process. It does not need any initial dictionary.

**G. Nonlocally Centralized Sparse Representation (NCSR) [1] [36]**

This algorithm is combination of all recent image restoration techniques. It begins with L1 regularization with sparse representation. It improves sparse representation by proposing non locally centralized sparse representation in which image is divided into overlapping patches. It also uses iterative shrinkage algorithm for solving L1 regularized least square problem. It used uses K-means clustering and PCA to form dictionary. To calculate estimation of sparse codes it uses weighted average formula similar to non local means algorithm. It also used maximum a posterior estimation (MAP) for evaluating regularization parameter  $\lambda$ . This algorithm works for denoising, deblurring and super resolution.

**H. Direct Regularization**

*Truncated SVD [26]:* SVD [53] [54] solution is given by  $A=U\Sigma V$ . If we approximate the SVD solution by considering some rank k matrix is known as truncated SVD solution.

**I. Iterative**

In iterative algorithms, during the iterations the blurred version of the current restoration result is compared to the recorded image. The difference between the two is scaled and added to the current restoration result to give the next

restoration result. Various iterative algorithms are Van Cittert Algorithm [39] [40], Landweber Algorithm [39] [41] [42] [43], Poisson Map Algorithm [39], Richardson-Lucy Algorithm [39], Iterative Shrinkage Thresholding algorithm (ISTA) [44], Fast Iterative Shrinkage Thresholding algorithm (FISTA) [45] [46], Two step Iterative Shrinkage Thresholding algorithm (TwIST)[47]. ISTA [44] implements Landweber algorithm followed by soft thresholding [8] for restoration. FISTA [45] [46] is same as ISTA except that iterative shrinkage step considers two previous points for calculation instead of one point. TwIST [47] combines advantages of two methods ISTA and Iterative Re-weighted Shrinkage (IRS) [55] [56] algorithm. It gives good denoising performance as IST algorithm and speed as IRS algorithm.

**J. Expectation Minimization (EM) [48] algorithm**

The **Expectation Minimization (EM) [48] algorithm** is a general procedure for finding maximum likelihood parameter estimates. It consists of two steps Expectation step and Maximization step. By alternating the E-step and the M-step, convergence to an optimum of the likelihood function is achieved.

**K. Bayesian Estimator:**

Bayesian estimators [49] [50] includes estimators such as Maximum a posterior estimation (MAP), Maximum Likelihood Estimation (ML), minimum mean square error (MMSE), minimum mean absolute value of error (MAVE), etc.

**L. Fusion:**

Fusion of two or more restored images can be done to improve quality of restored image. Wavelet based fusion of two restored images by two different algorithms like Lucy Richardson, Wiener are used in [51] [52].

Table I compares state of art algorithms and illustrates that all of them use as basic steps pixel grouping or clustering followed by PCA or SVD as decomposition method.

Table I. Summary of basic steps in all state of art algorithms

<i>Technique</i>	<i>Steps of Algorithm</i>
KSVD [31]	Orthogonal Matching pursuit → SVD
KLLD [38]	Clustering → PCA → Form Dictionary
NCSR [1]	L1 Optimization → K means Clustering → PCA → Form Dictionary → Shrinkage Algorithm
LPGPCA [19]	Local Pixel Grouping → PCA → Inverse PCA
SVD based [20]	Local Pixel Grouping → SVD → Aggregation
BM3D [16]	3D transform → Thresholding (Advanced version uses PCA)
CSR [35]	K means Clustering → PCA → Shrinkage Algorithm → L1 Optimization

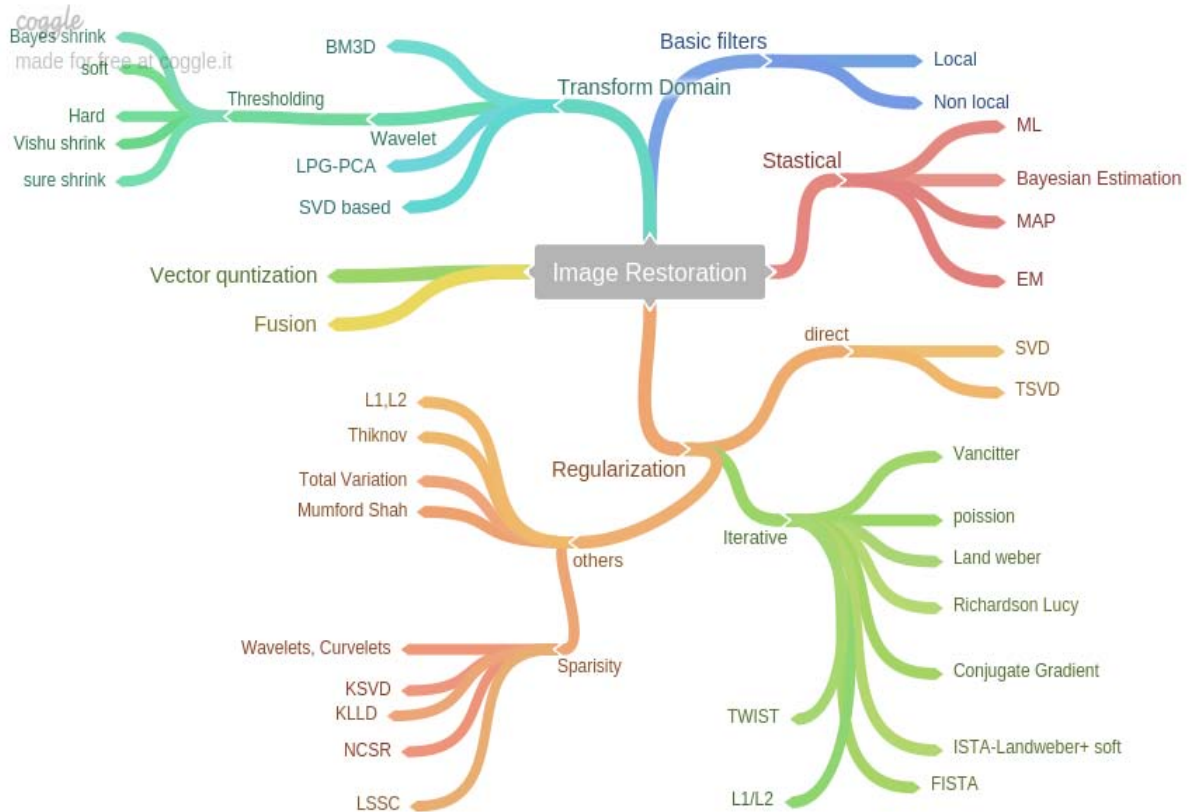


Figure1: Complete mind map of Image Restoration techniques.

Figure1 gives complete mind map of Image Restoration techniques discussed in the paper.

### III. CONCLUSION

This paper compared many restoration techniques and analyzed based on working and applicability. Out of all the algorithms discussed maximum basic filters and above compared algorithms in table 1 work for image denoising. For image deblurring inverse filter and all iterative techniques are used dominantly in literature but it can also be done by direct methods. NCSR gives results for denoising, deblurring and super resolution.

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