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# Survey of Various Methods for Image Denoising

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***Abstract: An Image is a worth, a thousand words & in this digital age, images are everywhere. Most of the digital images contain some form of noise. The purpose of denoising is to reconstruct the original image from its noisy observation as accurately as possible. The important property of a good image denoising model is that it should completely remove noise as far as possible. Estimation of the noise level in an image is a very important parameter to improve the efficiency of denoising. This article presents different approaches used so far by the researchers for the estimation of blind noise level using the statistical and averaging method and denoising of an image. The paper also contains problems in different approaches identified by the survey. Image denoising has a very rich history beginning from the mid-70s. Patch based image modeling has achieved a great success in low-level vision such as image denoising. In particular, the use of image nonlocal self-similarity (NSS) prior, which refers to the fact that a local patch often has many nonlocal similar patches to it across the image, has significantly enhanced the denoising performance. However, in most existing methods only the NSS of input degraded image is exploited, while how to utilize the NSS of clean natural images is still an open problem.***

***Keywords: Denoising, Filtering, Image, Noise Models, Review, Spatial Domain, Transform Domain.***

## 1. INTRODUCTION

As a classical problem in low-level vision, image denoising has been extensively studied, yet it is still an active topic for that it provides an ideal test bed for image modeling techniques. In general, image denoising aims to recover the clean image x from its noisy observation y = x + v, where v is assumed to be additive white Gaussian noise. A variety of image denoising methods has been developed in past decades, including filtering based methods, diffusion based methods, total variation based methods, wavelet/curvelet based methods, sparse representation based methods, nonlocal self-similarity based methods etc [1].

Image Processing is a technique to enhance raw images received from cameras or other sensors. Whenever an image is captured through a camera or any other sensor, it contains some amount of noise. Noise is the disturbance or unwanted signal that is present in the image and is an unavoidable intrinsic characteristic of any image, due to the physical & natural phenomenon of the world we live in. In other words, Noise is the unwanted signal that interferes with the original signal and degrades the visual quality of the digital image. The main sources of noise in digital images are imperfect instruments, the problem with data acquisition process, interference natural phenomena, transmission and compression [2].

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. However, images captured by modern cameras are invariably corrupted by noise [3].With increasing pixel resolution but more or less the same aperture size, noise suppression has become more relevant. While advances in optics and hardware try to mitigate such undesirable effects, software-based denoising approaches are more popular as they are usually device independent and widely applicable. In the last decade, many such methods have been proposed, leading to considerable improvement in denoising performance. The challenge of any image denoising algorithm is to suppress noise while producing sharp images without loss of finer details. The first modern adaptive method to successfully address these contradictory goals can be attributed to Tomasi et al., where the authors proposed a generalization of the SUSAN filter, which itself was an extension of the Yaroslavky filter. The authors there proposed denoising by weighted averaging pixels similar in intensity within a local neighborhood. Under strong noise, identifying such similar pixels can be challenging. Takeda et al. proposed a signal-dependent steering kernel regression (SKR) framework for denoising. This method proved to be much more robust under strong noise. A patch-based generalization of the bilateral filter was proposed, where the concept of the locality was extended to the entire image. A significantly different approach to denoising was introduced in K-SVD. Building on the notion of image patches being sparse representable, Elad et al. proposed a greedy approach for dictionary learning tuned for denoising. Authors proposed a hybrid approach (K-LLD) that bridged such dictionary-based approaches with the regression-based frameworks. The motivation there was that similar patches shared similar sub-dictionaries, and such sub-dictionaries could be used for better image modeling. A similar observation was exploited in the form of a nonlocal sparse model (NLSM) to improve the performance of the K-SVD framework [3].

Capturing a pinhole image (large depth-of-field) is important to many computer vision applications, such as 3D reconstruction, motion analysis, and video surveillance. For a dynamic scene, capturing pinhole images, however, is difficult: we have often to make a tradeoff between depth-of-field and motion blur. For example, if we use a large aperture and short exposure to avoid motion blur, the resulting images will have small depth-of-field; otherwise, if we use a small aperture and long exposure, the depth-of-field will be large, but at the expense of motion blur. Using multi-view images for noise reduction has a unique advantage: pixel correspondence from one image to all other images is determined by its single depth map. This advantage contrasts with video denoising, where motion between frames, in general, has many more degrees of freedom. Although this observation is a common sense in 3D vision, we are the first to use it for finding similar image patches in multi-view denoising. Specifically, our denoising method is built upon the recent development in image denoising literature, where similar image patches are grouped together and "collaboratively" filtered to reduce noise. When considering whether a pair of patches in one image is similar or not, we simultaneously consider the similarity between corresponding patches in all other views using depth estimation [5].

The various noise level estimation categories like filter based noise estimation, selection of block based, and also on the various model of noise model are proposed according to own of the interested researcher. Estimation method depends on a parameter. There performance depends heavily on the accuracy of noise level estimation. Blind noise level estimation is an important part of image processing. The different noise estimation model and de-noise algorithm are estimation to the noise and remove the noise from the image. But these noise estimation and de-noising algorithm still cannot achieve the best performance. These uses of Noise model which is well for single independent to additive white Gaussian noise. There are generally they are classifiable into filter based approach, patch-based approach, statistical approach [6].

Many algorithms are proposed for noise removals like wavelet filters and data mining. The algorithm is used for changing the neighboring pixels values through filters. Many types of filters are used to remove noise from an image. There are many procedures for this, but all attempt to determine whether the actual differences in pixel values constitute noise or real photographic detail, and average out the former while attempting to preserve the latter. Image noise is random (not present in the object imaged) variation of brightness or color information in images. Noise estimation from a single image seems like an impossible task: we need to find out whether local image variations are due to color, texture, or brightness from an image itself, or due to noise. Many algorithms have been proposed for gray-level. Generally, they are classifiable into segment-based and filter-based approaches, or some combination of them. Principal component analysis is a statistical procedure that uses an orthogonal property to transform to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables. The denoising phenomenon goal is to remove the noise while retaining the maximum possible the important signal or image features. To achieve a good performance in this respect, a denoising algorithm has to adapt to image discontinuities. Generally, the quality of the image can be measured by the peak signal-to-noise ratio (PSNR). Many algorithms are based on the PCA based denoising like CFA- PCA, two stage denoising PCA through LPG and Bayesian PCA [8] and so on. Generally, denoising algorithms can be roughly classified into three categories: spatial domain methods, transform domain methods and hybrid methods. The first class utilizes the spatial correlation of pixels to smooth the noisy image, the second one exploits the sparsity of representation coefficients of the signal to distinguish the signal and noise, and the third one takes advantage of spatial correlation and sparse representation to suppress noise [8].

Image nonlocal self-similarity (NSS) has been widely adopted in patch-based image denoising and other image restoration tasks. Despite the great success of NSS in image restoration, most of the existing works exploit the NSS only from the degraded image. Usually, for a given patch in the degraded image, its nonlocal similar patches are collected, and then the nonlocal means or 3D transforms or some regularization terms can be introduced for image restoration. However, how to learn the NSS prior from clean natural images and apply it to image restoration is still an open [1].

### 1.1 Types of Noise

Normally images are affected by different types of noise. Various types of noise have their own characteristics and are inherent in images in different ways. All the types of noises can be categorized into two models:

- Additive Noise Model
- Multiplicative Noise Model

Additive noise is the signal that gets added to the original image to generate the resultant noisy image. In the multiplicative model, the noise image is generated by multiplication of the original image and the noise signal. The most common noise types found in images are Gaussian Noise, Salt & Pepper Noise and Speckle Noise.

#### 1.1.1 Gaussian Noise

It is evenly distributed over the signal. Each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value [2]. Gaussian noise is an amplifier noise which is independent at each pixel and independent of the signal intensity. Gaussian noise is statistical noise that has its probability density function equal to that of the normal distribution. It arises due to electronic circuit noise & sensor noise due to poor illumination or high temperature. It is a constant power additive noise.

#### 1.1.2 Salt & Pepper Noise

The salt-and-pepper noise is also called shot noise, impulse noise or spike noise. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. It can be caused by dead pixels, analogue-to-digital converter errors, and bit errors in transmission. It has only two possible values, a high value and a low value. The probability of each is typically less than 0.1 [2].

 

### 1.1.3 Speckle Noise

Speckle noise is a granular noise that inherently exists in and degrades the quality of the active radar and synthetic aperture radar (SAR) images. Speckle noise in conventional radar results from random fluctuations in the return signal from an object that is no bigger than a single image-processing element. It increases the mean gray level of a local area [3]. It is a multiplicative noise. The source of this noise is random interference between the coherent returns [2].

## 2. RELATED WORK

In the last decade, great progress has been made in image denoising, for example, just to name a few. Among these methods, several produce very impressive results, such as non-local mean, BM3D, and SA-DCT. All these methods are built upon the same observation that local image patches are often repetitive within an image. Similar patches in an image are grouped together and "collaboratively" filtered to remove noise. While these methods have different algorithmic details, their performance is comparable. Although there one approach to breaking this limit is to use more input images, such as video denoising. To exploit redundant data in a video, similar patches need to be matched over time for noise removal. Another way of leveraging more input images is to reconstruct a clean image from noisy measurements from multiple viewpoints, proposed by Vaish et al. Only image redundancy across viewpoints is exploited and patch similarity within individual images is however neglected. Heo et al. proposed to combine NL-mean denoising with binocular stereo matching, therefore exploiting data redundancy both across views and within each image. Heo et al.'s main idea is to apply NL-mean to both left and right images and then use the estimated depth to average the two denoised images. Note that, when applying NL-mean, their method matches patches in each image independently; such an approach is fragile in the presence of large image noise. Indeed, their method has only been evaluated using images with a noise standard deviation up to 20 [5].

## 3. NOISE LEVEL ESTIMATION

Images are decomposed into a number of patches. We can consider an image patch as a rectangular window in the image with size W × W. The patch with the smallest standard deviation among decomposed patches has the least change of intensity. The intensity variation of a homogenous patch is mainly caused by noise.

### 3.1. Noise level estimation method based on principal component Analysis

S. Pyatykh, et al: New noise level estimation method based on principal component Analysis of image blocks. Show that the noise variance can be estimated as the smallest eigenvalue of the image block covariance matrix. It is at least 15 times faster compared with the methods with similar accuracy and it is at least 2 times more Accurate than other methods. The method does not assume the existence of homogeneous areas in the input image; hence it can successfully process images containing only textures. Our experiments show that only stochastic textures those only stochastic textures. It's near to true noise but not efficient result.
**Drawback:** Patch selection not homogeneous selection .so not stability in the result. Overestimate in case weak texture and lower noise level. Underestimate in case rich texture and higher noise level.

### 3.2. Kurtosis-Based Noise Estimation

Z. Daniel et al: Natural images are known to have scale invariant statistics. While some earlier studies have reported the kurtosis of marginal band pass filter response distributions to be Constant throughout scales, other studies have reported that The kurtosis values are lower for high-frequency filters than For lower frequency ones. They propose a resolution for this discrepancy and suggest that this change in kurtosis values is due to noise present in the image. Then suggest that this effect is consistent with a clean, natural image corrupted by white noise. Those propose a model for this effect and use it to estimate noise standard deviation in corrupted natural images. Noise estimation is Outperform State of art method.

### 3.3 Patch based Method Noise Estimation

D.-H. Shin, et al: In this paper a patch-based method in which the patches whose standard deviations of intensity close to the minimum standard deviation among decomposed patches are selected. Then the noise level is computed from the selected patches. This algorithm is simple and effective, but it tends to overestimate the noise level for small noise level cases and is underestimated in large noise level cases. The reason is that Patch selection result varies depending on the input Image and noise level [6].

## 4. IMAGE DENOISING METHODS

In this paper, we introduce different categories of PCA based denoising method. PCA based Denoising is different type patch based PCA, adaptive PCA, Local PCA, and Non-local PCA and two stage PCA denoised PCA with local pixel grouping etc

### 4.1. Patch-based Denoising

Xiaogang Chen et al. [6]: In this paper, present a novel fast patch-based denoising technique based on Patch Geodesic Paths (PatchGP). Patch GPs treat image patches as nodes and patch differences as edge weights for computing the shortest (geodesic) paths. The path lengths can then be used as weights of the smoothing/denoising kernel. Patch GPs can be effectively approximated by minimum hop paths (MHPs) that generally correspond to Euclidean line paths connecting two patch nodes. To construct the denoising kernel, hay further discretize the MHP search directions and use only patches along the search directions. This method is state-of-the- art methods such as NLM and BM3D but is a few orders of magnitude faster.

### 4.2 PCA-Based Spatially Adaptive Denoising of CFA images

Zhang presented a principal component analysis Based denoising algorithm which works on directly on the color filleting array (CFA) images. This algorithm can effectively suppress noise while preserving color edges and details. The technique of principle component analysis (PCA) is employed to analyze the local structure of each CFA variable block, which contains color components from different channels. These approaches are spatially adaptive PCA denoising scheme works directly on the CFA image and it can effectively exploit the spatial and spectral correlation simultaneously.

### 4.3 Denoising based Adaptive Principal Component's analysis

D. D. Muresan et al: This paper presents a novel approach to image denoising using adaptive principal components. In this image is corrupted by additive white Gaussian noise. That denoising technique performs well in terms of image visual fidelity, and in terms of PSNR values, they are new technique compares very well against some of the most recently published denoising algorithms. This approaches a novel and simple approach to decomposing an image using adaptive principal components. The paper emphasized the strengths of this new decomposition approach by applying it to image denoised.

### 4.4 Image denoising with patch based PCA

Deledalle and salmon et al. are in the recent year introduce three patches based PCA algorithm which performs hard thresholding on the coefficients of the patches in image specific orthogonal dictionaries that for the task of image denoising; nearly State-of-the-art results can be achieved using orthogonal dictionaries only. The algorithms differ in the methodology of learning the dictionary: There carry out a comprehensive empirical evaluation of the performance of these algorithms in terms of accuracy and running times. PCA-based denoising appears to be competitive with the state-of-the-art denoising algorithms, especially for large images and moderate signal-to-noise ratios. Image denoising based on orthonormal dictionaries learned from the image itself by three different strategies:

a. Patch based global PCA (PGPCA)
b. Patch based local PCA (PLPCA)
c. Patch based hierarchical (PHPCA)

Image denoising based on orthonormal dictionaries learned from the image to choose at most three parameters: size of patches, threshold level, and searching zone width (PLPCA) or the number of recursions (PHPCA).

### 4.5 Noise Reduction with Non-Local PCA

Joseph salmon et al, the Poisson distribution used to model this noise have variance equal to its mean so blind application of standard noise removals methods yields significant artifacts. The aim of the present work is to demonstrate that for the task of image denoising; nearly state-of-the-art results can be achieved using small dictionaries only, provided that they are learned directly from the noisy image. To this introduce patch-based denoising algorithms which perform an adaptation of PCA (Principal Component Analysis) for Poisson noise.

**Drawback:** This non-local PCA method especially for Poisson noise not efficient for additive Gaussian noise.

### 4.6 PCA with local pixel grouping,

Zhang et al, **t**his paper presents an image denoising scheme by using principal component analysis (PCA) with local pixel grouping (LPG).there are selected from the local window by using block matching based LPG. Statistics calculations for PCA transform that the image local features can be well preserved after coefficient shrinkage in the PCA domain to remove the noise. The LPG-PCA denoising procedure is iterated one more time to further improve the denoising performance, and the noise level is adaptively adjusted in the second stage. The denoising performance effectively preserves the image fine structures while smoothing noise.

**Drawback:** local image structure is preserving while denoise.so due to low peak signal to ratio the quality of the image is low. LPG-PCA method achieves very competitive denoising performance, especially in image fine structure preservation, compared with state-of-the-art denoising algorithms [6].

## 5. CONCLUSION AND FURTHER WORK

This brief study on the topic of Image Denoising attempts to illustrate the recent research work that has been done in the field. Some research papers were discussed, all focusing on different aspects & techniques of image denoising. Although no experimental comparisons were made the essence of the reviewed papers has been presented. All algorithms have some pros & cons of their own and this can be gleaned from this review. The major role of this paper is to draw a picture of the state of the art of the image denoising techniques. Noise level is an important factor of image processing. When the simultaneous noise estimation and denoise are performed than Denoise of the image depend on estimation noise level. Above discussed paper have mainly state of art method and computation complexity. The contrast in cases state of art in image denoises .and which is local properties of the image. Image quality assessment like MSE, Standard Deviation, and RMSE are best measurement method. Which define how many noises are present in image and quality of the image are define by the MSE and RMSE. There minimum standard deviation is measure quality of estimator and high PSNR and Low MSE is measure good Denoise. Noise estimation and Denoise is main aim discussed in this survey paper .we discussed the different denoising method by using PCA and some latest denoise algorithm. We can simple and effective with scene independent noise estimation .they are not directly markedly depend on the input noisy image.

 

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