A Novel Approach is proposed for Image Denoising by using Image Internal Clustering and External Patch Guidance  
Gadde Yasasvi¹, A. Durgaprakash²  
Assistant Professor²  
Department of ECE  
GVR&S College of Engineering and Technology, India  

Abstract:
Generally image framing plays a wide role in many aspects in that some vision oriented problems occurred. The major problem in the image framing is image denoising. The image denoising is an earlier method to recollect the original from noised image. In that process the transformation technique is applied to the total image. In this case some part of the image may be damaged or blurred. So previous denoising techniques are not possible for the selected portions. That type of problem is partially overcome by my new proposed technique. In this paper we only gave a way for aqua ring noise portion by segmentation or grouping the pixels and noise to denoising and restoration or reconstruction for the original image. In this purpose we clustering the image and applying GMM, Adaptive patches are also used for external prior images clustering. The image quality improvement is shown by values only.

Key Terms: GMM, Image Restoration, Adaptive Patches, Image clustering algorithm, Segmentation

I. INTRODUCTION:
Noise is a fundamental problem in measuring light in an image. No matter how good the captures are, there is Noise in images, especially in low-light conditions. Image denoising is the problem of reducing undesired noise in images. It has been studied extensively over the last half century because of its practical importance. The problem is mathematically ill-posed and image priors are used to regularize it such that meaningful solutions exist. There are two kinds of image priors one can use: priors learned from the given image and priors learned from a separate set of images. We follow the common naming convention and refer to the former as internal priors and the latter as external priors (or generic priors). Smoothness and piecewise smoothness are probably the simplest form of internal priors. They led to many successes of PDE based denoising algorithms in the nineties. Recently, more interesting internal priors, such as patch self-similarity, have been proposed. They have led to methods such as BM3D, which is still regarded as one of the state-of-the-art methods in image denoising. The obvious limitation of internal priors is that external images are completely ignored. For instance, for any given image, one can find similar images (at least in terms of parts) that contain significantly less noise and use these similar images to do a better job of denoising. It was a breakthrough in image denoising in going beyond internal priors to external priors. Allowing external images opens a wide range of possible priors. One of the top-performed image denoising algorithms is based on external images.

There is one problem with external priors:
It is well known that images form a heavy tail distribution. No matter how large the external image set is, some images will fall in the heavy tail, i.e., will not be well-modeled by the learned priors. We believe this problem Prevents methods that use external images from significantly outperforming those that do not.

\[ p(Y|X) \propto \exp\left(-\frac{1}{\sigma^2}(Y-X)^2\right), \]

\[ E(X) = \frac{1}{\sigma^2}\|Y-X\|^2 + \tau\|X\|_s, \]

Low-rank approximation methods have exhibited exciting performance on denoising. It is accepted that the latent structure underlying image similar patches forms a low-dimensional subspace. Given a noisy observation set of similar patches \(Y = [y_1; y_2; \ldots; y_m]\) \(2R_{n \times m}\) and \(X = X + V\), where \(X\) and \(V\) are the corresponding patch matrices of original image and noise, respectively, the independence of noises at the different pixels implies that Under the assumption that the image patches in \(Y\) have similar structures, the latent clean data matrix \(X\) has a low-rank property, i.e., \(p(X) / \exp(kX_\gamma)\). In terms of logarithmic likelihood \(E = \sum\ln p\), we can minimize the posterior energy: where \(\gamma\) is a positive constant. It is shown in Cai et al. [4] that the optimal solution to this problem is \(\gamma = US^*_T\) where \(Y = U\gamma V^T\) is the SVD of \(Y\) and \(S^*_\gamma\) is the soft-thresholding function on \(\gamma\) with parameter \(\tau\). In the nuclear norm minimization has been extended to weighted nuclear norm minimization (WNNM) and has achieved excellent denoising results.
II. RESULTS ON 12 TEST IMAGES

We first evaluate the proposed algorithm and its competing algorithms on 12 popularly used test images. Gaussian white noise with standard deviations \( \sigma = 10; 30; 50; 100 \) are added to those test images. It can be seen that our method has almost the same PSNR results as WNNM on all noise levels, and higher PSNR than other methods. The proposed method effectively exploits the external GMM prior to guide the similar patch grouping, and it can search for the patches in the whole image. This makes the proposed method very robust to reduce strong noise in textural area. In particular, significant improvements can be observed for images Peppers and Montage since these images contain strong textures and weak local similarity. In addition, the proposed method demonstrates higher superiority to other methods in terms of visual quality. The visual comparisons of competing denoising methods at noise levels 50 and 100 are shown in Fig. 6 and Fig. 7, respectively. One can see that the visual quality improvements achieved by the proposed method are more convincing. It can preserve more textures and fine details than the competing methods. Although WNNM[18] has demonstrated a good trade-off between noise removal and edge preservation, it still tends to over-smooth image details and cause ringing artifacts. By more effectively exploit the image external priors and internal priors, the proposed method shows very strong capability to reconstruct the image latent structure from strong noise corruption.
III. CONCLUSION

In this paper, a new denoising approach based on image internal self-similarity prior and external patch priors was presented. Our approach differs from the low-rank based models (e.g., models in [13] and [18]) in two ways. Firstly, we conducted low-rank regularization of similar patches based on global patch clustering but not local block matching. Therefore, we can globally search the similar patches within the whole image. Secondly, we learned a GMM prior model from image patches to guide the patch clustering and the subsequent low-rank subspace learning. Such a clustering based low-rank approximation makes the latent patch reconstruction very robust to noise. Experimental results showed that the proposed algorithm can achieve very competitive denoising performance. In particular, it can preserve much better the image texture structures than the other state-of-the-art denoising algorithms under severe noise environment.

IV. REFERENCES


