Comparative Analysis of Patch Based Image Restoration Techniques for Diversified Field Images.

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Abstract— Recently there has been considerable increase in the casual and commercial uses of image and video capturing devices. Apart from their applications in photography, the captured data are often inputs to sophisticated object detection and tracking, andaction recognition methods. Captured images are often not of desired quality and need to be enhanced by software. One of the major causes of the performance degradations for most methods is the presence of noise. In literature, many image restoration techniques exists for the reduction of noise from degraded image, but they usually do not succeed when applied to diversified fields degraded images with Speckle, Poisson, Gaussian and Salt & Pepper noise. So if an Image restoration technique works well for a particular type of image we cannot assure its performance for other type of image. Similarly if one technique works well in restoration of image corrupted with a particular noise we cannot assure its performance in presence of another noise. So in this paper, we provide performance analysis of state of art image restoration techniques i.e. patch based image restoration technique for various combinations of noise and diversified field images. Along with that a comparative result is drawn which gives the details of efficiency of all the image restoration techniques taken into consideration. In this paper we propose a new patch based image restoration scheme for the removal of noise. This new restoration technique is compared with the existing state-of-art patch based techniques such as K-SVD, FoE and Gaussian FoE. The proposed restoration technique is shown to outperform alternative state-of-the-art restoration methods with synthetic noise to diversified field images both in terms of speed and restoration accuracy.

Keywords— *Image restoration, optimization, synthetic noise, diversified field image, Patches of images.*

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I. INTRODUCTION

Inrecent years, images and videos have become integralparts of our lives. Applications now range from the casual documentation of events and visual communication to themore serious surveillance and medical fields. This has led to anever-increasing demand for accurate and visually pleasing images.However, images captured by modern cameras are invariablycorrupted by noise.Image data obtained by camera sensors are generally contaminated by noise. Image data may be degraded by imperfect instrument, problem with the data acquisition process, and interfering natural phenomena.Similarly image is greatly affected by capturing instruments, data transmission media, quantization and discrete sources of radiation. Furthermore, noise can be introduced by transmission errors and compression. Medical images are used in many biomedical applications for diagnosis from x–ray, computerized tomography (CT)and magnetic resonance imaging (MRI).Similarly in geosciences scientists use remote sensing images to monitor planetary bodies, distant starts, and galaxies, so images used for these applications must be without the interference of the noise. Digital images are prone to a many of types of noise. Noise is nothing butthe errors in pixel values of the image, that do not reflect the true intensities of the real scene [1][2].

There are lots of types of noise which degrade the image. Each noise has its own source and its own characteristics. So if one image restoration technique works well for a specific type of noise it does not guarantee its performance in presence of other types of noise. So calibrating the performance of any image restoration technique with just one type of sample image and one type of degradation that to AWGN is not sufficient. So in our paper for comparing the performance of our proposed patch based image restoration technique with other state-of-art techniques we have chosen to take four noises into consideration. The noises taken for comparative analysis are Speckle, Gaussian, Salt& Pepper and Poisson noise. Similarly Evaluating the performance of the above four techniques on the basis of one sample image is also not correct so we have taken seven different images, divided in three categories i.e. Medical, Natural and Arial. Let us now discuss in brief the characteristics of noises that we have considered, Speckle is a characteristic phenomenon in laser synthetic aperture radar images, or ultrasound images. Its effects are caused by interference between coherent waves that, back scattered by natural surfaces, arrive out of phase at the source [3].Gaussian noise is an additive, which degrades image quality that originate from many microscopic diffused reflections leads to discriminate fine details of the image in diagnostic purposes [4].Impulse noise or Poisson noise in digital image is present due to bit error while source coding in transmission or introduced during the signal acquisition steps. Salt & Pepper noise can degrade the images where the affected pixel takes either maximum or minimum gray level [5][6].

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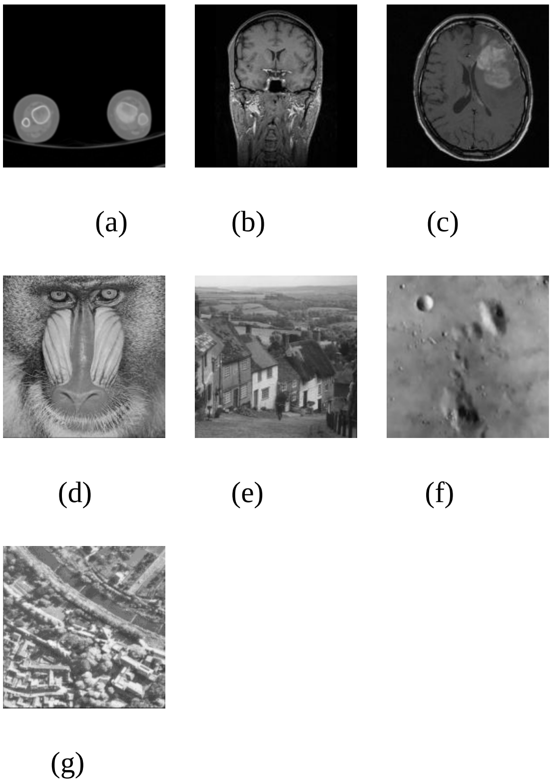

Figure 1.Ideal Original Images used in experimentation of size 256 x 256, 256 gray levels, Medical Field: (a) Apperts (b) Bone (c) Brain; Natural Field; (d) Baboon (e) House; Arial Field: (f) Planet (g) Chemical Plant.

Similar to noise, images can also be of many different types for example image taken for clinical purpose like X-Ray, CT-Scan, MRI are called as Medical images. In the same way images taken from sky or satellite are called as Arial Images. Images of nature, forest, dense vegetation, etc. are coined under natural images. For this paper we consider different types of images i.e. we classify images into three different type's natural images, medical images and satellite images. Classification of image is necessary because different type of images have different features. For example medical image has different feature as compared to Arial images and Natural Images. So classification of image is necessary, because different filters have different characteristics which may suit specific type of image and may not suit other.For this paper we have chosen three images under Medical image category they are X-Ray (Bone), MRI (apperts) and CT (Brain). Similarly under Arial Image category we have two images named Planet, Chemical Plant,and under natural image category we two images named as Baboon, House. These images are chosen with such care that they cover all the features of their respective categories.

No image restoration technique is perfect because of inherent physical limitation. During the image restoration, one question definitely arises if, and if yes, to which extent the effects of the degradation can be reverted? Inverting the effects of known or unknown degradation in images is known as restoration. Degradation that can be modeled by linear system theory, closely related to image restoration is image reconstruction from indirect imaging techniques [7]. Image prior have become a universal technique to restore the images. Different priors have been applied to specific task such as image restoration, image inpainting [7][8][9]. A prior probability model for both the noise and uncorrupted image is of central important for this application. JavierPortilla and VasilyStrelasuggested thatrestoration technique based on log coefficient magnitude, log of infinite mixture of Gaussian vectors is called lognormal prior for independent positive scalar random variable [7][8].Antonibuades, B. Coll, proposed restoration technique, the non local mean (NL-Mean) with help of non local averaging of whole image pixels. It controls the decay of the exponential function and therefore the decay of weights as function of the Euclidean distance [9]. K-SVD Based restoration technique described the image content effectively this restoration technique is known as global image prior that forces sparsity over image in every location in the particular image. It is an iterative restoration method and update of dictionary on column at a time [10]. Image restoration method exploiting regularized inversion and the block-matching 3D filtering (BM3D) restoration technique based on patches in 3D arrays [11].Stepen Roth has explained expressive image prior that capture the statistics of natural scenes and can be used for variety of machine vision tasks, this field of experts model (FOE) with two application restoration and image inpainting [12][13]. Many priors have been applied to various tasks such as image restoration, image inpainting, and hyper-laplacian based on lookup table [14]. However, learning existing effective priors from specific field image is a doubting task, high dimensionality of image make learning, inferences and optimization with such types of prior very difficult to prohibited. Guassian scale mixture based model Guassian Fields of expert model described a flexible and efficient tool for modeling the statistics of wavelet coefficients of photographic image. The local statistical properties of photographic images, when represented in a multi-scale basis, have been described using Gaussian scale mixtures (GSMs).Performances of NL Mean, Sparse model, BM3D and Mapping functions priors are learned related to small patches of particular image. It is advantageous to making computational tasks such as learning inferences and likelihood estimation much faster and easier than implementing to whole image directly.

II. STATE-OF-THE-ART TECHNIQUES

Image denoising has been a well-studied problem. The challenge faced by anydenoising algorithm is to suppress noise artifacts while retaining finer details andedges in the image. Over the years, researchers have proposed many different methodsthat attempt to achieve these contradictory goals. In this section we discussmethodology of three state-of-art patch based image restoration techniques:

A.K-SVD Technique

One of the most popular model-based methods is the K-SVD algorithm.This algorithm is a way to learn a dictionary, instead of exploiting pre-defined ones. In the later ones a patch-based framework is proposed where each patch in the image isrepresented as a linear combination of patches from some over-complete set of bases. This algorithm builds a dictionary that leads to sparse representations for the given set of training signals. This dictionary can be learned either from set of natural image patches or the noisy image itself. Using this dictionary all overlapping patches of the image are denoised independently and then averaged to obtain new reconstructed image.The K-SVD is an iterative method that alternates between sparse coding of the examples based on the current dictionary and an update process for the dictionary atoms so as to better fit the data. The update of the dictionary columns is done jointly with an update of the sparse representation coefficients related to it, resulting in accelerated convergence. The K-SVD algorithmis flexible and can work with any pursuit method, thereby tailoring the dictionary to the application in mind.K-SVD performs well for both synthetic and real imagesin applications such as filling in missing pixels and compression, feature extraction and more.

B. Fields of Experts technique(FoE)

FoE is a framework for learning generic, expressiveimage priors that capture the statistics of natural scenesand can be used for a variety of machine vision tasks.The approach extends traditional Markov Random Field (MRF) models by learning potential functions over extended pixel neighborhoods. Field potentials are modeledusing a Products-of-Experts framework that exploits nonlinearfunctions of many linear filter responses.

The goal of the FoEis to develop a frameworkfor learning rich, generic prior models of natural images(or any class of images). In contrast to example-based approaches, this method develops a parametric representation that usesexamples for training, but does not rely on examples aspart of the representation. Such a parametric model hasadvantages over example-based methods in that it generalizesbetter beyond the training data and allows for moreelegant computational techniques. The key idea is to extendMarkov random fields beyond FRAME by modeling the localfield potentials with learned filters. To do so, this method exploits ideas from the Products-of-Experts (PoE) framework.

Previous efforts to model images using Products of Expertswere patch-based and hence inappropriate for learninggeneric priors for images of arbitrary size. The Field-of-Experts framework provides a principled way to learn MRFs from examples and the greatly improved modelingpower makes them practical for complex tasks.

C. Guassian Fields-of-Expert Technique

A Guassian Mixture Model(GMM) is among most statistically mature method for clustering. A Gaussian mixture (GM) is defined as a convex combination of Guassian densities. A Gaussiandensity in a d-dimensional space, characterized by its mean m $\in \mathrm{IR}^d$ and d $\times$ d covariance matrixC. Since Gaussian potentialsare not well suited to models of natural images. It turnsout, however, that many of the potentials used in low-level vision are well fit by a Gaussian Scale Mixture (GSM). GMMs are commonly used as a parametric model of the probability distribution of continuous measurements or features in image. GMM parameters are estimated from training data using the iterative EM(Expectation Maximization) algorithm or MAP(Maximum-a-Posterior) estimation from a well-trained prior model.

III. FRAMEWORK OF PROPOSED TECHNIQUE

A. Patch log likelihood (PLL)

The basic idea behind proposed patch based image restoration method is to maximize the expected patch log likelihood (PLL) while still being near about to the corrupted image.In PLL a way which is dependent on the degraded model. Image 'q' in the form of victorised defined the expected PLL under prior as equation (1)

$$PLL_p(q) = \sum_i \log p(\mathrm{P}_i\, q) \text{.............}(1)$$

Where P_i is a matrix which extracts the ith patch from the image (q) out of all overlapping patches, while $\log p(\mathrm{P}_i\, q)$ is the likelihood of the ithpatch under the image prior p . Assuming the patch location in the image is chosen uniformly **at** random patch log likelihood (PLL) is expected of a patch in the image. Now we have to assume that the given degraded image 'r', and a model of image corruption in the form of $\left\|A_q - r\right\|^2$, corruption model is quite general as a deconvolutionapproachthat several orders of magnitude related to Hyper Laplacian Priors [17]. The cost we propose to minimize in order to find out the reconstructed restored image using the patch prior p is as equation (2).

$$f_p(q|\mathrm{r}) = \frac{\lambda}{2}\left\|Aq - r\right\|^2 - PLL_p(q)\text{....}(2)$$

Aboveequation has familiar form of a likelihood term and a image prior terms, but note that $\mathrm{PLL}_p(q)$ is not the log probability of a whole image. It is the sums over the log probabilities of all overlapping image patches, it double count the log probability. It is the expected log likelihood of a random selection of patch in the whole image. The cost function is depends on the likelihood patches. The PSNR obtained with different images from Medical, Natural and Arial images from standard data set corrupted with Gaussian, Speckle, Salt & Pepper and Poisson noise at the same density and restored using the each image priors according to the equation (1). Restored images are as shown in figure 3. We obtain the result using simple image patch with Field of Expert (FoE) and our expected PLL frame

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work. And we have provided the optimum solution to researcher which technique is highly suitable for specific type of degradation. It is explained in details in the next section this paper. It can be seen that indeed better likelihood on image patches leads to better restoration both independent and whole image to specific type of noise. Additionally, it can be seen that expected PLL improves restoration results significantly when compared with simple patch technique. We have seen that, it provides optimum results to specific type of image from particular field as shown in table 1.

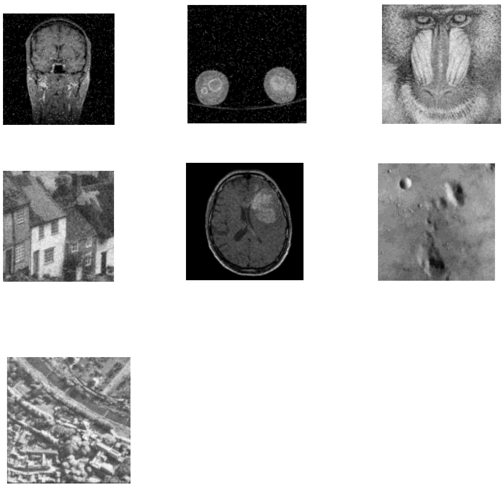


Figure 2.Ideal Original Images used in experimentation of size 256 x 256, 256 gray levels, Medical Field: Apperts with salt & pepper noise; Bone with salt & pepper noise; Baboon with Gaussian noise; House with Gaussian noise; Brain with speckle noise; Planet with Poisson noise; Chemical Plant with Poisson noise.

B. Patch log likelihood optimization

The cost function is used for optimization in equation (2) depending on the prior used. We present in this technique an alternative optimization method described in papers of D. Geman and C.Yang[18][17]. It is related to Half Quadratic Splitting (HQS) which has been proposed in state of art in several relevant contexts.Half Quadratic Splitting allows for efficient optimization of the cost function in equation (2). In HQS, we introduce a set of patches $\{S^i\}_0^{N-1}$, for each overlapping patch $P_i q$ in the image yielding the cost function as shown in equation(3) as follows.

$$c_{p,\beta}(q,\{S^i\}|r) = \frac{\lambda}{2}\|Aq-r\|^2 + \sum_i \frac{\beta}{2}(\|P_i q - s^i\|^2) - \log p(S^i) \text{....(3)}$$

In equation (3) as $\beta \rightarrow \infty$, we restrict the image patches $P_i q$ to be equal to the auxiliary variable $\{S^i\}_0^{N-1}$ and the solution of above equation (3) and (2) converge. For fixed value of $'\beta'$ isoptimizing the equation (3) in an iterative manner by solving for $'q'$ while keeping $\{S^i\}$ constant, and solving $\{S^i\}$ given the while $'q'$ keeping constant. Optimizing an equation (3) for fixed value of $'\beta'$ requires two steps.In first step, solving for $'q'$ given $\{S^i\}$ is in closed form. By taking the first derivative of $c_{p,\beta}(q,\{s^i\}|r)$ with respect to the victories form of $'q'$,with initial condition is zero and getting the new equation (4) as follows.

$$\hat{q} = \left(\lambda A^T A + \beta \sum_{j=0}^{N-1} P_j^T P_j\right)^{-1} \left(\lambda A^T r + \beta \sum_{j=0}^{N-1} P_j^T S^i\right) \text{......(4)}$$

Where the sum over $'j'$ is for all overlapping patches in whole image and all corresponding auxiliary variables $\{S^i\}$. In the second step, solving for $\{S^i\}$, given $'q'$; the exact solution to this depends on the image prior $'p'$. Inimage restoration by solving any image prior it means solving a maximum a posteriori problem of evaluating the most likely patches under the prior given the degraded measurement $P_i q$ and parameter $'\beta'$. In iteration process is solved to $\{S^i\}$ given $'q'$ and to solve for $'q'$ the $\{S^i\}$, both given the current value of $'\beta'$. Then it is increased $'\beta'$ and continuous to the further iteration. These two steps improve the cost $c_{p,\beta}$ from equation (3) and for increased value of $'\beta'$ improves the original cost function f_p in equation (2). We note that it is necessary to find the optimum of each of the above steps, by approximate method can improve the cost. The choice of value of $'\beta'$ is to optimizing the values on a set of images and tried to estimate $'\beta'$ in every step with estimating the amount of noise density $'\sigma'$ present in $\hat{q}$, and setting $\beta = \frac{1}{\sigma^2}$. The base of noise estimation procedure is the assumption that the original, uncorrupted images had a scale of invariant statistics [19].

The prior used ICA prior which the likelihood is easily calculated. Even though the Half Quadratic Splitting (HQS) is only definite reliable to monotonically decrease the cost for infinite $'\beta'$ values. We showed experimentally that the cost decreases for different schedules of $'\beta'$ where the schedule affects mostly the convergence speed. We concentrate on three attractive properties of our general scheme. First, it can be use any image patch based prior and second, its execution time is only five to six times the execution time required of restoring with simple patch averaging related to iteration. Third, perhaps the most important is that used framework does not require learning a model $P(q)$, where q is a various images from diversified fields like medical, Natural, and Arial images, learning required only to concentrate on modeling the probability of image patches.

IV. GAUSSIAN MIXTURE MODEL (GMM)AND RESTORATION OF DEGRADED IMAGE

A. *Image Restoration*

In restoration, we have four synthetic noise, Gaussian, Poisson, Speckle and Salt & Pepper noise. And degraded images are from various fields by same noises. We set matrix A according to the equation (4) to be the identity matrix and set $'\lambda'$ to be related to the standard deviation of degradation. The solution for $'q'$ at each optimization steps is just a weighted average between the noisy image $'r'$ and the average of pixels as they appear in the auxiliary overlapping patches. The solution for $'S'$is just a maximum a posterior (MAP) estimate with prior 'p' and noise density $\sqrt{1/\beta}$. If initialize 'q' with the noisy image 'r', then setting $\lambda = 0$ and $\beta = 1/\sigma^2$, results in simple patch averaging when iterating first step. However, difference is that in proposed restoration technique based on PLL, because iterates the solution and $\lambda \neq 0$ at each and every iteration used the latest estimated image, averaging with it with degraded one and obtaining new set of $'S'$patches. While increasing 'β' obtaining a new is estimated for 'q' in the iteration process.

B. *Learning Gaussian Mixture Model and implication to PLL*

We learn the finite Gaussian Mixture Model over the pels of images from various fields is mentioned in literature has been used. GMM is used with mean and covariance matrices while learning GMM based prior [19][20]. We learn the means, full covariance matrices with mixing weight over all pixels. It can be easily performed with the help of Expectation Maximization technique which is shown as equation (5) as below.

$$logp(q) = \log\left(\sum_{i}^{N-1} \pi_i (q|\mu_i, Cov_i\right) ....(5)$$

Where the π_i is the mixing weight for each of the mixture component μ_i and Cov_i are corresponding means and covariance matrices [21][22]. Restoration a patches with this particular scheme is performed using the approximate maximum a posterior procedure [23].

V. EXPERIMENTAL RESULTS &COMPARISON TO STATE-OF-THE-ART TECHNIQUES

In this paper we present thecomparison of performance of our proposed PLL based restoration techniques with K-SVD,FoE and Gaussian FoE which are recent image restoration methods. All experiments were performed on seven images from the standard datasets (University of California- SIPI, The Berkeley Data set and Benchmark, University of San Diego). From all experiments, we have shown some typical medical images: X-ray, MRI, CT and natural: Baboon, house, Arial images: planet, and Chemical plant. All experiment were performed using the same realization of the images from same fields. In each experiment, we have set the value of $\lambda = N/\sigma^2$, where N are the number pixels in each image patch. We used image patch size of 8x8 pixels in each and every experiment. In GMM image prior, we optimized the set of values for $'\beta'$on the typical seven images from various fields.Execution time is computed on duel core processor also shown in tables respectively. All experiments performed on MATLAB version 7.12.0.635 with windows 7, version 6.1. Summary of results is in the form of PSNR are shown in tables I,II, and III, it is clear that our proposed PLL based restoration technique outperform the current state-of-the-art restoration methods mentioned in literature to particular combination of specific noise and image from particular field. PLL based model is easier to learn and to work with many types of image models.

Experiment is divided into three parts initially we have performed with Medical images. We observed that PLL technique is highly suitable to reduce the noise from X-ray image (Bone) degraded by all four types of noise and only suitable for degraded MRI image (Aperts) by Poisson, and Salt & Pepper noise with PSNR values 30.91dB, 23.00dB respectively. CT image (Brain) also restored with highest values of PSNR than other two restoration techniques. Performance of same restoration technique to Natural images (Baboon & House) as shown in table II. And performance to degraded images from Arial fields as shown in Table III.

We have showed that PLL based model which gives high likelihood values for patches sampled from various field images perform better in patch and restoration tasks. Given results, we have proposed a new framework which allows the use of patch model for image restoration, motivated by the idea that patches in the restored image must likely under the image prior. We have shown that proposed frame work improves the results of whole image restoration when compared to simple patch averaging used in a day for restoration. We have proposed a simple yet rich Gaussian Mixture prior which performs well to restore the degraded images from various fields. GMM through used is extremely a simple mixture model of Gaussian with covariance matrices. The GMM is extremely studied area, incorporating more sophisticated technology in to learning representation of the model.

Table I. Performance of PLL Based Restoration Method to Medical Images is shown in PSNR Measure. All Values of PSNR in (dB) of all Restoration Techniques. Comparison with recent state-of-the-arts restoration techniques for Gaussian noise, Speckle Noise, Poisson Noise and Salt & Pepper noise.

Methods	Gaussian	Speckle	Poisson	Salt & Pepper	Average
Bone (X-Ray Image: 256x256): Medical Field					
Proposed	24.56	30.02	37.89	23.54	29.00
K-SVD	18.89	21.23	22.20	22.02	21.09
FoE	22.43	25.49	28.41	19.79	24.04
Guassian FoE	21.32	25.79	33.10	22.05	25.56
Aperts (MRI Image: 256x256): Medical Field					
Proposed	23.20	26.39	30.91	23.00	25.88
K-SVD	21.07	25.46	26.49	22.72	23.93
FoE	24.29	25.99	33.07	19.37	25.68
Guassian FoE	22.89	24.36	31.21	21.75	25.05
Brain (CT Image: 256x256): Medical Image					
Proposed	23.41	26.06	29.45	22.84	25.36
K-SVD	21.57	21.75	22.76	21.63	21.92
FoE	22.02	25.79	28.72	20.26	24.19
Guassian FoE	21.98	23.76	25.86	22.14	23.43

Table II. Performance of PLL Based Restoration Method to Natural Images is shown in PSNR universal qualitative Measure. All Values of PSNR in (dB) of all Restoration Techniques. Comparison with recent state-of-the-arts restoration techniques for Gaussian noise, Speckle Noise, Poisson Noise and Salt & Pepper noise to Natural Field Images.

Methods	Gaussian	Speckle	Poisson	Salt & Pepper	Average
Baboon (Animal Image: 256x256): Natural Field					
Proposed	21.67	21.35	24.10	21.70	22.21
K-SVD	16.54	14.84	15.86	15.82	15.77
FoE	19.27	18.32	22.53	18.72	19.71
Guassian FoE	20.27	21.60	23.22	21.06	21.53
House (Building, Trees Image: 256x256): Medical Field					
Proposed	22.23	22.70	28.37	22.42	23.93
K-SVD	17.43	17.41	15.42	15.40	16.42
FoE	20.74	21.64	26.56	20.41	22.34
Guassian FoE	23.05	21.18	28.41	21.34	23.49

Table III. Performance of PLL Based Restoration Method to Arial Images is shown in PSNR universal qualitative and quantitative Measure. All Values of PSNR in (dB) of all Restoration Techniques. Comparison with recent state-of-the-arts restoration techniques (K-SVD, Field of Experts) for Gaussian noise, Speckle Noise, Poisson Noise and Salt & Pepper noise to Arial Field Images (Planet and Chemical Plant).

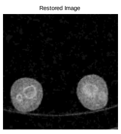
Methods	Gaussian	Speckle	Poisson	Salt & Pepper	Average
Planet (Satellite Image: 256x256): Arial Field					
Proposed	22.28	21.86	29.44	22.41	24.00
K-SVD	17.27	16.27	15.28	13.24	15.52
FoE	20.70	20.01	26.30	20.58	21.90
Guassian FoE	23.69	22.50	28.59	20.72	23.87
Chemical Plant (Arial Image: 256x256): Arial Field					
Proposed	22.11	21.66	26.31	22.17	23.06
K-SVD	14.55	14.51	15.56	15.52	15.04
FoE	25.48	19.23	25.13	20.02	22.47
Guassian FoE	21.69	20.15	26.09	23.18	22.77

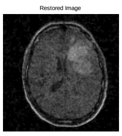
Table IV. Comparison of the Execution Time in Seconds of PLL with GMM based Restoration to Technique to Different size of images from diversified fields. To Allow for Fair ComparisonMethod is Implementedin MATLAB with Optimization. Reported Values are The Execution Time Over Average 5 to 6 Iteration.

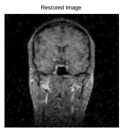
<table>
<tr><td rowspan="5">Proposed Method</td><td colspan="4">Input Image Size 256x256</td><td>Remark</td></tr>
<tr><td>Gaussian</td><td>Speckle</td><td>Poisson</td><td>Salt &Pepper</td><td rowspan="4">Size is increased time also increased</td></tr>
<tr><td>175</td><td>169</td><td>169</td><td>169</td></tr>
<tr><td colspan="4">Input Image Size 512x512</td></tr>
<tr><td>265</td><td>257</td><td>256</td><td>256</td></tr>
</table>

VI. CONCLUSION

In this paper we have proposed a new restoration technique for reduction of synthetic noise. In this technique a PLL modeling of images in vectotrised form has been used to handle the optimization resulting from HQS approach. We have analyzed the performance of four image restoration techniques for diversified field images corrupted with various types of noise. From the analysis we found that our proposed method out performs rest of image restoration techniques in presence of various types of noise and diversified field images. For medical image in presence of all types of noise our technique does comparatively well. In Natural images our technique performs well but along with our technique Gaussian FoE also does a pretty good job. In Arial field images our technique surpasses the performance of K-SVD and FoE to a considerable extent but Gaussian FoE's efficiency is nearly same as our proposed technique. So finally we can conclude that, we obtain significant measure that quantifies the reduction of various type of noise from diversified field images and lower computational time, while being competitive with recent state-of-the-art image restoration methods.


Elapsed time 175.97 S
PSNR:24.56dB


Elapsed time182.48 s.
PSNR :23.20d**B**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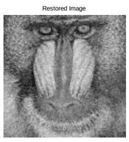
PSNR 23.41dB


Elapsed time 189.03 s
PSNR :21.67dB


Elapsed time 189.38 s.
PSNR :22.23dB


Elapsed time 183.43 s
PSNR :22.28dB

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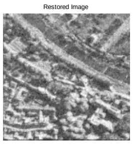
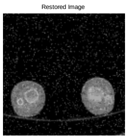
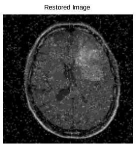


Elapsed time 182.69 s
PSNR :22.11dB

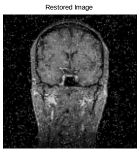
Figure 3.Result of proposed restoration method for Medical Images (Aperts 256x256, Bone 256x256, Brain 256x256), Natural (Baboon, House) and Arial Images (Planet , Chemical Plant) to Gaussian noise at same noise density



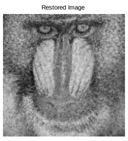
Elapsed time 168 S
PSNR.: 23.54 dB



Elapsed time 173 S
PSNR :23.00 dB

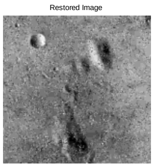


Elapsed time 169 S
PSNR 22.84 dB



Elapsed time 169 S
PSNR :21.67dB

Elapsed time 168 S
PSNR :22.23dB



Elapsed time 169S
PSNR :22.41dB

Elapsed time 170 S
PSNR : 22.17 dB

Figure 4.Result of proposed restoration method for Medical Images (Aperts, Bone, Brain), Natural (Baboon, House) and Arial Images (Planet, Chemical Plant) to Salt & Pepper noise at same noise density, Restored images for subjective analysis and objective analysis according to the values of PSNR. And time required is to restoring degraded images in second.

VII. REFERENCES

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