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# Performance Analysis and Optimization of Patch Based Image Restoration Techniques for Diversified Field Images

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***Abstract— Images, captured with digital imaging sensors, transmitted through various channels, often contain 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. 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, and also a new scheme for the removal of noise is proposed. The resulting 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 image.***

## I. INTRODUCTION

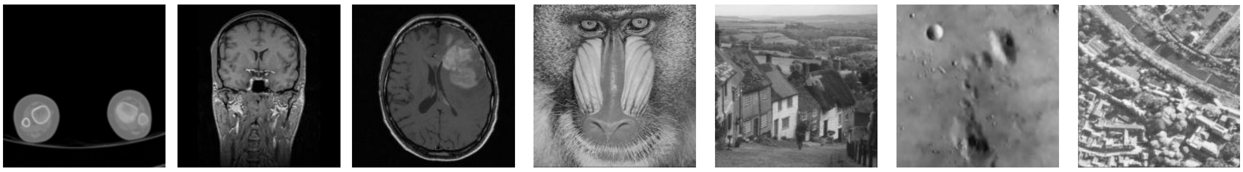
Digital images play an important role in daily life application such as satellite television, imaging under water, magnetic resonance, computer tomography as well as in area of research and technology such as Medical, geographical information system and astronomy. Visual information is usually considered the most illustrative, informative, direct and comprehensive among all kinds of information perceived by human beings. Data sets collected by image sensors are generally contaminated by noise. Imperfect instrument, problem with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. 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. Many diagnoses in Medical field are based on biomedical images derived from x–ray, computerized tomography (CT), ultra-sound, magnetic resonance imaging (MRI) and in geosciences scientists use remote sensing images to monitor planetary bodies, distant starts, and galaxies, so image must be without noise. Digital images are prone to a variety of types of noise. Noise is the result of errors in the image processing that result in pixel values that do not reflect the true intensities of the real scene [1][2].

Speckle is a characteristic phenomenon in laser synthetic aperture radar images, or ultrasound images. Its effects is 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 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]. No image restoration technique is perfect because of inherent physical limitation. During the image restoration, the question 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]. The goal of image restoration is to relieve human observers from patch based technique by reconstructing a plausible estimate of the original image from the degraded observation. A prior probability model for both the noise and uncorrupted image is of central important for this application. Javier Portilla, and Vasily Strela, suggested that restoration 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]. Antoni buades, 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. 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. PATCH LIKELYHOOD TO IMAGE RESTORATION

Image priors are closed form of log likelihood, Bayesian least squares (BLS), estimates can be easily computed. We can with simple problem like, priors that give high likelihood for diversified field images patches also produce significant result in a restoration task. So many popular priors MRF , neither the MAP nor log likelihood estimate can be calculated properly given in [15]. We compare the log likelihood each model gives on a set of diversified field image patches [16] and performance of model in patch restoration in MAP. The model we used here are, multivariate Gaussian over pixels with learned covariance, PCA with learned marginals and ICA with learned marginals. Motivated by the results of above, we now wish to apply to whole images from diversified fields like Medical, Natural and Arial images for restoration degraded by Gaussian, Salt & Pepper, Poisson and Speckle noise. To learn this prior, consider to all overlapping patches from the image and remove their DC component and estimate histogram of all patches in the image and also counting the number of patches they appear in it. Using this prior, the most likely patches would be the flat, the second most likely patches would be tip of a diagonal edge. This prior is both easy to learn and easy to restore the image with by finding the maximum a-posteriori estimate from our prior and restore the whole image by placing each of the cleaned patches into its original position. This may create artifacts at patch borders like happened in DCT while compressing the image. A more sophisticated solution may be to decompose the image the image into all overlapping patches, restoration of each one independently and then average each pixel as it appears in the different patches to obtain the reconstructed restored image.

This yields good results but still has its problems, while averaging the pixels together we create new patches in the restored images which are not likely under prior used for the same. We can take the central pixel from each of an overlapping patches but this suffers from the artifacts problem.



(a) (b) (c) (d) (e) (f) (g)

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.

We take random patch which is likely under prior while keeping the restored image still close to the degraded image, maximizing the expected patch log likelihood (PLL) of the reconstructed image, subject to constraining it to be closed to the degraded image. The results of same prior using PLL like same prior mentioned in literature of this paper, it produces superior results showed in next section of this paper.

## III. FRAMEWORK AND OPTIMIZATION

### *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 ith patch under the image prior $\mathrm{p}$. 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 '$\mathrm{r}$', and a model of image corruption in the form of $\left\| A_q - r \right\|^2$, corruption model is quite general as a deconvolution approach that 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 $\mathrm{p}$ is as equation (2).

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

Above equation 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 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 $\{\mathrm{S}^i\}_0^{N-1}$, for each overlapping patch $P_i q$ in the image yielding the cost function as shown in equation(3) as follows.

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

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

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

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 $'\mathrm{q}'$; the exact solution to this depends on the image prior $'p'$. In image 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 $\mathrm{P}_i q$ and parameter $'\beta'$. In iteration process is solved to $\{S^i\}$ given $'\mathrm{q}'$ and to solve for $'\mathrm{q}'$ 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. RESTORATION OF DEGRADED IMAGE AND GAUSSIAM MIXTURE MODEL (GMM)

*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 identy 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 pixels 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.

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

Where the $\pi_i$ is the mixing weight for each of the mixture component and $\mu_i$ 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

Several existing techniques are related to same framework, but these are fundamentally different from the PLL based restoration technique. First related technique is FoE described by Roth and Black [12]. The same technique, a MRF whose filter is trained by approximately maximizing the likelihood of the training image is learned. The learning this method is extremely difficult due to the intractability of the partition function and performed using contrastive divergence. Inference in FoE is actually special case of PLL restoration technique because inference of this particular technique is equivalent to optimizing the equation (2) with prior such as ICA. A approximation to learning marquo random field is to approximate the log probability as a sum of conditional probabilities as in the technique of composite likelihood [24]. So we can learn a much richer patch image prior easily and incorporate it to PLL restoration method. In K-SVD technique learns a image patch based dictionary which is to maximize the sparsity of resulting coefficients. In dictionary based learning, all overlapping patches of the image are restored independently and average to obtain a reconstructed image using several iteration processes. NL-Mean technique look for similarities within the degraded image itself and operate of these similar patches together [9][11][25]. BM3D technique based on similar patches into blocks, transform them into thresholding technique both soft and hard thresholding using wavelet transform.

We compare the performance of PLL based restoration technique with FoE, and K-SVD which are recent image restoration methods. All experiments were performed on thirty 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 $N$ is 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 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.

**Bone (X-Ray Image: 256x256): Medical Field**

| Methods | Gaussian | Speckle | Poisson | Salt & Pepper | Average |
|---|---|---|---|---|---|
| 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 |
| **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 | 29.99 | 33.07 | 19.37 | 26.68 |
| **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 | 96.79 |

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.

| **Baboon (Animal Image: 256x256): Natural Field** | | | | | |
|---|---|---|---|---|---|
| Methods | Gaussian | Speckle | Poisson | Salt & Pepper | Average |
| 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 |
| **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 |

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).

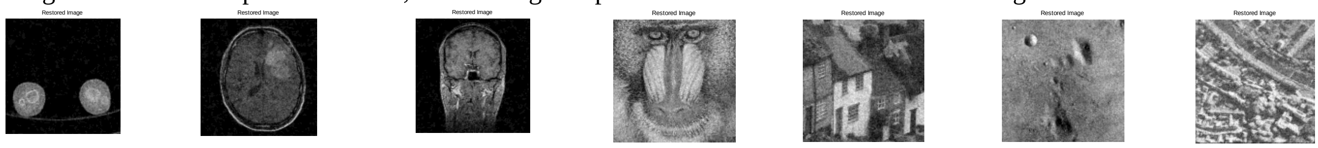
| **Planet (Satellite Image: 256x256): Arial Field** | | | | | |
|---|---|---|---|---|---|
| Methods | Gaussian | Speckle | Poisson | Salt & Pepper | Average |
| Proposed | 22.28 | 21.86 | 29.44 | 22.41 | 24.00 |
| K-SVD | 17.27 | 16.27 | 15.28 | 13.24 | 15.52 |
| FoE | 20.70 | 20.01 | 26.30 | 20.58 | 21.90 |
| **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 | 29.48 | 19.23 | 25.13 | 20.02 | 23.47 |

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 Comparison Method is Implemented in MATLAB with Optimization. Reported Values are The Execution Time Over Average 5 to 6 Iteration.

| | Input Image Size 256x256 | | | | Remark |
|---|---|---|---|---|---|
| Proposed Method | Gaussian | Speckle | Poisson | Salt & Pepper | Size is increased time also increased |
| | 175 | 169 | 169 | 169 | |
| | Input Image Size 512x512 | | | | |
| | 265 | 257 | 256 | 256 | |

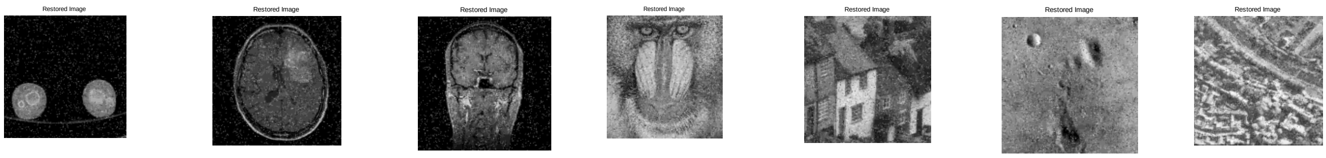
## VI. CONCLUSION

A new restoration technique for reduction of synthetic noise from diversified field degraded images has been presented. In this technique a PLL modeling of images in vectotrised form has been used to handle the optimization resulting from HQS approach to the restoration of degraded images from Natural, Medical, and Arial fields. When we used combination with noise and image, we obtain significant measure that quantifies the reduction of noise from various 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 time 182.48 s. PSNR :23.20d**B** | Elapsed time 176.25 s 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 | 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.

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