Image Restoration using Advanced Patch Processing Algorithm

Sree Lakshmi M[1], Vysak Valsan[2]

[1]MTech Scholar, Dept. of Electronics and Communication Engineering, Jawaharlal College of Engineering and Technology, Lakkidi, Ottapalam, Palakkad, Kerala, India
[2]Asst. Prof Dept. of Electronics and Communication Engineering, Jawaharlal College of Engineering and Technology, Lakkidi, Ottapalam, Palakkad, Kerala, India

---***---

Abstract - *The key challenge in image restoration is that a certain amount of information has been lost during the degradation process. The degradation may be due to several reasons like the addition of noise, failure of camera sensors or misfocus. Image restoration is of different types like denoising, inpainting and deblurring. The main area, going to deal with is denoising and deblurring. Inorder to yield a better estimation of the image, prior knowledge is necessary needed to provide the supplementary information. Therefore how to model the prior of high quality image is the key issue. The restoration method used during recent years is based on patch processing. This method has some drawback instead of appending prior on final outcome, it imposes prior on intermediate patches. This method has some drawback which can solve by the proposed method multi-scale EPLL (Expected Patch Log Likelihood).Multi-scale EPLL is based on multi-scale prior. The proposed algorithm appends same prior on different scale patches which are extracted from the target image. This algorithm serves as a global stochastic phenomenon rather than a local one. Gaussian Mixture Modeling (GMM) is used to model the image prior. MultiscaleEPLL together with Gaussian Mixture Modelling (GMM) is the proposed method which yield a better result. The performance metrics used to evaluate the restored image is PSNR and MSE.*

Key Words: Deblurring, Denoising, EPLL (Expected Patch Log Likelihood), GMM (Gaussian Mixture Modelling), PSNR, MSE

1. INTRODUCTION

Over the last three decades there was an expansive growth in both the range of techniques and applications of image processing. One of the leading applications in image processing is image restoration since recovering the original without any loss of information is inevitable. Image restoration deals with a range of process such as image denoising, inpainting or interpolation, deblurring and super resolution. Let us assume a clean image X is corrupted by a linear operator A and an additive white Gaussian noise with standard deviation σ, given a noisy image Y which is corrupted as **Y =AX+N**, the key task is to recover the original image X .The goal is to remove the noise from Y, getting as close as possible to the original image X. For to recover the original image from its degraded version, image prior is necessary till its end which provides the supplementary information. In order to achieve this, the requirement of a good model is necessary. The requirement can be fulfilled by using Gaussian Mixture Model (GMM). The different types of algorithm which we are commonly using for image denoising include KSVD, BM3D, FOE, WNNM etc. Since patches are the most important component of an image, have extended the processing based on image patches. Recent algorithm suggests that patch processing makes the image denoising task simpler because patches are low dimensional and easy to model ,patch priors are readily available. There are several models which operate on patch prior like sparsity inspired model, independent component analysis(ICA)model, principal component analysis model and Gaussian mixture model(GMM).When the patch prior is set, denoising of an image can be accomplished by decomposing it into overlapping patches, then denoising each patch independently and at last merging the result by plane averaging. This method has some major flaws since every denoised patch is handled well below the selected image prior, the averaging of the patches destroy this behaviour, as the resulting patches extracted from this image are no longer in all likelihood with respect to the nearby prior. In order to solve the mentioned problem Zoran and Weiss proposed a new method EPLL (Expected Patch Log Likelihood), suggesting that the pattern selected will be applied on the final image patches being restored. Since the algorithm apply prior on final image patches, which in turn contributes to an iterative decreasing impact recover. Their scheme utilizes a global priori that scans an image in such a way that any patch picked from it is presumably assigned the local prior The full opposed image becomes the unknown in the process of reconstruction, rather than tiny and isolated pieces, leading to this delicate transition from a local to global priori. The half quadratic splitting approach is used to basically solve the MAP (maximum a posteriori) problem under this prior. This concept has been seen in the sense of a Gaussian-Mixture-Model to the state-of- the art results in image denoising.

The proposed method further expanding enhancing the EPLL by considering a prior multi-scale solution. On various scale patches extracted from the target image, the algorithm imposes the very same previous. Although all the patches handled are of the same dimension, their footprint in the picture of the destination differs. This paper motivates the multi-scale method by discussing first a toy problem of Gaussian signals, demonstrating how local patch average, EPLL and its multi-scale expansion both approximate the optimum global filtering. In the sense of image denoising and deblurring, the proposed algorithm, showing an increase in efficiency, both visually and quantitatively. The multi-scale treatment propose here bares some similarity to denoising through the use of multi-scale –dictionary learning. The quality metrics used to analyse the restored image is PSNR and MSE.

2. PROPOSED METHOD

2.1 Multi-scaleEPLL

The proposed method is based on multi-scale EPLL which is an expansion of the method EPLL (Expected Patch Log Likelihood) proposed by Zoran and Weisis.Multi-scale image treatment leads to a global image prior composed of local pieces. The key idea is to keep the flexibility of a low dimensional model while loving the non-locality of wider areas within the image by using a spatial construct on different scales.
The multi-scale EPLL prior is defined as

$$\text{MSEPLL(X)} = w_1 \sum_i \log P_1(R_i X) + w_2 \sum_i \log P_2(\hat{R}_i SX)$$

Where the operator S=DH applies a low-pass filter H followed by the down-sampling D, the operator $\hat{R}_i$ extracts the i-th patch from the decimated signal SX, and the weights $w_1$and w_2 represent the importance of different scales.$P_1$and P_2 represent the prior since the patches obtained before and after decimation is different. The MAP objective for denoising task changes accordingly to

$$min_x \frac{\lambda}{2} \parallel AX - Y \parallel_2^2 - w_1 \sum_i log\, P_1(R_i \text{X}) - w_2 \sum_i log\, P_2(\hat{R}_i \text{SX})$$

For a general degradation operator A, the multi-scale EPLL objective is

$$min_x \frac{\lambda}{2} \parallel AX - Y \parallel_2^2 - w_1 \sum_i log\, P(R_i X) - w_2 \sum_i \log P\, (\hat{R}_i \text{SX})$$

From the above two equations it is clear that MAP objective for denoising uses two different priors P_1and P_2while the multi-scaleEPLL appends the same prior on different scale patches which are extracted from the target image. Half Quadratic Splitting is used to optimize the function. Let $z_i$and $\hat{z}_i$denotes the patches extracted from the original scale and from the added scale. First, assume the reconstructed image X is fixed and then update the auxillary variables z_i and$\widehat{z}_i$.Secondly assume that the auxillary patches are fixed and use those to update the reconstructed image.

z_i will be computed by solving MAP on patches from the original scale as

$$min_{z_i} \frac{\beta}{2} \| R_i X - z_i \|_2^2 - \log \text{P}\, (z_i)$$

To update$\widehat{z}_i$, solve other MAP problem comprising patches from the added scale as

$$min_{\hat{z}_i} \frac{\hat{\beta}}{2} \| \hat{R}_i SX - \hat{z}_i \|_2^2 - \log \text{P}\, (\hat{z}_i)$$

Where β is proportional to the variation between the local model and the reconstructed image and $\hat{\beta}$ is proportional to the local model and the decimated version of reconstructed image SX.

By using the values of the original scale $z_i$and the added scale $\hat{z}_i$, X is updated by solving an easy quadratic problem as

$$\text{X}= (\lambda A^T A + w_1 \beta \sum_i R_i^T R_i + w_2 \hat{\beta} \sum_i S^T \hat{R}_i^T R_i S)^{-1} (\lambda A^T \text{Y} + w_1 \beta \sum_i R_i^T z_i + w_2 \hat{\beta} \sum_i S^T \hat{R}_i^T R_i \hat{z}_i)$$

2.2 Scale Invariance

Scale–invariance is an essential property while dealing with different scale patches. The proposed algorithm appends an image prior on patches of different scales, which is extracted from the target image. This is called as scale –patches. The entire process is carried out using GMM model for the prior of original scale. For other scales like the added scale, the filter parameters have to be tuned. The filter use here is assumed to be Gaussian. By assuming the scale invariance property throughout the process, there is no need to model for each scale separately.

2.3 Stein Unbiased Risk Estimator (SURE)

SURE shows an indication of accuracy of given estimator. During the denoising process, on each iteration there are several test images involved, which are originated from different scales. They are summed up, in order to create an estimate of the image. SURE is used to find the optimal weights of each image rather than per dataset.

Unbiased estimate of mean square error (MSE) can be found using SURE. Simply, this can be represented as

$$\text{E \{SURE (h(Y, θ))\} =MSE (h(Y, θ))}$$

Where h(Y, θ) represents denoising of noisy image Y and θ parameter-vector.

2.4 Image Denoising

The proposed algorithm restores the degraded image in two process image denoising and deblurring. More detail about how the proposed algorithm operates in the denoising process is discussed here.The noise effecting the patches is Additive White Gaussian Noise (AWGN) .This section can be divided into three parts; 1) Extraction of patches, 2) Patch Log likelihood; 3) combining of patches. Then finally evaluating the performance from PSNR and

MSE. The image denoising process is carried with a range of standard deviations (15, 25, 50,100).The beta values will be set accordingly.

Initially the image is loaded, which is corrupted with AWGN. The main reason for occurrence of AWGN is from acquisition problem and also from the reset noise of capacitors. The algorithm proposed here is based on patch processing. The next step during the denoising process is extraction of image patches. The patches are extracted from the image. Then calculate the assignment probabilities for each mixture component for all patches. Denoise each patch independently by finding the MAP estimate for the original scale of extracted patches and the added scale of extracted patches. After finding the likelihood of patches, perform Weiner filtering. The filter here used for denoising process is Weiner filter .Combine the cleaned patches to its original position to get the restored image.

The figure shows block diagram of denoising

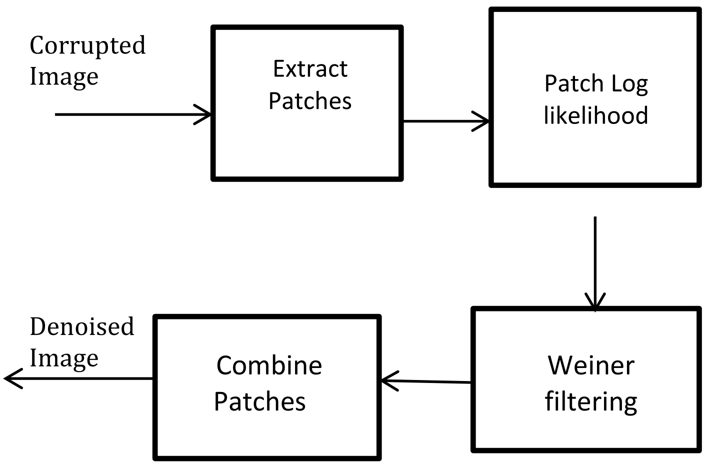

Fig 1: Block Diagram of Denoising

STEP 1: Load the target image to be reconstructed (which may be noisy)
STEP 2: Set the parameters like patch size, noiseSD, betas Filter length and down sampling factors
STEP 3: Add AWGN
STEP 4: Extract the patches of the target image
STEP 5: Find the most likely log likelihood component Of each patch
STEP 6: Perform Weiner Filtering and upsampling
STEP 7: Combine the patches of cleaned image to its Original position
STEP 8: Denoised image is obtained
STEP 9: Examine PSNR and MMSE
The denoising process is carried on a set of 10 test images which are commonly used in image processing such as babra, lena, pentagon, house, pepper, cameraman, boat, hill.

Finally the denoised image performance is decided on the basis of PSNR and MSE.

2.5 Deblurring

Deblurring is the process of removing the blurring effects due to camera shake or defocus .It is an inverse problem.Assume that W be the input image which is blurred. To recover the sharp image S from blurred image W is stated as the deblurring process. Mathematically, this can be represented as

$$S=W*K$$

Where K represents the blur kernel.
Deblurring operation is similar to that of denoising process except that it does not use a filter before down-sampling factors. At each iteration of the multi-scale EPLL, by using patch-averaging the decimated version is reconstructed. This alone has the effect of a low-pass filter. Deblurring operation is carried out using the beta values:

betas =15*[1 2 4 8 16 32 64]

The workflow of deblurring process:
STEP 1: Load target image to be reconstructed (which may be noisy)
STEP 2: Set the parameters like down sampling factors. Blur Kernel, range (betas) and patch size
STEP 3: Convolve with kernel and add noise
STEP 4: Extract the patches of target image
STEP 5: Find the most likely component of each patch
STEP 6: Perform Weiner filtering
STEP 7: Up sampling process and estimating clean image
STEP 8: Deblurred image is obtained
STEP 9: Examine PSNR

3. RESULT AND ANALYSIS

Denoising and deblurring operation is carried out using the advanced patch processing algorithm.MatlabR2014a is used for its implementation. The overall process is carried out over a set of natural images.
Figure 2 and 3shows the deblurred result for noiseSD=√2 and betas=15*[1 2 4 8 16 32 64].The test image used is butterfly and starfish.

Fig2: Deblurring result for the image Butterfly blurred with 9 × 9 filter and corrupted by noise of standard deviation σ=√2 . From left to right: original image blurred image, MSEPLL (σ=√2, PSNR=29.750)

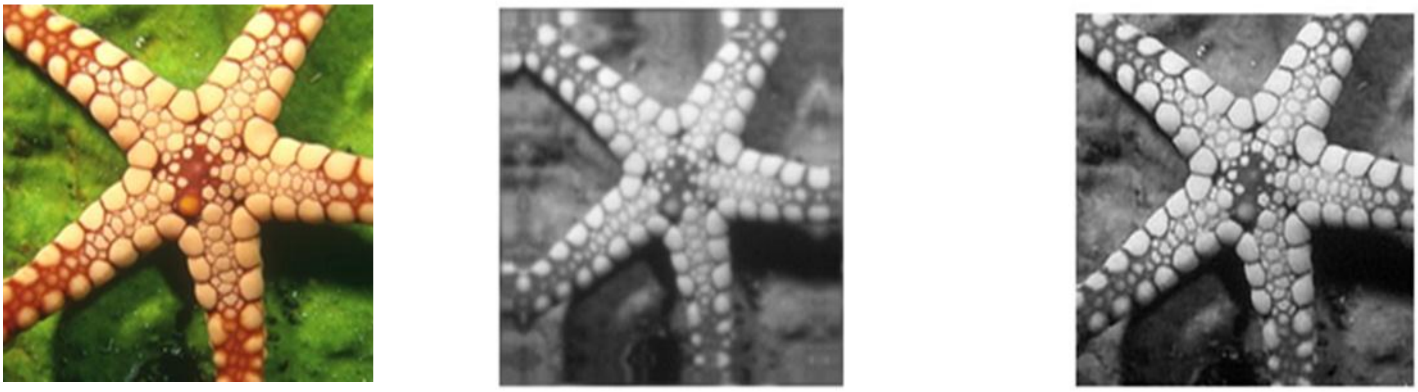

Fig 3: Deblurring result for image starfish blurred with noiseSD=√2 .Left to right: original image, blurred image and MSEPLL (PSNR=29.740)

PSNR=31.4690	PSNR=28.7724	PSNR=25.0446
MSE=0.0023	MSE=0.0055	MSE=0.0180

PSNR=22.4210
MSE=0.0620

Original image

Fig 5: Output of denoising of the image Barbara for noise standard deviations σ =15, 25, 50, and 100

Image	Noise Standard Deviations	PSNR (in dB)
Butterfly	$\sqrt{2}$	29.750
Starfish	$\sqrt{2}$	29.940

Table I: PSNR is obtained by comparing the original image, blurred image and the deblurred image for noiseSD=√2 for the
Process –Deblurring

Noise Standard Deviations	PSNR(in dB)	MSE
15	31.4690	0.0023
25	28.7724	0.0055
50	25.0446	0.0180
100	22.4210	0.0605

Table II: PSNR and MSE for various standard deviations for the image barbara.PSNR and MSE is obtained by comparing the
Original image, noisy image and the clean image for the process-Denoising

4. CONCLUSION

The proposed method implements the restoration process based on advanced patch processing. The image prior is modelled in an effective way by without creating visual artifacts. The proposed algorithm narrows the gap of global modeling by preserving the local process. The experiment is conducted throughout by considering a simple Gaussian case. For denoising process several iterations are conducted by changing the standard deviation of noise and the beta values. Denoising process uses upsampling and Weiner filtering that results a better estimate of the PSNR and MSE.Deblurring process uses 90degree rotated kernel which is convolved with AWGN to produce a blurred image. Here also Weiner filtering is used which yield a better result compared to the convolutional methods.

CASE I: Deblurring

In the case of deblurring process, the simulation is carried out using test images starfish and butterfly for noiseSD=$\sqrt{2}$.The PSNR values obtained is 29.750(butterfly) and 29.9740(starfish)

CASE II: Denoising

In the case of denoising simulation is carried out using Barbara as the test image for various standard deviations. From table II it is clear that PSNR and MSE is inversely proportional. Let us take an example at high value of noiseSD =100, the PSNR obtained is 22.4210, which is very low compared to the smallest noise SD=15, PSNR is 31.4690.The mean square error between the original image, noisy image and the clean image at noiseSD=15 is very low. So obtain a high quality image which is free from noise is having high PSNR value with low MSE.

ACKNOWLEDGEMENT

I am ineffably indebted to my guide Mr. Vysak Valsan for his active guidance and encouragement to accomplish this assignment and Wikipedia for the correct source of information.

REFERENCES

[1] Idan Ram and Israel Cohen, 2013.Image Processing Using Smooth Ordering of its Patches: IEEE Transactions on Image Processing

[2] M.Elad and M.Aharon, 2006.Image Denoising via Sparse and Redundant Representations over Learned Dictionaries: IEEE transactions on Image Processing.

[3] W.Richardson (1991), Bayesian Based Methods on Image Restoration: Journal of Optical Society of America

[4] X.Li (2008) .Patch Based Image Interpolation: Algorithms and Applications: International Workshop on Local and Non Local Approximations in Image Processing.

[5] Yaniv Romano and Michael Elad (2015).Boosting of Image Denoising Algorithms: Society for Industrial and Applied Mathematics (SIAM)

[6] Michael Elad and Mario AT Figueiredo. On the Role of Sparse and Redundant Representation in Image Processing: IEEE Special Issue on Applications of Sparse Representation and Compressive Sensing