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Image Restoration by Linear Regression for Gaussian Noise Removal from Natural Images

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Abstract— ***Image restoration improves the features information of degraded or corrupted image. The degradation of image because of addition of noise when acquiring the image. Many algorithms are developed by many researches. In this paper image is corrupted by Gaussian noise to generate degraded image. The image is restored from this degraded image by supervised learning based algorithm. Few images are considered for training the dictionary with each element of size 9x9. The degraded image is considered patch by patch for restoring the patch from the trained set of images by support vector machine. The quality assessment of the image done by comparing the quality matrices like mean square error, root mean square error, peak signal to noise ratio, structural similarity index measure and feature similarity index measure. In this paper the images are considered are cameraman, house, Lena, Barbara and Parrot.***

Keywords: Image restoration, Dictionary Learning, About six key words separated by commas (Minimum 4 key words)

I. INTRODUCTION

Image processing is one of emerging area for researches as it is having many applications like image enhancement, image compression, image restoration, image segmentation and many more. Basically gray image is a two – dimensional matrix with each entry is intensity of the image at a particular location, Image restoration drawing attention for researchers. Image restoration aims to restore the image from a degraded image. Image restoration process used in various applications like image deblurring, denoising and medical applications [2, 4]. The original image is degraded due to addition of noise while capturing the image because of atmospheric turbulence, motion blur and camera focus. Let f is original image and g is restored image. The generalised expression for image restoration is given by

$$g = Hf + \eta \qquad (1)$$

Where H is degraded model function and η is inferred additive noise. Depending upon the H the problem of image is varied. If H is identity element the equ(1) represents image denoising [5 – 7], if H is a blur operator then equ (1) becomes image deblurring,The noise may Gaussian, salt and pepper, Rayleigh, uniform noise etc. The objective of image restoration to eliminate the noise from degraded image [8]. For image restoration the prior knowledge of image is indeed for regularization. Various algorithms are implemented for image denoising like Total variation model [8, 9]. The support vector machine (SVM) learning method proposed by Vapnik [10, 11] applied for regression.

Chapter 2 describes various supervised algorithms, Chapter 3 describes methodology algorithm flow for image restoration, Chapter 4 discuss various image quality assessment parameters, Chapter 5 discuss the results obtained and Chapter 6 conclusions of proposed restoration process.

II. LITERATURE

In supervised leaning mechanism, dictionary is trained with a known input and output images. Where as in unsupervised training for finding hidden structure in input image. The regression methods in supervised learning mechanisms are Support Vector Machine, Naïve Bayes and k-Nearest neighbor (kNN) algorithms. These methods are best to use for isolated linear boundary from one feature to another feature.

SVM classify objects by hyper line separator for maximizing the boundary between one types to another type class. SVM suits for high dimensional data set. Naïve Bayes classifies based on high probability of a particular feature. It is also used for less trained dictionary. Image restoration is done by linear regression based SVM [12, 13]

kNN classify objects based on distance metrics. It classifies based on neighbors for a test image from the dictionary. kNN used for lesser dictionary sized trained images.

III. PROPOSED METHOD

In the proposed method the restoration is done by two steps. In initial step the training of the dictionary later restoration takes place. During training the original image and noisy image are extracted patch by patch of size 3x3 to form dictionary. In support vector machine is used for regression in training the dictionary.

The SVM problem is solved by maximizing the kernel

$$\sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i\, \alpha_j y_i y_j K(\alpha_i \alpha_i) \qquad (2)$$

Here α is LaGrange multiplier, x, y are set of training samples.

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The algorithms for training dictionary as follows

Algorithm for training the dictionary
Step1: Consider a clean image
Step2: Add Gaussian Noise with required noise level
Setp3: Extract the patches of size 3x3 from both clean and noisy image
Steo4: Train the dictionary by linear regression SVM model
Step5: Update the dictionary

In restoration process, the degraded images are given as input. In this process the each patch of degraded images is checked with the atoms of the dictionary and the corresponding patch is restored. After restoring the image is enhanced using log filter.

The algorithms for training dictionary as follows

Algorithm for restoration
Step1: Consider an image degraded by Gaussian noise
Step2: Extract the patches of size 3x3 from the degraded or corrupted image.
Step3: For each patch extract the restorable patch from the trained dictionary.
Step4: Enhance the image by LOG Filters.
Step5: Output the restore image by displaying or storing
Step6: Evaluate quality matrices like MSE, RMSE, PSNR, SSIM and FSIM.
Step7: Compare with existing methods.

The proposed method applied for different images by considering each one at a time. The quality design metrics evaluated for different amount of noise level added to the images. The test images considered are cameraman, house, Lena, Barbara and parrot images.

IV. IMAGE QUALITY ASSESEMENT

In image restoration, the quality of the image restored in this paper are measured by four factors namely mean square error, peak signal to noise ratio (PSNR), structural similarity index measure (SSIM) and FSIM. Let the original input image *f(x, y)* and the restored image is *g(x, y)* and are of equal size *M x N.*

a. *Mean Square Error (MSE)*

The MSE is one of pixel dissimilarity measurement. The MSE defined as it the squared of the difference in the dissimilarity between original image and resultant image. The dissimilarity is measured with the image pixel values. The expression for MSE is given by (9)

$$MSE = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[f(x,y)-g(x,y)]^2 \quad (9)$$

The deviation between *f(x, y)* and *g(x, y)* is the error difference between two images. The lesser MSE gives more quality of the image.

b. *Root Mean Square Error (RMSE):*

The RMSE is evaluated by square root of MSE. The RMSE is given by equation (10).

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[f(x,y)-g(x,y)]^2} \quad (10)$$

c. *Peak signal to noise ratio (PSNR):*

The PSNR is pixel dissimilarity measurement. It gives the pixel value difference between original and reconstructed image. It is used to measure the quality of the reconstructed image. The PSNR for 8-bit gray image is given as equation (11).

$$PSNR = 10\log\frac{255^2}{MSE} \quad (11)$$

d. *Structural Similarity Index Measure (SSIM):*

SSIM is image quality assessment based on error sensitivity. It measures similarity between two images. SSIM is given by equation (12).

$$SSIM = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (12)$$

Where μ_f, μ_g, σ_f, σ_g, σ_{fg} are mean of *f, g,* standard variation of f, g and covariance of *f, g* respectively.

e. *Feature Similarity Index Measure (FSIM):*

FSIM image quality assessment based on phase congruency and gradient magnitude. It gives low level feature similarity. The FSIM is given by equation (13).

$$FSIM = \frac{2PC_1(x).PC_2(x)+T_1}{PC_1^2(x)+PC_2^2(x)+T_1} \quad (13)$$

Where PC_1, PC_2 are phase congruency of *f, g* respectively.

V. RESULTS AND DISCUSSION

The proposed method is used to restore the image corrupted by Gaussian noise. The image quality assessment metrics are evaluated for cameraman, house, Lena, Barbara and parrot images. The comparative analysis of mean square error is tabulated in Table1. The MSE values are evaluated for the different image corrupted by 10% to 50% Gaussian noise.

Table 1: MSE measurement for different Gaussian noise levels

Image\Noise Level	**0.1**	**0.2**	**0.3**	**0.4**	0.5
Cameraman	0.0049	0.0119	0.0224	0.0339	0.0448
House	0.0048	0.0113	0.0208	0.0317	0.0425
Lena	0.0048	0.0117	0.0223	0.0349	0.0474
Barbara	0.0048	0.0117	0.0224	0.0352	0.0486
Parrot	0.0047	0.0114	0.0219	0.0347	0.0479

The mean square error evaluated for different images are tabulated in Table 1. The MSE value obtained in the range of 0.0047 to 0.0479.

Table 2: RMSE measurement for different Gaussian noise levels.

Image\Noise Level	0.1	0.2	0.3	0.4	0.5
Cameraman	0.0698	0.1093	0.1496	0.1842	0.2116
House	0.0691	0.1065	0.1441	0.1779	0.2062
Lena	0.0695	0.1083	0.1494	0.1868	0.2178
Barbara	0.0695	0.1084	0.1495	0.1877	0.2205
Parrot	0.0683	0.1068	0.1480	0.1862	0.2188

Similarly the root mean square values are tabulated in Table 2. The peak signal to noise ratio specifies the quality of the image reconstructed. The PSNR values are compared in table 3 for different images at different noise levels.

Noise Level	10%	20%	30%	40%	50%

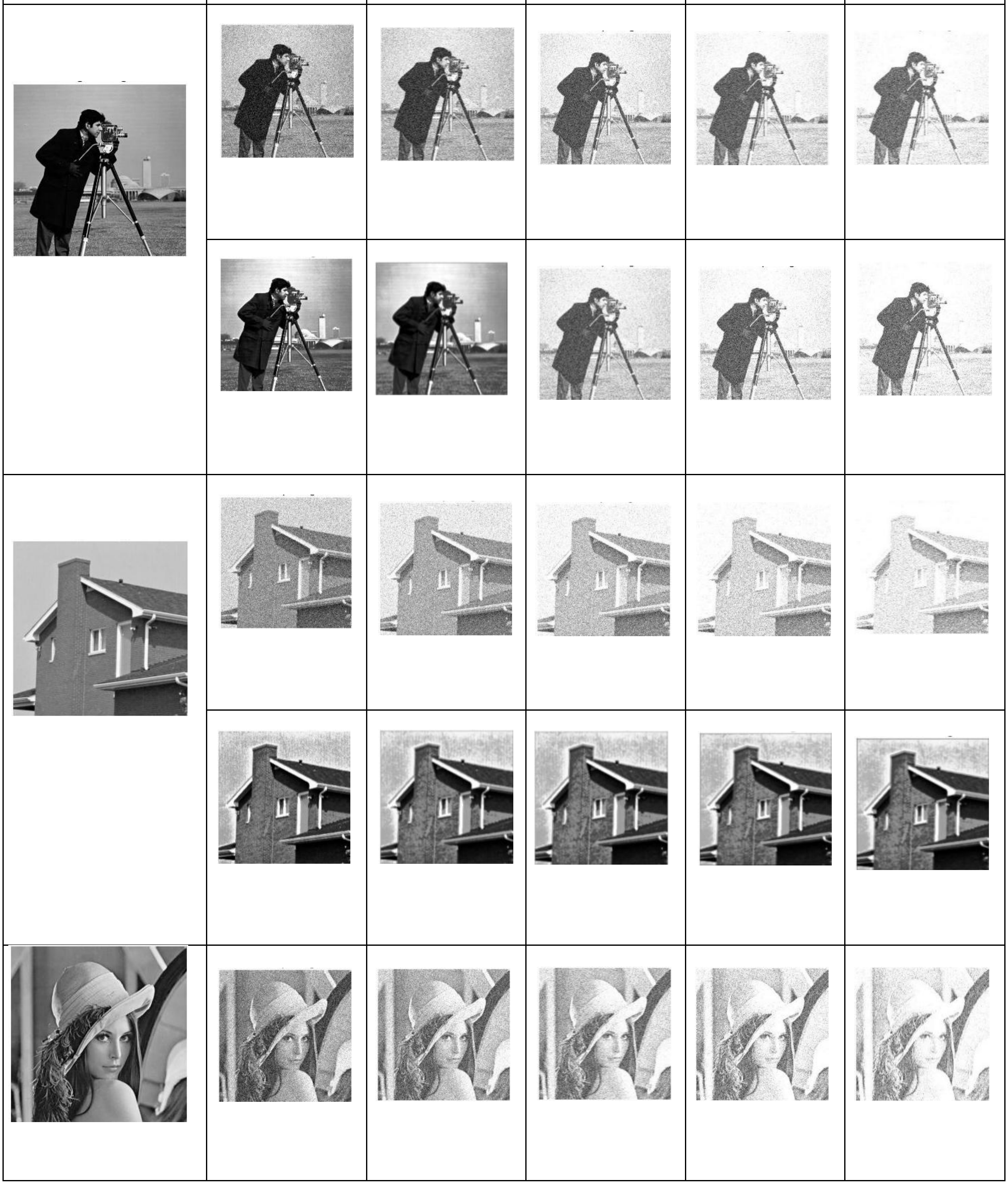

Figure 4: Original image, Degraded image and restored image

Table 3: PSNR measurement for different Gaussian noise levels.

Image\Noise Level	0.1	0.2	0.3	0.4	0.5
Cameraman	41.1855	37.2933	34.5641	32.7545	31.5498
House	41.2695	37.5163	34.8898	33.0564	31.7749
Lena	41.2204	37.3667	34.5776	32.6335	31.3009
Barbara	41.2197	37.3625	34.5680	32.5928	31.1953
Parrot	41.3722	37.4886	34.6590	32.6629	31.2594

The error sensitivity is estimated with SSIM parameter. The measured SSIM values for the test images are per Table 4 for different noise levels. The Feature Similarity Index Measure is estimated by equ (13) and it is compared for different noise levels as displayed in Table 5.

Table 4: SSIM measurement for different Gaussian noise levels.

Image\Noise Level	0.1	0.2	0.3	0.4	0.5
Cameraman	0.3127	0.2948	0.3030	0.3770	0.4846
House	0.2676	0.2711	0.3134	0.4181	0.4544
Lena	0.3391	0.3328	0.3419	0.3623	0.3952
Barbara	0.4014	0.3908	0.3897	0.3877	0.3780
Parrot	0.3480	0.3324	0.3214	0.3321	0.3809

The Figure 4 refer to the original image on left most column. For each image first row shows the images corrupted by Gaussian noise from 10% to 50%. And second row shows the restored images. Here the image are considered are cameraman, House, Lena, Barbara and Parrot.

Table 5: FSIM measurement for different Gaussian noise levels.

Image\Noise Level	0.1	0.2	0.3	0.4	0.5
Cameraman	0.9611	0.9614	0.9632	0.9649	0.9633
House	0.9619	0.9632	0.9636	0.9547	0.9337
Lena	0.9532	0.9546	0.9543	0.9487	0.9359
Barbara	0.9570	0.9571	0.9543	0.9479	0.9386
Parrot	0.9614	0.9616	0.9611	0.9597	0.9563

The proposed image restoration is implemented using support vector machine linear regression. The same can be extended by applied for other noises like salt and pepper, uniform and speckle noise. The larger the dictionary size the more similarity between original image and reconstructed image.

VI. CONCLUSION

In this paper supervised learning method is used is used for image restoration. For the restoration two phases are implemented. Initially the dictionary is trained of each atom of size 3x3 for both clean and noisy images later for restoration the corrupted image is considered patch by patch. For each patch of corrupted image the restored one is fetched from the trained image dictionary. After restoration enhancement is done by LOG filter. The performance of the proposed method is evaluated for the parameters mean square error, root mean square error, PSNR, SSIM and FSIM.

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