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Image Enhancement, Deblurring and Noise Removal by GSR Algorithm

Amit Verma[1*], Isha Vats[2] and Aarti Dogra[3]

ABSTRACT

This paper emphasizes on improving the quality of image from the degraded one with the help of group based sparse representation technique and gives more satisfied results than existing one. Some of the sophisticated techniques have been developed to deal with various image restoration problems like noise types and blurring functions. Every technique works on different parameters.The necessary conditions for modern communication system and multimedia includes provision for detection of tampered images, their localization and restoration. In high level image processing image restoration becomes an important issue which deals with extracting an original and sharp image from degraded one using a degradation and restoration model. Normally an image is degraded when it comes under acquisition process. Image restoration is a technique with the help of which the original contents of image can be bring back from degraded one with or without having prior knowledge about degradation process where due to atmospheric and environmental conditions images may be degraded. Thus for a fore mentioned problem ,in this paper a GSR(Group based Sparse Representation) algorithm is implemented for denoising, enhancing images and deblurring. In this degraded image is divided into patches and then groups of patches are constructed and further these groups are replaced with the groups matched in original image. Results are carried out on the basis of PSNR, MSE, SSIM and Speed. Application/Improvements: In this GSR algorithm gives better results than patch based algorithm which exploits the relationship among patches.

Keywords: Image restoration, image enhancement, denoising, deblurring, PSNR, MSE, SSIM and speed.

1. INTRODUCTION

The process of recovering the high quality image from degraded low quality image is referred to as Image restoration It is an operation in which a corrupt/noisy image is taken and the clean, original image is estimated. Corruption may take many forms such as camera mis-focus, atmospheric turbulence, camera or object motion, etc.

Image restoration techniques are implemented with objective of reducing noise and recovering resolution loss. Implementation of these techniques can be performed in both domains i.e the frequency domain or the spatial domain. The mostly usedtechnique in the frequency domain is Deconvolution which computes the Fourier Transform of both the PSF and the image and resolution loss caused by the blurring factors is recovered. In DE convolution technique noise is absent and that the blurring process is shift-invariant and hence it introduces more sophisticated techniques to deal with the different types of noises and blurring functions.

Image restoration is performed when the process that blurred the image is reversed- and that is performed by imaging a point source and use Point Spread Function known as the point source image and the information lost can be restored with this.

[1*] Professor and Head of Department, Computer Science & Engineering,Chandigarh Engineering College, Landran, Punjab, India, *Email: dramitverma.cu@gmail.com*

[2] M. Tech. Research Scholar, Computer Science & Engineering, Chandigarh Engineering College, Landran, Punjab.

[3] Assistant Professor, Computer Science & Engineering, Chandigarh Engineering College, Landran, Punjab.

1.1. Point spread function

Point spread function can be stated as linear position-invariant function $h(x, y)$. When it gets convolved with the original image then it gives the degraded image. Some common linear and position-invariant image degradations are given below.

1.2. Motion Blur

Images are blurred because of camera movement during capturing an image. Suppose the relative motion is of velocity ν at an angle θ with the horizontal axis and if T is the exposure duration, then L = νT is termed as blur length and the motion blur PSF can be expressed as

$$h(x, y) = \{1/L \text{ if } 0 \leq |x|d \leq \cos\theta;\ y = L\sin\theta$$
$$= \{\ 0 \text{ otherwise} \quad (1)$$

1.3. Camera Defocus

Due to improperly focussed camera, there is another commonly occurring blurring. Assuming the lens system is of circular aperture, with radius r the point spread function is represented by :

$$h(x, y) = \{\ 0 \text{ if} \sqrt{(x2 + y2)} > r$$
$$= \{1/\pi r2 \text{ otherwise} \quad (2)$$

Depending uponthe knowledge of Point Spread Function (PSF) Image Restoration Techniques are categorized as:

(a) BLIND IMAGE RESTORATION: In this technique degraded images are restored into original images when knowledge about PSF is not known or known in little amount. Blind Image Deconvolution (BID) comes under this category.

(b) NON-BLIND RESTORATION: In this technique original image is reconstructed from degraded image when both prior knowledge about PSF and factors degrading the image are known.

Currently our focus is on group based sparse representation technique which will solve three image restoration problems ie denoising, deblurring and image enhancing an image. The rest of the paper is summarized as : section 2 explains a previous work related to image restoration problems. Section 3 completely explain the proposed method. Section 4 contains the result analysis of the proposed method on sample images. Section V concludes the work done in the proposed scheme.

2. RELATED WORK

In this computing era, many sophisticated techniques have been developed for improving the quality of image from the degraded one. Following are the techniques used by some researchers.

In[1] Authors have proposed a multi-scale EPLL, which imposes the very same patch-based model on different scale patches, extracted from the image. Its use is motivated by looking at the simplified Gaussian case, showing that such an approach manages to narrow the gap to the global modeling while preserving the local treatment. Then comparison of the proposed method to the original EPLL on the tasks of image DE noising, DE blurring and super-resolution is made which shows clear improvement across all tasks.

In[2] Authors have worked upon the concept of group which has been treated as sparse representation's basic unit, which combines various similar structured non local patches and different sparse representation demonstrating of images is established called as group-based sparse representation (GSR).

In[3] Authors have introduced a new image restoration model based on wavelet frame in which images are explicitly treated as piecewise smooth functions. The image to be restored and its singularity set are restored by this. An important image feature namely singularities are well protected and at the same time enough regularization in smooth regions is provided by them.

In[5] Authors have mainly focused on medical images for their research. Various image restoration techniques have been used for their restoration. LRA and BID are two techniques which are mostly used and with these the recovery of X-ray images are analyzed.

In[6] Authors have proposed new HSI restoration method based on (LRMR) low-rank matrix recovery which removes the Gaussian noise ,stripes, dead lines and impulse noise at the same time. The proposed LRMR-based HSI restoration method can be verified byconducting several experiments in both data conditions i.e simulated and real .

In[7] Authors have worked on a high-fidelity image restoration in which nonlocal self-similarity and local smoothness of natural images are characterizedstatistically in a unified manner. Effectiveness of the proposed algorithm is verified by extensive experiments on applications like image deblurring, inpainting and removal of Gaussian , salt pepper noise.

In[8] In this authors have proposed an effective approach through which computational efficiency and high restoration quality are achieved. Both the optimization algorithm and the model of image are combined together into a single unit by proposed shrinkage fields and a random field-based architecture. Through DFT as the core components and construction with the help of convolution, computational efficiency is achieved with the training of all model parameters which must be loss basedand high restoration quality is attained through the use of cascade architecture .

In[10] Authorsdeals with estimation of parameters for motion blurred images. The accurate estimation of both the the blur angle (θ) and length (*L*) of the given degraded image as possible so that the restoration performance can be optimized are main objectives. To estimate the blur angle,Gabor filter is utilized whereas a trained radial basis function neural network (RBFNN) estimates the blur length.

In[11] Authors have used Discrete Cosine Transform (DCT) having high energy compaction property and with which both the cost and computational time are reduced .DCT takes less computation time as compared to wavelet transform.

Table 1
shows techniques used.

Year of publication	*Technique used*	*Pros*	*Cons*
2015	M_{PBR}	It impose the same P_{bm} on different S_p from img.	It ignores the R_p.
2014	G_{SR}	The proposed G_{SR}represents n_{img} in group domain, enforcing the i_{nt} l_p and NSS_{img} simultaneously in a uf.	It is less t_r and $r_b$and has minimization problem.
2015	W_F	This model explicitly models img as $P_{sf}$and is insensitive to the estimation of the ss.	In this txt_s cannot be modeled as P_{sf}.
	LRA and BID.	The p_{er} of BID tch while recovering X-ray img is commendable .	The REpresent at the edges of the r_{img} due to the process of dc_{on} need imp.
2013	HSI r_{st} mthd based on LRMR	The proposed HSI r_{st} mthd can $e_{ff}$and s_{mt} remove the mixed noise of G_n, I_n,D_l and S_{rp}.It is qt r_b and stb. with regard to noise types	Neighboring p_x of the HSI has no Sc imposed, causing an unsatisfactory p_{er} for very large areas of missing p_x,
2014	SF with C_A	The model provides more flx and enabled efficient learning of all model parameters.	It has slow rt for large img_s.
2012	ADMM-B	Algo is r_b, fast and e_{ff}.	It requires little improvement in rt .

M_{PBR}: Multi scale patch based image restoration, G_{SR}: Group based sparse representation, W_F: Wavelet frame based approach, LRA: Lucy Richardson algorithm, BID: Blind image deconvolution, HSI: LRMR: low-rank matrix recovery,C_A: Cascade architecture, SF: Shrinkage Fields, ADMM-B: Alternating direction method, e_{ff}: effectively, qt: quite, stb.: stable, P_{bm} patch based model, $S_p$scale patches, G_{SR}: group based sparse representation, n_{img}: natural image , i_{nt}: intrinsic, l_p: local sparsity, NSS_{img}: nonlocal self-similarity,uf: unified framework, img: image, P_{sf}: piecewise smooth functions, ss: singularity set, tch: technique,G_n: Gaussian noise, I_n: impulse noise, D_l: dead lines, r_{st}: restoration, mthd: method, S_{rp}: stripes, r_b: robust, s_{mt}: simultaneously, flx: flexibility, Algo: Algorithm, e_{ff}: efficient, R_p: relationship among patches, t_r: tractable, txt_s: textures, RE: ringing effects, r_{img}: restored image, d_{con}: deconvolution, Sc: spatial constraint, p_{er}: performance, p_x: pixels, rt: runtime.

3. PROBLEM FORMULATION

- The proposed algorithm used here is Group Based Sparse Representation which will remove the flaws occurred in existing system i.e patch-based sparse representation model.
- In dictionary learning Patch based sparse representation model is considered independently and there is sparse coding for each patch, which ignores the relationship among patches.
- Existing system has used the simplified Gaussian case, showing that such an approach manages to process each patch independently, because of which coordination among patches is neglected, and inaccurate sparse coding coefficients are obtained as results.
- Another problem with existing system is in dictionary learning which includes large-scale optimization with high computational complexity.
- The proposed system would be capable of resolving the problems of existing system by using GSR algorithm for image restoration. Images are represented sparsely in the domain of group and are processed. The proposed model would be worked for image restoration in three applications: De blurring, Noise removal and image enhancement.

4. EXPERIMENTAL DESIGN

Various image restoration techniques are executed for noise removal and recovering resolution loss. These are performed either in the image domain or in the frequency domain. The appearance of an image can be more improved. Different correction methods like Linear Filtering, Median filtering and Adaptive Filtering etc. are executed in order to restore an image to its original quality. The process for image degradation is as follows:

$$g(x, y) = H(x, y).f(x, y) + n(x, y)$$

In above equation, a convolution matrix is represented by degradation function $H(x, y)$ and it models the blurring introduced by many imaging systems due to many environmental conditions, camera defocus, motion blurs, imperfections of the lenses all can be modeled by H. The values $K(x, y)$ is for additive noise, original image represents $f(x, y)$, & degraded image represents $g(x, y)$.

Restoring an image is the main aim of this approach like extracting original one by providing degraded one as the input. Through this approach three image restoration problems i.e image DE blurring, noise removal and image enhancement can be dealt. Some operations are required to perform in order to restore the images from degraded images like blurred or noisy.

In order to retain the quality of image from various types of degraded ones like noisy, blurred, compressive image some operations are performed on both images as explained below.

Operations on original images :Construction of groups, modelling by GSR and learning of self adaptive dictionary are main operations which are executed on original image and are explained below.

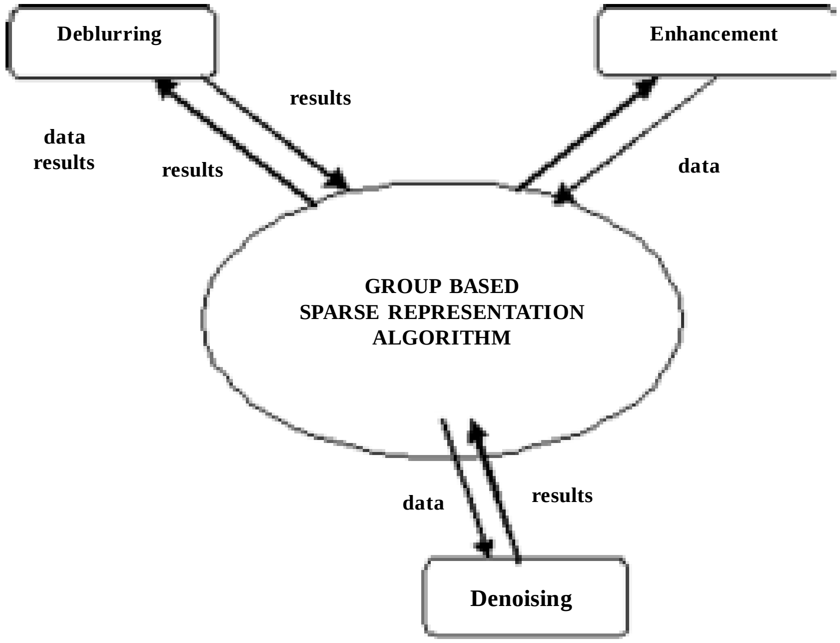

Figure 1: Context Diagram

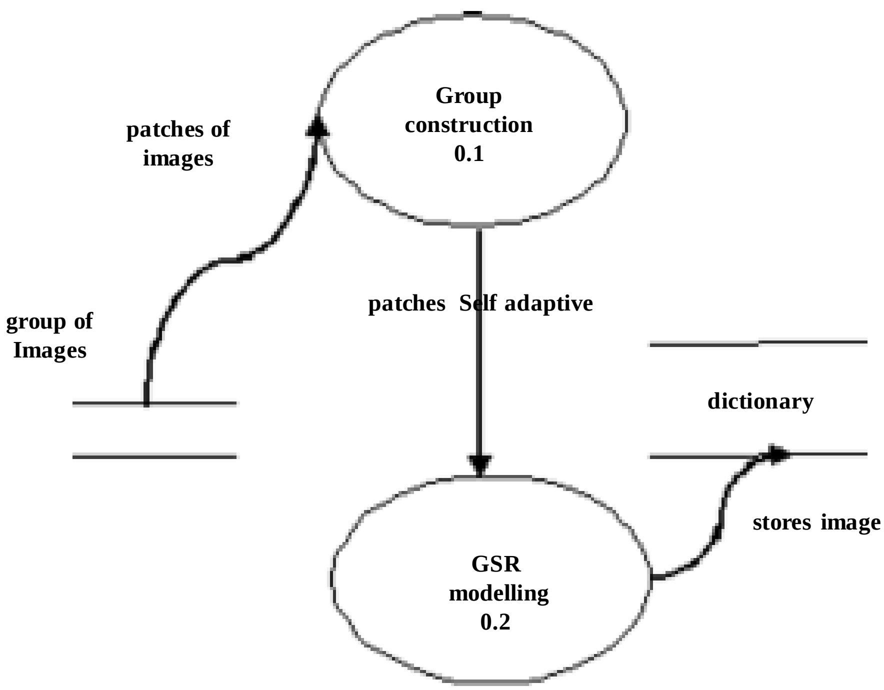

Figure 2: Level 1 DFD

1. Group Construction: It describes how the group is constructed. Four steps are required to carry out group construction which are explained below:

Step 1: An image x of size N is decomposed into n overlapped patches of size $\sqrt{B_s} \times \sqrt{B_s}$ and each patch is represented by the vector $x_k \in \mathbb{R}^{Bs}$ is used where $k = 1, 2, \ldots, n$.

Step 2: Best matched patches containing the set S_{xk} are searched within the $L \times L$ size training window c for each patch (x_k). Similarity between the patches is done by Euclidian distance.

Step 3: $x_{Gk} \in \mathbb{R}^{Bs\times c}$ denotes all the patches in the set $_{xk}$ into a $B_s \times c$ matrix, which refer every patch in S_{xk} as its columns, $x_{Gk} = \{x_{G(k\otimes 1)}, x_{G(k\otimes 2)......} x_{G(k\otimes c)}$. The matrix indicates group and can be represented by equation

$x_{Gk} = R_G(x)$ Eqn. 3 The group x_{Gk} is extracted from x with the help of $R_{Gk}(\cdot)$ operator. In the reconstructed ones groups can be placed back into its k-th position by using the transpose of the operator $R_{Gk}{}^T(\cdot)$ or zeroes are padded with image. Thus the whole image x can be recovered from $\{x_{Gk}\}$.

$$x = \sum_{k=1}^{n} \left(x_{Gk}\right) ./ \sum_{k=1}^{n} R_{Gk}^{T} \left(I_{B(s\times c)}\right) \tag{4}$$

Where the two vectorsare represented element wise by ./ and $I_{B(s\times c)}$ is matrix having $B_{(s\times c)}$ size with 1 for all the elements.

2. Modeling of Group-Based Sparse Representation: According to GSR model to accurately describe each group x_{Gk} some atoms of the self-adaptive learning dictionary D_{Gk} can be used which are as follows:

Therefore, $D_{Gk} = \{D_{Gk\otimes 1}, D_{Gk\otimes 2}, D_{Gk\otimes m}\}$ is known. D_{Gk} is of size $(B_s \times c) \times m$, that is, $x_{Gk} \in \mathbb{R}^{(Bs \times c) \times m}$.

The sparse coding process focuses on sparse vector $x_{G(k\otimes 1),}$

$\alpha_{Gk} = \{\alpha_{Gk\otimes 1}, \alpha_{Gk\otimes 2}, \ldots\ldots, \alpha_{Gk\otimes m}\}$ where $\alpha_{Gk} \approx \sum_{i=1}^{m} {*}\alpha_{Gk\otimes i} D_{Gk\otimes i}$. In simple representation form $D_{Gk}\alpha_{Gk}$ is used to represents $\sum_{i=1}^{m} \alpha_{Gk\otimes i} D_{Gk\otimes i}$. After this the set of the sparse codes which is represented by $\{\alpha_{Gk}\}$ sparsely represents the whole image. Thus, $\{\alpha_{Gk}\}$ can be used to construct x which can be represented by

$$x = DG\ \ \alpha_G \underset{=}{def} \ \sum_{k=1}^{n} R^T{}_{Gk}(\alpha_{Gk})./\sum^n k = 1\ R^T{}_{Gk}(I_{B(s\times c)}) \tag{5}$$

the concatenation of all α_{Gk} is represented by D_G.

Thus, the formulation of GSR is expressed as:

$$\alpha_G = argmin_{\alpha G}\ (1/2)\ \|HD_{G^\circ}\alpha_G - y\|\ 2_2 + \lambda \ \|\ \|\ \alpha_G\ \|_0 \tag{6}$$

3. Self-Adaptive Group Dictionary Learning: During dictionary learning for each group following instructions must be noted carefully:

1) Cost of computation must be minimized.
2) For a group xGk there must be learning dictionary, which means the same dictionary D_x is used to represent all the groups $\{x_{Gk}\}$.
3) For each group x_{Gk}, properties containing the patches with similar patterns must be considered.

In the process of optimization estimated r_{Gk} is selected by default which is used to learn the adaptive dictionary for each group directly. Apply K-SVD after obtaining r_{Gk},. This can be formulated as follows:

$$r_{Gk} = U_{Gk} \sum G_k\ \ V^T{}_{Gk} = \sum_{i=1}^{m}\ \gamma_{rGk\otimes}\ (u_{Gk\otimes ivGk\otimes iT}) \tag{7}$$

where $\gamma_{rGk} = [\gamma_{rGk\otimes 1}; \gamma_{rGk\otimes 2}; \ldots \gamma_{rGk\otimes m}] \sum{}_{Gk} = dia\ g(\gamma\ rGk)$ is a diagonal matrix having main diagonal elements as $u_{Gk\otimes i}$, the columns of $U_{Gk\otimes i}$ & $V_{Gk\otimes i}$ are $v_{Gk\otimes i}$.

For each group x_{Gk}, each dictionary D_{Gk} atom is defined as,

$$d_{Gk\otimes i} = u_{Gki}\ v^T{}_{Gk\otimes},\ i = 1, 2, \ldots, m, \tag{6}$$

where $d_{Gk^\cdot} \in \mathbb{R}^{(Bs \times c)}$.

Thus, for the group x_{Gk} the learned dictionary is given by

$$D_{Gk} = [_{\otimes 1}, D_{Gk\otimes 2}, \ldots., D_{Gk\otimes m}] \tag{8}$$

4.1. Operations on degraded image

To recover the image which is approximately approaches original image following operations are performed on degraded image.

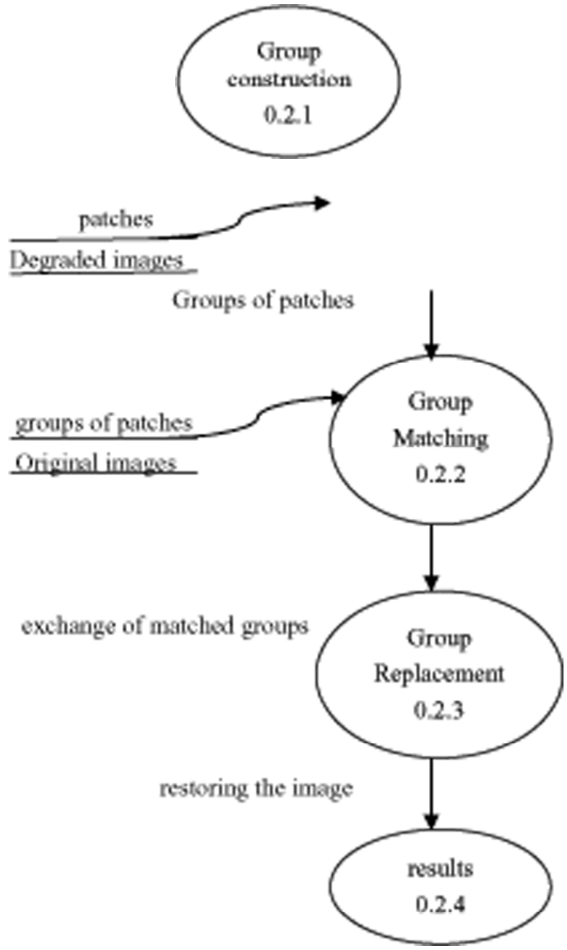

Figure 3: Level 1 DFD

1. Group Construction : In this groups of non-local patches with similar structures are constructed same as in original image.
2. Matching and Replacement of groups: In matching of groups , the groups which are obtained from degraded image and from original image are compared and exchanged. After this if any of the group is matched thenit is exchanged with the original image group.
3. Restoring an Image: After interchanging all the groups, the recovered image is obtained which is somewhat similar to the original image.

5. EXPERIMENTAL RESULTS

Various systems were implemented using MATLAB 2013a and these are tested on an Intel Core i5 with 4GB of RAM running Windows 7. Automated image restoration has become the holy grail of computer vision artificial intelligence. Most of the computer vision projects that are being studied are demanding this and is not just a fascinating theoretical problem, but there is a real-world need for such a system. This section of thesis represents some computational results of proposed model.

5.1. Performance Evaluation Parameters

There are various available metrics used to evaluate different techniques. In current work, performance parameters like PSNR, MSE, SSIM, speed and time have been used[28].

To calculate these parameters, there is the need to understand the following terms as below:

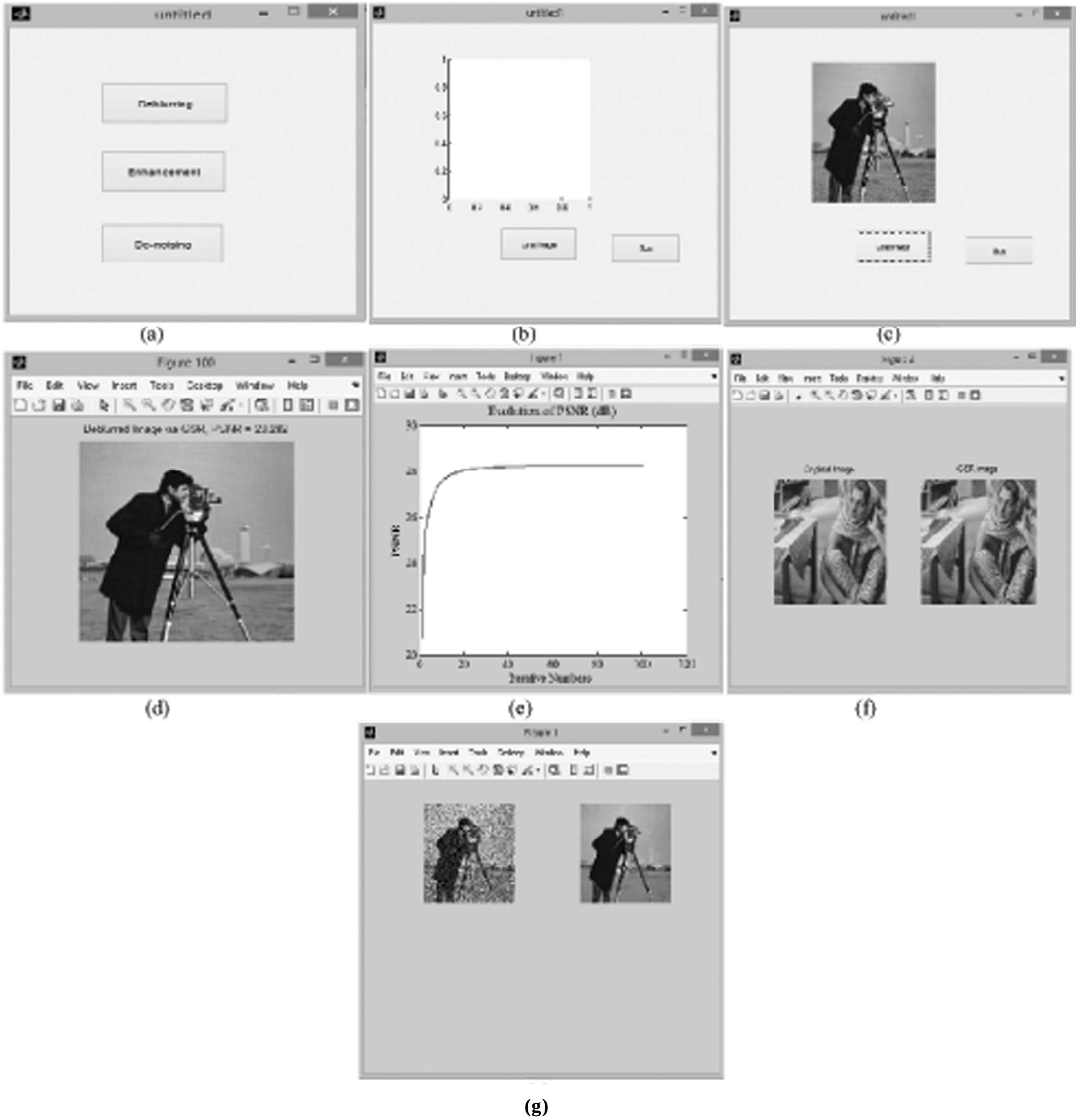

Figure 4: (a) shows the main screen designed for the proposed model. The main screen contains three options i.e Deblurring, enhancement and Denoising. Here, by clicking on any option, it will give the corresponding results. (b) shows screen where image is uploaded by clicking on LOAD IMAGE Button and after pressing the RUN button, corresponding dialog boxes will be open and results are shown. (c) shows the screen where image is uploaded. (d) shows the screen which displays the deblurred image with better PSNR value. (e) shows during deblurring process the PSNR value is incrementing upwards for corresponding value of iterations. (f) gives the results when GSR works for image enhancement. (g) gives the results when GSR is implemented for noise removal

PSNR : PSNR is used to measure how much quality exists after lossy compression codecs have been reconstructed (e.g., for image compression). The original data is represented by the signal, and the error introduced by compression is represented by the noise.

MSE : It denotes Mean squared deviation (MSD) or mean squared error (MSE) and the average of the squares of the errors/ deviations are estimated or,it represents the difference between the estimator and what is estimated.

SSIM : SSIM is used for measuring how two images are similar to what extent.

Sno.	*Sigma*	*MS-EPLL*	*GSR*
1	15	29.01	34
2	25	28.23	32
3	50	30.16	28
	100	23.8	25.6

(a) shows the comparison of PSNR values for existing and proposed method for denoising process.

Restoration problem	*PSNR Value*
Image	41.89
Enhancement Deblurring	34

(b) shows the PSNR values for restoration problems

Restoration problem	*MSE*	*SSIM*
Denoising	0.32	1.87

(c) shows the value for MSE and SSIM in denoising.

Restoration Problem	*Values (in Kb/secs)*
Denoising	33.87
Image enhancement	33.24
Deblurring	0.47

(d) shows the values of speed for different problems

Restoration Problem	*Values (in secs)*
Denoising	60.45
Image enhancement	61.60
Deblurring	1075.06

(e) shows the values of speed for different problems

Figure 4.5 shows table measures for different values

There is comparison between results of existing and proposed algorithm namely, GSR and MS-EPLL for average PSNR, MSE, SSIM, speedand time in various applications like De-noising, deblurring and image enhancementwith different values. Proposed model shows the better results in comparison of existing scheme.

6. CONCLUSION

Since there are number of techniques for solving image restoration problems, each having different consequences. In this paper GSR (Group Based Sparse Representation) algorithm isproposed which is based on concept that group of patches are constructed which maintains the relationship among various patches of images and it is implemented for three image restoration problems i.e Denoising, Deblurring and Image enhancement. Various parametrers are taken into account like PSNR, MSE, SSIM, speed and time. The simulation experiments have been conducted in MATLAB and the results have been compared with existing scheme i.e patch based sparse representation. Both standard and real time images have been included in simulation. It has been observed that after the recontruction of an image values of parameters

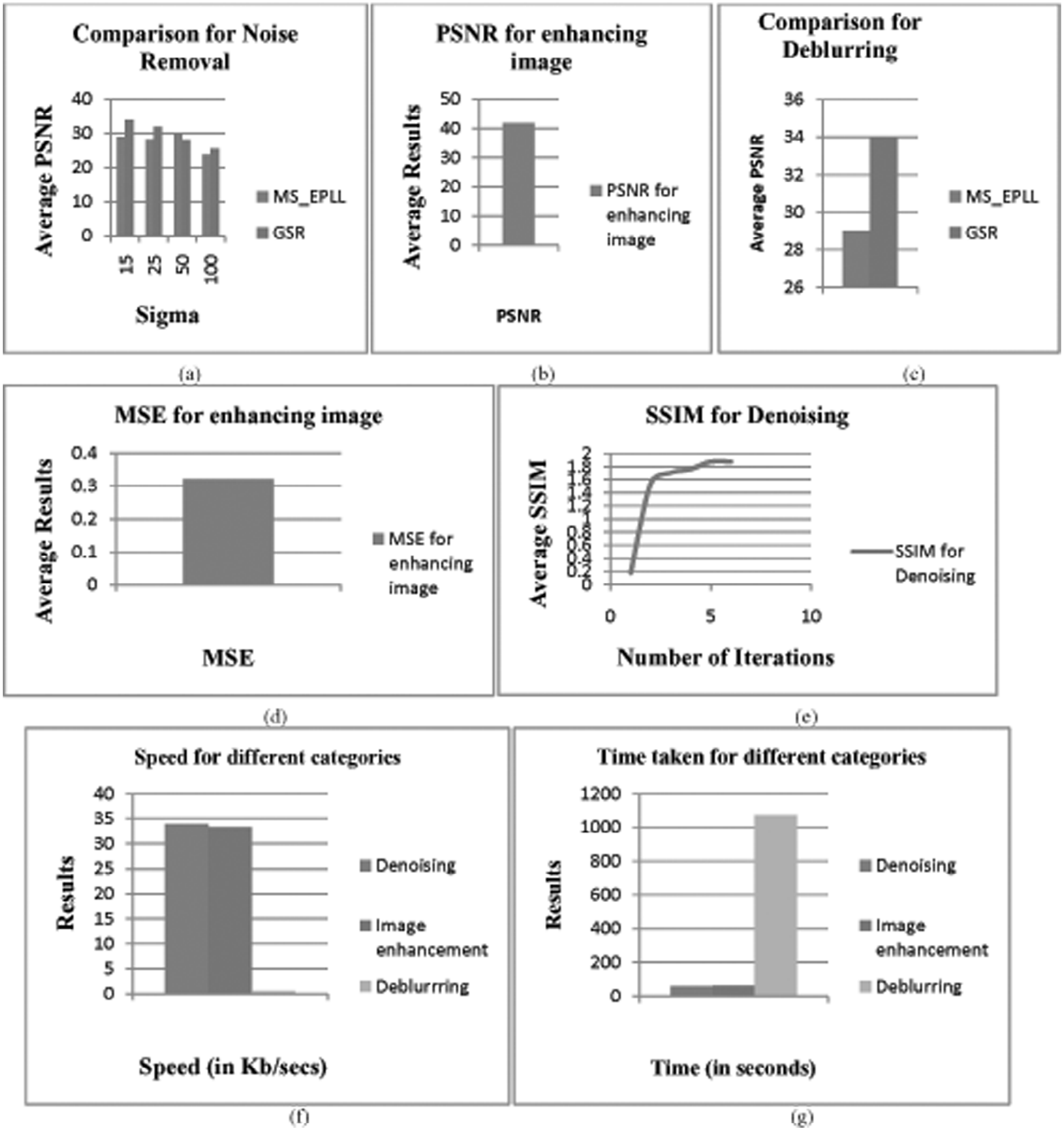

Figure 4.6 shows graph for the above table measures: (a) shows the comparison of PSNR values for existing and proposed method. (b) shows the average PSNR for different images. (c) shows the comparison for deblurring. (d) shows the average MSE for different images. (e) shows SSIM values on a graph for no. of iterations (f) shows values of speed during different image restoration problems (g) shows time taken during different image restoration problems.

are increased which are more than existing scheme. In all cases the proposed schemehas an upper hand in parameter estimation as well as restoration performance.

In Future, this research could be improved for fasten the results. Working upon speed for the system could further enhance this research/ technique. Now the GSR technique has very slow rate for image restoration, which takes lots of time to produce the results. This technique could also be designed without taking the original image for restoration.

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