IMAGE INPAINTING OF DIGITAL IMAGES USING JOINT STATISTICAL MODELING TECHNIQUE

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Abstract— Image Inpainting has wide applications in image and photo restoration, text removal, special effects in movies, digital zoom-in, and edge-based image compression and coding etc. It is a very active field of research. The objective is to improve the general quality of an image or remove defects. Different methods from linear algebra and partial differential equations (PDEs) are used for this purpose.In present work, enhanced approach based on JSM (Joint statistical Modeling) is used to inpaint the digital image. Various functions like Image denoising, deblurring and text removal are also performed.

Keywords— Image inpainting, Image restoration, JSM inpainting, Text removal, Noise removal.

I. INTRODUCTION

Image inpainting problem is one of the most essential image restoration problems. It is the technique of modifying an image in an undetectable form to an observer not familiar with the original image and is as ancient as art itself. It also refers to the practice of the artists of restoring paintings. Researchers working on different applications have adopted different names: image interpolation, disocclusion, image replacement, and error concealment though each of them carries its own individual characteristics.

Image restoration problems such as inpainting and deblurring have always been important image processing tasks with many real world applications. Often images may have regions with missing data. Examples may include scratches on frames, scratches on images, the occlusion of objects in an image, or even from irregularities in the imaging device itself (scratched lenses).

To remedy these problems, image inpainting which is the lying in missing data based on known information is considered. Any semblance of order in an observation is a manifestation of redundancy of its present representation. Such redundancies have been exploited for different purposes in innumerable applications, one canonical example being data compression. Specifically, in video compression, motion compensation and transform coding are used to exploit the spatiotemporal redundancy in the video signal. But the types of redundancies exploited by current methods are rather limited.

This is exemplified by the success of error concealment techniques. Moreover, Discrete cosine transform (DCT), the most commonly used transform coding technique in video compression, has been found to be effective only for small block sizes, which shows its inability to exploit redundancies extending upto larger extent. Wavelet has been relatively more successful in this respect for certain classes of images but hasn't found much use in general purpose video compression.

It is interesting to compare aforementioned techniques with texture synthesis and image inpainting both of which also assume the existence of redundancies in images and video, but exploit it for other purposes different from compression.

II. LITERATURE REVIEW

Zhang *et al.* [12] (2014)proposed a novel strategy for high-fidelity image restoration by characterizing both local smoothness and nonlocal self-similarity of natural images in a unified statistical manner. The main contributions are three-fold. From the perspective of image statistics, a joint statistical modeling (JSM) in an adaptive hybrid space-transform domain is established, which offers a powerful mechanism of combining local smoothness and nonlocal self-similarity simultaneously to ensure a more reliable and robust estimation.

Kohler *et al.* [13] (2014)presented a novel and efficient algorithm that combines the advantages of texture synthesis and inpainting techniques.Authors also proposed a mapping from image patches, corrupted by missing pixels, onto complete image patches. This mapping is represented as a deep neural network that is automatically trained on a large image data set.In comprehensive experiments on various images, it demonstrates that the learning-based approach is able to use this extra information and can achieve state-of-the-art inpainting results. Further-it shows that training with such extra information is useful for blind inpainting, where the exact shape of the missing region might be uncertain, for instance due to aliasing effects.

Guillemot*et al.* [3] (2014), the term inpainting first appeared with a process used in art restoration. Image inpainting is an ill-posed inverse problem that has no well-defined unique solution. To solve the problem, it is therefore necessary to introduce image priors. All

methods are guided by the assumption that pixels in the known and unknown parts of the image share the same statistical properties or geometrical structures. This assumption translates into different local or global priors, with the goal of having an inpainted image as physically plausible and as visually pleasing as possible.

Zhu *et al.* [16] (2014)presented an enhanced Curvature Driven Diffusion (ECDD) model is proposed to improve the repairing performance. then a fast local non-texture inpainting scheme is performed based on ECDD and total variation (TV) to make the computing of the PDE basedimage inpainting more efficient. The proposed strategy not only can repair the long disconnected objects more accurately, but also can greatly shorten the time of inpainting.

III. PROPOSED METHODOLOGY

The main obstruction in restoration technique could be the lack of knowledge about degradations. In most of the cases, the degradation actually destroys the information in an image, and the knowledge of degradation can be insufficient to counteract the degradation. On the other hand, most restoration algorithms require some amount of prior information in order to get a restored image. This information can be provided in many ways. The best source of information can be obtained by making an assumption that the original scene is smooth i.e. there is a degree of correlation between the various neighbouring points in an image or say, all the pixels in an image are somehow related to each other. Therefore, we compute the mean value in a filtering window and replace the corrupted pixel by mean of its neighbours. This holds true for every real-life image, but, the degree and the type of correlation may vary significantly from one image to other.

We consider the nearest neighbours of a pixel. In this paper, we consider for N=1, i.e. a total of eight neighbours of each pixel are considered in a filtering window of 3x3.The size of the window can be more than 3x3 too. In the 2D grid of picture elements, each element has a certain correlation with its nearest elements. With the aid of this property, we can write algorithms to replace a noisy pixel by a value which happens to be the mean of all the nearest neighbours. This ensures a good level of restoration as shown in the results. The algorithm proposed carries out an iterative process wherein the mean intensity is found and further replacement of noisy pixel is done.

Proposed Algorithm

1. Read an image into MATLAB environment.
2. Display the image read.
3. Consider a pixel(say im(i,j)) and identify its nearest neighbours. Take all the eight neighbours for chessboard distance and four for city-block distance.
4. Extract a sub-matrix containing the elements of im(i,j).
5. Calculate the mean value of all the neighbours of the sub-matrix.
6. Approximate mean value obtained in Step 5.
7. Replace the pixel at im(i,j) with the value obtained in Step 6. Go to Step 3.
8. Display the restored image.

Fig 1 shows the flowchart of the proposed methodology algorithm discussed previosly.

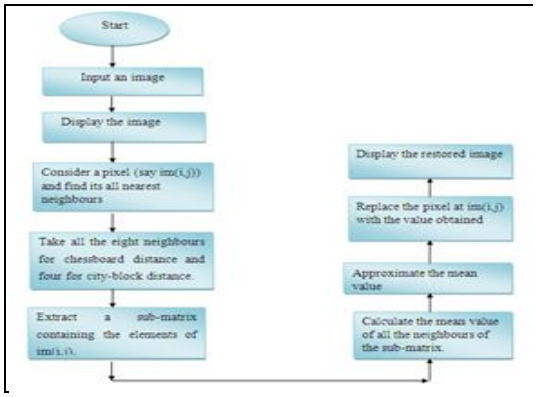

Fig 1: Proposed methodology Flowchart

IV. RESULTS AND DISCUSSIONS

4.1 Dataset

It includes a set of standard dataset consisting of more than 20 images to evaluate the performance of the proposed system.The results of the deblurring are tabulated in table 1. The line graph for the results in table 1 is also shown in fig 2.

Table 1: Result for deblurring

Image	Existing System PSNR	Proposed System PSNR
Fig 1	31.26	41.8
Fig 2	35.12	55.5
Fig 3	36.68	44.17
Fig 4	32.18	54.64

The line graph in fig 2, clearly show that, for deblurring, the PSNR of the proposed system is more than the existing system. So the proposed system is better than the existing system for deblurring.

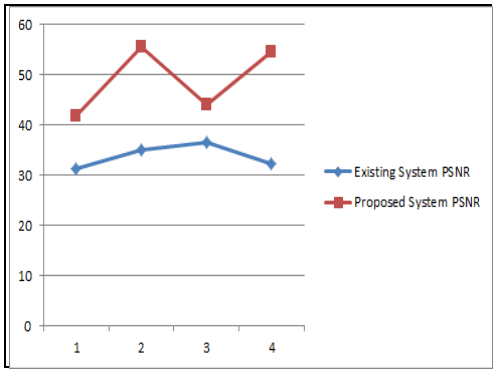

Fig 2: Graph for deblurring

The results of the mixed noise removal are tabulated in table 2. The line graph for the results in table 2 is also shown in fig 3.

Table 2: Results for mixed noise removal

Image	Existing System PSNR	Proposed System PSNR
Fig1	31.81	41.94
Fig 2	34.33	46.54
Fig 3	30.92	41.73
Fig 4	33.49	46.06

The line graph in fig 3, clearly show that, for mixed noise removal, the PSNR of the proposed system is more than the existing system. So the proposed system is better than the existing system for mixed noise removal.

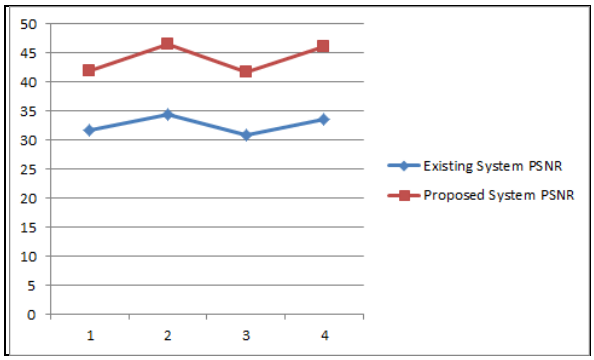

Fig 3: Graph for mixed noise removal

The results of the mixed noise removal are tabulated in table 3. The line graph for the results in table 3 is also shown in fig 4.

Table 3: Results for Inpainting

Image	Existing System PSNR	Proposed System PSNR
Fig 1	37.99	51.49
Fig 2	44.92	54.50
Fig 3	41.91	49.99
Fig 4	34.43	54.67

The line graph in fig 4, clearly show that, for inpainting, the PSNR of the proposed system is more than the existing system. So the proposed system is better than the existing system for inpainting.

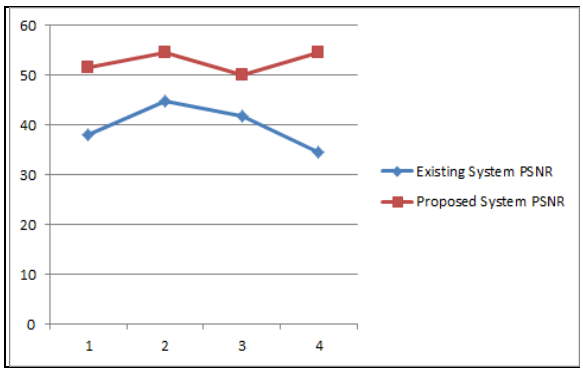

Fig 3: Graph for Inpainting

The consolidated results of the average PSNR for deblurring, mixed noise removal and inpainting are tabulated in table 4. The line graph and bar graph for the results in table 4 are shown in fig 4 and fig 5.

Table 4: Consolidated Results

Type	Existing System Avg. PSNR	Proposed System Avg. PSNR
Deblurring	33.81	49.02
Mixed Noise Removal	32.63	44.06
Inpainting	39.81	52.66

The line graph in fig 4, clearly show that, for deblurring, mixed noise removal and inpainting, the average PSNR of the proposed system is more than the existing system. So the proposed system is better than the existing system for deblurring, mixed noise removal and inpainting.

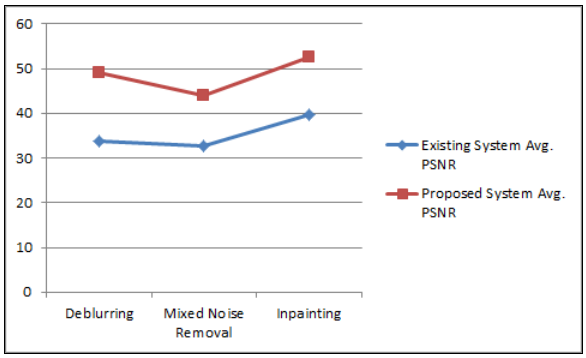

Fig 4: Line graph for consolidated results

The bar graph in fig 5, clearly show that, for deblurring, mixed noise removal and inpainting, the average PSNR of the proposed system is more than the existing system. So the proposed system is better than the existing system for deblurring, mixed noise removal and inpainting.

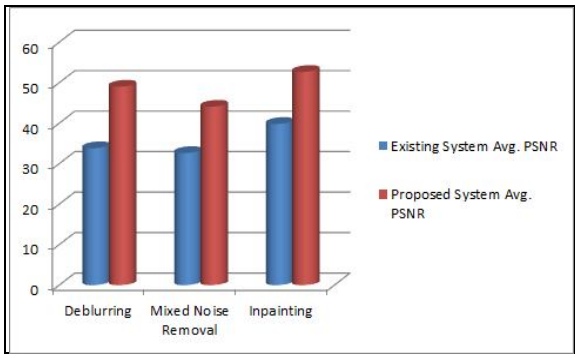

Fig 5: Bar graph for consolidated results

CONCLUSION AND FUTURE SCOPE

In the proposed work, an algorithm to remove the noise and inpaint the given image by removing the mask from the image is proposed and implemented. Proposed system has been tested on various images.It can also be clearly seen that there is a high

improvement than the existing systems.As the PSNR value is increased to a distinguished level as compared to the existing systems. Also the Average time taken to inpaint the given image is reduced. Hence the proposed system worked satisfactory with good accuracy over the existing system.

In future, system can be enhanced to minimize the time to inpaint the image without any decrease in its PSNR value. Future work may also include the investigation of the statistics for natural images at multiple scales and orientations and the extensions on a variety of applications, like video restoration tasks.

REFERENCES

[1]. A. Criminisi, P.Perez, K. Toyama (2004), "**Region filling and object removal by exemplar-based image inpainting**", IEEE Transactions on Image Processing, Vol. 13, Issue 9, pp.1200-1212.

[2]. A.Dewangan, I. Sahu (2014), "**Survey on exemplar based super-resolution based inpainting**", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering ,Vol. 3, Issue 2, pp.7559-7563.

[3]. A. S. Awati, M. R. Patil (2014),"**Comparison of digital image inpainting techniques based on SSIM**", International Journal for Research in Applied Science and Engineering, Vol. 2, Issue 12, pp. 497-503.

[4]. C. Guillemot, O. L. Meur (2014), "**Image Inpainting: overview and recent advances**", IEEE Signal Processing Magazine, Vol. 31, Issue 1, pp.127-144.

[5]. C. P. Sathe, S. Hingway, S. S. Suresh (2014), "**Image Restoration using Inpainting**", International Journal of Advance Research in Computer Science and Management Studies ,Volume 2, Issue 1, pp. 288-292.

[6]. C. Zhu, H. Jia, M. Li, X. Huang, X. Xie (2014), "**Highly efficient local non-texture image inpainting based on partial differential equation**", IEEE International Conference on Computational Science and Engineering, pp. 803-807.

[7]. J. H. Choi , C. H. Hahm (2013), "**An Exemplar based Image Inpainting Method with Search Region Prior**", IEEE Global Conference on Consumer Electronics, pp. 68-71.

[8]. J. Xie, L. Xu, E. Chen (2014), "**Image denoising and inpainting with deep neural networks**", Springer, pp. 1-9.

[9]. J. Xu, D. Feng, J. Wu, Z. Cui (2009), "**An image inpainting technique based on 8-neighborhood fast sweeping method**", International Conference on Communications and Mobile Computing, pp. 626-630.

[10]. J. Zhang, D. Zhao, R. Xiong, S. Ma, W. Gao (2014), "**Image restoration using joint statistical modeling in a space-transform domain**", IEEE Transactions on Circuits and Systems for Video Technology, Vol. 24, Issue 6, pp. 915-928.

[11]. L. Yin, C. Chang (2012), "**An Effective Exemplar-based Image Inpainting Method**" IEEE International Conference on Communication Technology, pp.739-743.

[12]. M. Mahajan, P. Bhanodia (2014), "**Image inpainting techniques for removal of Object**", IEEE International Conference on Information Communication and Embedded Systems, pp. 1-4.

[13]. O. L. Meur, M. Ebdelli, C. Guillemot (2013), "**Hierarchical super resolution based inpainting**", IEEE Transactions on Image Processing, Vol. 22, Issue 10, pp. 3779-3790.

[14]. V. Soni, Y. Rathore (2014), "**Survey report on various image inpainting methods**", International Journal of Electrical Electronics & Computer Science Engineering, Vol. 1, Issue 6, pp. 40-43.

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