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Implementation of Proposed of Examplar Based Image with Noise Removal Filters

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Abstract- *Restoration means filling of corrupted/edited areas/regions of an image or video in such a way that the modified region(s) is visually agreeable to human eye. Restoration technique has many applications such as, object removal in digital photos, removal of occlusions (date ,stamps ,logo etc.), such as large unwanted regions, red eye correction, super resolution, restoration of old films and paintings etc. Inpainting can also be use to create special effects by removing unwanted object or text from the image. A digital image is essentially a matrix of numerical values, where each value represents the color or grayscale component Cracks and holes within the image are denoted by unknown values within the matrix. Image Restoration fills in these unknown values by the support of the values of known nearby pixels. To achieve our objectives I have used noise removal method which will help us to complete the restoration task. Here my base method is exampler based Texture Synthesis image restoration approach but I have used image noise removal filters also to improve the quality of resulted image and later the results are compared with previous exampler method and my results shows that my proposed technique is better than the previous approach in terms of MSE, PSNR and time consumption*

Keywords: *Image Restoration, Digital Image, MSE, PSNR, CCR*

I. INTRODUCTION

Biometrics Restoration of a damaged/historical image has always been an important part of image processing and finds use in a surfeit of spheres. This restoration process can be done manually or by using some digital image processing techniques. Image inpainting is one such technique which helps us to accomplish these objectives by means of filling up the missing regions in the damaged images. We click many images and always want to keep them preserve for long time. And as the time past, those pictures got damaged (starches, cracks, Scratch, image data loss), the solution is image Inpainting. This technique can restore the lost parts of an image and reconstruct them based on the neighbor's information.

Image inpainting can also be called image completion, where the missing region of an image is filled in a visually plausible way. We can also define image inpainting that it is a way of filling unwanted area in an image according to the area specified by the user. Here the area which is not required is marked by the user and our process will fill those areas on the basis of neighbor's values.

II. How it Works

Image inpainting refers to repairing a damaged picture where part of the information has been lost. As shown in Figure 1, for a corrupted image, where the inpainting domain D is missing and the content outside D (Ω) is known, image inpainting is to fill domain D which makes the whole picture "meaningful" and looks like undamaged.

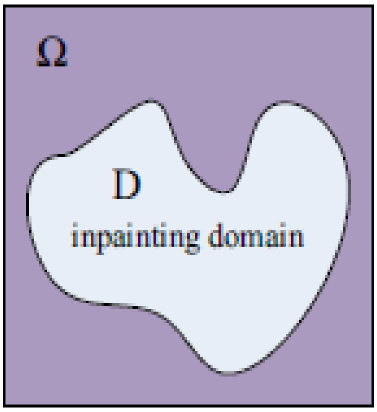
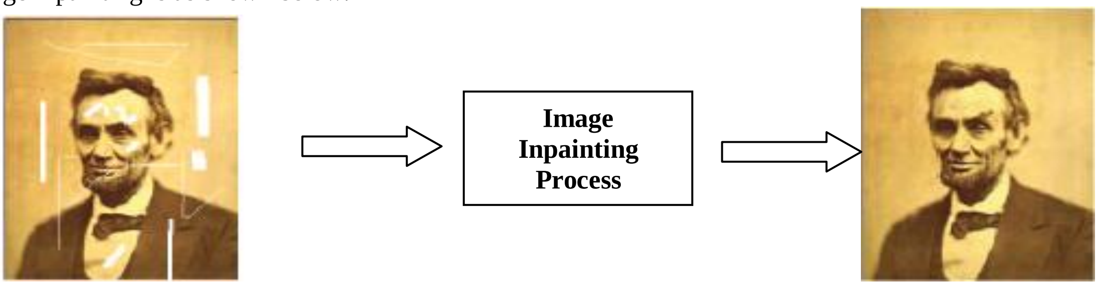


Figure 1: In a damaged picture, image inpainting is to fill the lost region D based on the known region Ω .

III. Digital Image Inpainting

As we have already discussed using image inpainting we can recover lost or deteriorated portions of pictures by using information from its neighbors. If done manually, than this process can be very dreary and time consuming, for example, the task pertaining to restoring a valuable classic painting, would be assigned to a skilled art conservator. Artists and conservators have been using manual inpainting to revive damaged paintings for ages. But we can improve it, with the help of automation, digital image processing techniques available today, the same task can be carried out more efficiently and effectively in considerably lesser time. Techniques like partial differential equations (PDEs) are used to automate this process. The PDEs function just as trained restorers would do: They interpolate the structural data around the missing or cracked region in order to fill it. The basic process of image inpainting is as shown below:



Damaged Image **Inpainted Image**

Figure 2: Image Inpainting Basic Technique.

The image inpainting methods may vary but the idea is to take a distorted and damaged image as input and to process it to yield an output image which is much more enhanced

IV. REVIEW OF LITERATURE

Bertalmio et al. (2000) [5] were the pioneers in the field of image inpainting. They proposed a method that attempted to restore the lost regions of damaged images by manually demarcating them by the use of some color. It used diffusion of information from its exterior parts along with the application of partial differential equations at the edges of the corrupt area.

Chan and Shen et al. (2001) [6] formulated their respective inpainting algorithms. The Total Variational (TV) model which makes use of an Euler Lagrange equation was designed for inpainting smaller regions and is very efficient for noise removal, but broken edges could not be repaired. The extension of TV algorithm, Curvature-Driven Diffusion (CDD) model was aimed at obtaining the broken connectivity.

Shen et al. (2003) [7] aimed at providing an inpainting method that was based upon the Euler Elastica model. They studied the use of the existing models and partial differential equations for curves and their applicability to image inpainting. Euler Lagrange equation for curvature based inpainting was formulated.

Criminisi et al. (2004) [8] provided an algorithm that could remove considerably larger objects from images. The algorithm used exemplar-based texture synthesis which was modulated by a unified approach to decide the sequence of filling target areas but was high on time complexity.

Wen Li et al. (2005) [9] provided JLBNM approach i.e. Jump & Look around Best Neighborhood Matching. This method aimed to lower down the computational cost of BNM approach and make it faster by using two different search methods along with certain optimizations for restoration. It provided better quality and computation time as compared to BNM approach.

Awate et al. (2006) [10] proposed an unsupervised, information theoretic, adaptive filter (UINTA) that improves predictability of intensities of pixels from their respective neighborhoods by reducing their combined entropy. Thus being nonlinear, nonparametric, adaptive, and unsupervised, it can restore a wide range of images with almost no parameter tuning data.

Ntogas et al. (2008) [11] presented a binarization mechanism for historical manuscripts and images. It divided the process into five distinct steps for the six defined categories of images and applied a refinement procedure on these to obtain enhanced results. The improved visual quality and readability of the image texture makes this technique viable and efficient to be used in various applications for preliminary processing of document images.

Zongben Xu et al. (2010) [12] presented exemplar based inpainting by using the natural image patch's sparsity. In contrast to traditional exemplar inpainting this method performs better in terms of distinguishing the structure and the texture and also sharper and consistent inpainted regions are obtained due to sparse representations. The results were demonstrated on both real and synthetic images.

Zhen Xie et al. (2011) [2] compared and analyzed four existing inpainting algorithms and provided a novel inpainting algorithm that divided the damaged image into blocks with specific traits. The adaptive matching algorithm proposed could automatically choose suitable methods to inpaint every block to generate optimal results. They experimentally proved their algorithm could inpaint more effectively and efficiently.

Sandhya N. et al. (2012) [13] analyzed the various kinds of noise that are present in historical documents that are based on Kannada, the predominant language in the state of Karnataka, India. Each noise is categorized by its source, obstacles posed to character recognition and the effects they have. The major types of noise identified in in historical documents are: a) border, b) skew, c) noisy background, d) touching characters and e) degraded characters.
Guillemot et al. (2013) [14] presented an exemplar-based inpainting technique based on a locally linear embedding algorithm with a low-dimensional neighborhood representation (LLE-LDNR). The technique initially locates the K nearest neighbors (K-NN) of the region to be inpainted and linearly combines them with LLE-LDNR to recover the unknown pixels values. To improve the nearest neighbor method, linear regression is then introduced.
Chuang Zhu et al. (2014) [15] presented an Enhanced Curvature-Driven Diffusions (ECDD) model to be applied first to improve the performance. Fast non-texture local inpainting technique is successively applied to obtain better computing results than that of the PDE-based methods. The results depict reduced iteration time and efficiently repaired long broken objects.
Li et al. (2014) [16] proposed an algorithm that uses compressed sensing (CS) in the frequency domain in order to recover damaged images. The image is disintegrated into two functions - structure and textual parts. The method ensured a decent restoration of the structure and quality of the image. The PSNR is generally high and the method has an edge in terms of time complexity.

V. PROBLEM STATEMENT

After reviewing the literature work done in this field I observe that Image inpainting is a very extensively researched and very useful technique for reconstruction of an image. Earlier algorithms introduced so far have provided great ideas and directions to the reconstruction but have been quite application specific in their parameter consideration, methodology etc. Here I have chosen Exampler based image inpainting technique. To improve the quality of output and the outcomes I will use some filter with exampler based inpainting technique. Existing algorithms is good but I am try to get better results in terms of time, quality, MSE and PSNR values. Their application in this field leads to

- Poor performance in terms of time.
- Poor visual quality.
- Less Accuracy.

In this research work, a novel approach is proposed ‘Improved Exampler Based Image Inpainting Method with Image Filtering Approach’. The proposed methodology aims to use of exampler based inpainting technique with image filtering process to produce more efficient results and performance.

VI. OBJECTIVES

Image inpainting is the procedure of restoring/reconstruction and regenerating unknown regions in the image from the known regions by using their available information. There are many inpainting algorithms however each method has its own set of advantages and shortcomings. Majority of the techniques are working well but my goal is to address the issue of an image by laying emphasis on defects and degradations that are peculiar to such images. The images may contain damages such as: Scratches, Holes, Cracks, Water effects and unwanted marks on the image.
The objectives of our work will be developing an improved algorithm having a:

- Remove of all types of damages (Scratches/holes/cracks) and reconstruct it.
- Better performance in terms of time, MSE, PSNR values compare to previous exampler based method
- Good visual quality.

VII. FLOW CHART OF PROPOSED WORK

We are well familiar with the fingerprint biometric and we know that in fingerprint matching technique matching algorithms compare the database stored image templates against a candidate fingerprints for authenticity. In this proposed work the authentication will be done but with multi-biometric system model using NN_SVM. In this proposed algorithm my concentration is on physiological Palm-Print and face recognition methods. I have considered both objects as images, fused and stored those images in a database as templates. Whenever we have to recognize a person than first scan his Palm-Print and photo using a scanner/digital camera. These new objects will be fused and compared with our created database using NN and SVM. The complete process of this proposed work is divided into three panel named load panel, Fusion panel and the Matching panel. Figure 3 is showing the flow chart of the proposed work.

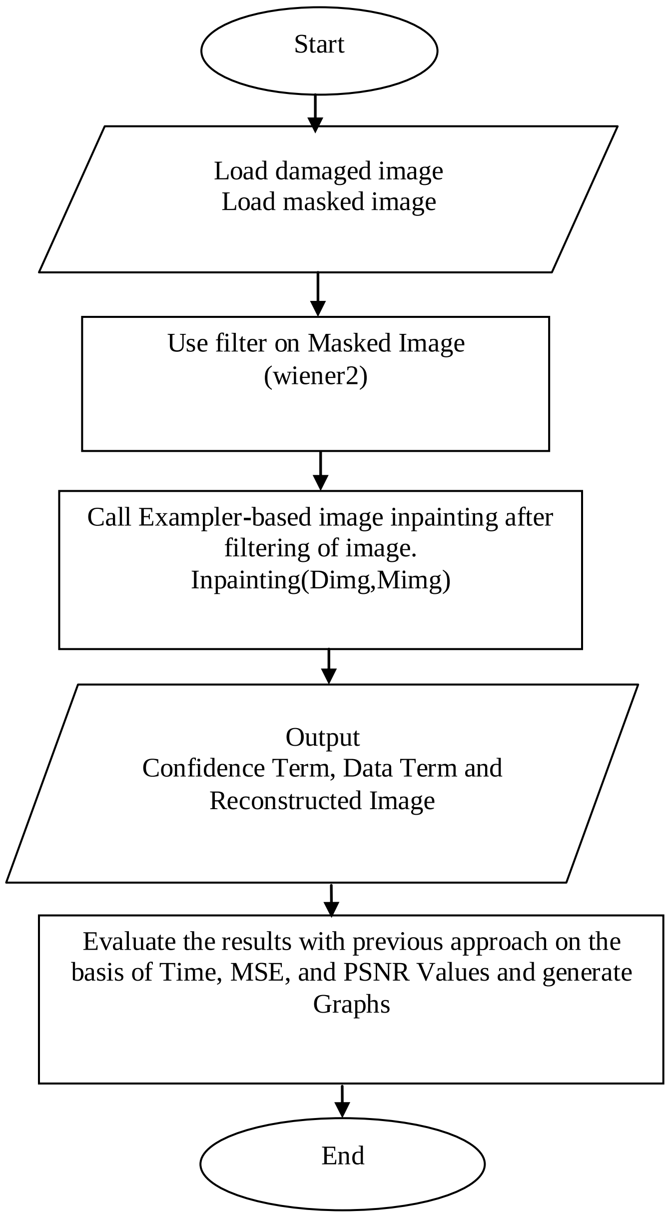


Figure 3: Flowchart of proposed work

As is clear from the flowchart the steps to be carried out are:-

- A database of damaged images (Dimg) and another for the masked images (Mimg) shall be constructed for which restoration is to be carried out.
- GUI implementation will be done followed by development of a code in MATLAB software for loading the image file from the database.
- Develop a code for the proposed improved exampler based inpainting method using filter approach and to evaluate the performance of the proposed method with the previous.
-

VIII. RESEARCH METHODOLOGY

A Exampler Based Texture Synthesis Approach

This algorithm is based on two fundamental principles. First, exemplar-based texture synthesis is sufficient to propagate extended linear structures and an additional synthesis mechanism is not required for handling isophotes (line of equal gray values). Second, the order of filling patches is of fundamental importance. [18-19].

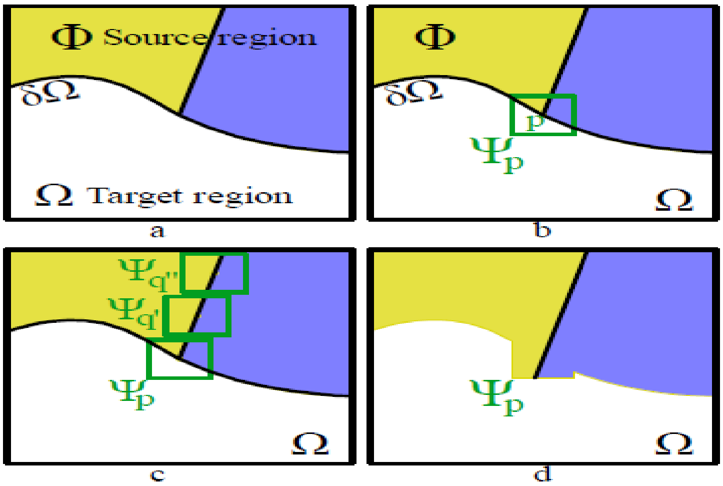


Figure 4: (a) Original image with the target region Ω, filling front δΩ, and the source region Φ, (b) The patch Ψp Centered at point p that has to be inpainted, (c) The most similar candidate patches for the source region, (d) The best matched patch has been copied into Ψp [18]

B **Image Filtering**

Image filtering means removal of unwanted noise to an image we have many filters which help us to remove those added noise. For better results by our proposed method we have used filter technique which help us to remove unwanted noise from our image.

- **Noise Removal Filter wiener2**

wiener2 filter which is a 2-D adaptive noise-removal filtering. wiener2 lowpass-filters a grayscale image that has been degraded by constant power additive noise. wiener2 uses a pixel wise adaptive Wiener method based on statistics estimated from a local neighborhood of each pixel.

- **Syntax**

J = wiener2(I,[m n],noise)
[J,noise] = wiener2(I,[m n])
The input image I is a two-dimensional image of class uint8, uint16, int16, single, or double. The output image J is of the same size and class as I.

C **Algorithms**

wiener2 estimates the local mean and variance around each pixel.

$$\mu = \frac{1}{NM} \sum_{n_1,n_2 \in \eta} a(n_1,n_2)$$

and

$$\sigma^2 = \frac{1}{NM} \sum_{n_1,n_2 \in \eta} a^2(n_1,n_2) - \mu^2,$$

where η is the N-by-M local neighborhood of each pixel in the image A. wiener2 then creates a pixelwise Wiener filter using these estimates,

$$b(n_1,n_2) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}(a(n_1,n_2) - \mu),$$

where v^2 is the noise variance. If the noise variance is not given, wiener2 uses the average of all the local estimated variances.

IX. EXPERIMENTAL RESULTS

A To implement the proposed work I have used GUI environment of MAT Lab 12.0. The main layout of my proposed research work is shown in next figure. As we can see that there are three load buttons one for reference image second for corrupt image and third button is used to load a mask image. Let us discuss the completer working of this work.work;

Figure 5: Edit image (Corrupt image) is appeared on the right side

B As we can see in the figure 5.8 the new added text is covered with the green color to make a mask image. The mask image is loaded and displayed in the next figure.
C

Figure 6: Mask image is loaded.

D Now it is the time to execute our proposed method. The execution results of our proposed work are shown in the next figure. The result image (restored image) by our approach, the confidence term and the data term all are appear on the right side.

Figure 7: Restored images by both methods

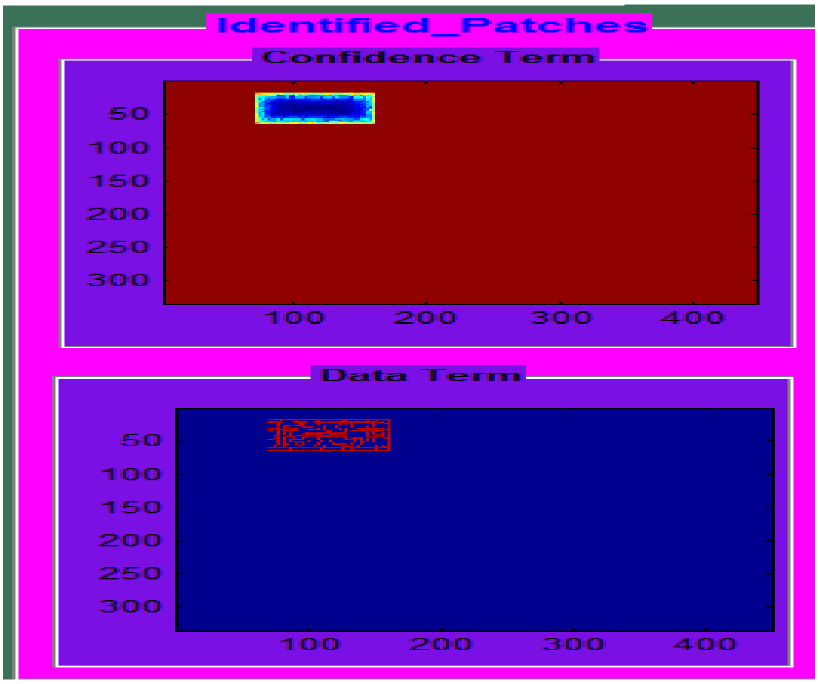


Figure 8: Confidence term and Data term of our approach

E Next work is to compare the results of both the previous approach and our proposed work. The results are analyzed in term of MSE, PSNR and Time taken values. The next figure is showing the comparative list of both the approaches.

Table 1: Comparative analysis of Both Approaches in terms of MSE, PSNR and Time

	MSE	PSNR	TimeTaken
Previous Method	0.1086	57.7716	30.8164
Our Approach	0.0993	58.1592	27.6314

As we can analyze from the above given figure our results are much better in terms of MSE, PSNR and time.

X. CONCLUSION

The historical document restoration process is a difficult and daunting task if done manually, but with the advent new techniques like cloud computing, parallel processing, etc, unlimited storage and computational power is available at our disposal and can be made use of to improve the existing techniques. In this pre thesis work, a number of inpainting algorithms have been analyzed and compared to find out their pros and cons.

REFERENCES

[1] Chuang Zhu, Huizhu Jia, Meng Li "Highly Efficient Local Non-Texture Image Inpainting Based on Partial Differential Equation", 2014 IEEE 17th International Conference on Computational Science and Engineering.

[2] Zhen Xie; Fan Zhang; Conggui Zhang, "An adaptive matching algorithm for image inpainting,", International Conference on Electronics, Communications and Control (ICECC), vol., no., pp.1293,1296, 9-11 Sept. 2011.

[3] Prof. Kawade M.D., Prof. Ufade A.S., 'Multiple Object Removal Using Exemplar based Image Inpainting'. International Journal of Computer Science & Engineering Technology, Volume 5, Issue 5, pp. 488-493, May 2014.

[4] Xiaobao Lu, Weilan Wang, Duojie Zhuoma, "A Fast Image Inpainting Algorithm Based on TV Model", Proceedings of International MultiConference of Engineers and Computer Scientists 2010 Vol II, IMECS 2010, Hong Kong.

[5] M. Bertalmio, J. Sapiro, V. Caselles, et al. "Image Inpainting". In: Proceedings of SIGGRAPH[C], New Orleans, USA, 2000: 417～424.

[6] Chan T, Shen J, "Non-texture Inpainting by Curvature-Driven Diffusions(CDD)", Journal of Visual Communication and Image Representation, 2001.l2(4): pp436-449.

[7] Shen, Jianhong, Sung Ha Kang, and Tony F. Chan. 'Euler's Elastica And Curvature-Based Inpainting'. SIAM J. Appl. Math. 63.2 (2003): 564-592.

[8] Criminisi, A., P. Perez, and K. Toyama. 'Region Filling And Object Removal By Exemplar-Based Image Inpainting'. IEEE Trans. on Image Process. 13.9 (2004): 1200-1212.

[9] Wen Li; Zhang, D.; Zhiyong Liu; Xiangzhen Qiao, "Fast block-based image restoration employing the improved best neighborhood matching approach," Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on , vol.35, no.4, pp.546,555, July 2005.

[10] Awate, S.P.; Whitaker, R.T., "Unsupervised, information-theoretic, adaptive image filtering for image restoration," Pattern Analysis and Machine Intelligence, IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol.28, no.3, pp.364,376, March 2006.

[11] Ntogas, Nikolaos and Ventzas, Dimitrios, "A Binarization Algorithm for Historical Manuscripts", International Conference on Communications, pp. 41-51, 2008.

[12] Zongben Xu, and Jian Sun. 'Image Inpainting By Patch Propagation Using Patch Sparsity'. IEEE Tranactions on Image Processing. 19.5 (2010): 1153-1165.

[13] Sandhya N, R. Krishnan and D. R. Ramesh Babu, "A language independent Characterization of Document Image Noise in Historical Scripts", International Journal of Computer Applications, Vol. 50, No. 9, pp. 11-18, 2012.

[14] Guillemot, C.; Turkan, M.; Le Meur, O.; Ebdelli, M., "Image inpainting using LLE-LDNR and linear subspace mappings", IEEE International Conference on Acoustics Speech and Signal Processing(ICASSP), pp.1558-1562, 26-31 May2013.

[15] Zhu, Chuang, Huizhu Jia, Meng Li, Xiaofeng Huang, and Xiaodong Xie. "Highly Efficient Local Non-Texture Image Inpainting Based on Partial Differential Equation." In Computational Science and Engineering (CSE), 2014 IEEE 17th International Conference on Computational Science and Engineering, pp.803-807.IEEE,2014.

[16] Li, Q., Han, Y., & Dang, J. "Image decomposing for inpainting using compressed sensing in DCT domain", 2014 Frontiers of Computer Science, Volume 8, Issue 6, pp 905-915 , 905-915.

[17] Chen, Weihai et al. "An Improved Edge Detection Algorithm For Depth Map Inpainting", 2014, Optics and Lasers in Engineering 55,69-77.

[18] A. Criminisi, P. Pérez, and K. Toyama, "Region filling and object removal by exemplar-based image inpainting," IEEE Trans. Image Process., vol. 13, pp. 1200-1212, 2004.

[19] A. A. Efros and T. K. Leung, "Texture synthesis by non-parametric sampling," in IEEE Conf. Computer Vision, 1999, pp. 1033-1038.]

