Digital Image Inpainting based on Median Diffusion and Directional Median Filtering

Anupama Sanjay Awati
Asst. Prof. Dept of Electronics and comm..
KLS Gogte Institute of Technology, Belgaum

Meenakshi R. Patil
Prof. Dept of Electronics and communication
A G. M. R. College of Engg & Tech, Hubli.

ABSTRACT
Inpainting refers to the art of restoring lost elements of image and reconstructing them from the background data. Filling the region of missing data of a picture from the data of the encompassing and reconstructing the image is that the basic work of Image Inpainting algorithms. Here in this paper we have compared two techniques for image inpainting namely median diffusion (median filtering) and directional median filtering. In both the techniques the area to be inpainted is manually selected by the user. In first method a rectangular region of D x D pixels is selected and the center pixel is replaced by the median of this block. In second method D x D block size is selected in the region to be inpainted and median in all direction is taken then the centre pixel is replaced by the median of these medians. The techniques are implemented in matlab and results are obtained and compared using standard images.

General Terms
Image Inpainting Algorithms.

Keywords
Median diffusion (median filtering) and Directional median filtering

1. INTRODUCTION
Digital image inpainting deals with filling in missing pixels of **a** picture. Its applications embody removing scratches from recent photos, removing text, repairing broken areas in unfaithfully transmitted pictures, image zooming, removing unwanted objects from a picture, and making inventive effects[1]. Inpainting operation itself isn't new technique. This operation has been done manually from many decades by specialists to switch painting or repair broken space in a painting. From the time once storage media is wide used, this operation was additionally brought into digital operation by experts. One of the major concerns in image processing is estimation of ‘pixel’ values. For example, interpolation or resizing is to estimate plausible pixel values located between known ones while denoising or deblurring is to estimate clean pixel values from corrupted ones. On the other hand, image inpainting, completion, disocclusion or object removal is to estimate spatially connected pixels in a region. The algorithms for filling in missing data can be broadly categorized into the following groups:[2]

1. Partial Differential Equation (PDE) based algorithms.

2. Texture based algorithms.

3. Exemplar and search based algorithms

4. Hybrid both texture and structure

The fundamentals of image inpainting can be explained by figure1.Let Ω stand for the region to be inpainted, and δΩ for its boundary. In representing the image, the patch is Ψp, np is the normal to the contour δΩ of the target region Ω and ΔIp⊥is the isophotes (direction and intensity) at point p.[6]

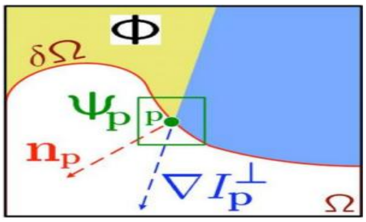

Fig. 1

Most of the inpainting techniques include texture and structure reconstruction that is filling in the texture of the region omega and reconstructing its boundary.

2. LITERATURE SURVEY
A Partial Differential Equation (PDE) based iterative algorithm was proposed by Marcelo Bertalmio [1] which established the way for modern digital image inpainting. Inspired by manual inpainting concepts, this method extends the line of equal intensities(isophotes) into the damaged region. This paper proposes an algorithm, which is an iterative process propagating linear structures (edges) of the surrounding area called Isophotes, into the hole region denoted by Ω. This diffusion process is defined [1] by the following equation

$I^{n+1}(i,j) = I^n(i,j) + \Delta t.It^n(i,j), \forall(i,j) \in \Omega$---------------[1]

where n is the iteration time, (i;j) are pixel co-ordinates, Δt is the rate of the change of inpainting, $It^n(i,j)$is the update factor on the image$I^n(i,j)$ The update factor in the above equation, is a smoothed image obtained by applying a Laplacian operator in the direction perpendicular to the gradient in an iterative fashion.

Partial differential equation based algorithms(PDE) are also proposed in [3],[4],[5], which fill in missing regions in an image by extending lines of equal intensity values, from the source region into the target region, via diffusion. The main drawback of this type of inpainting algorithms consists of introducing post-inpainting blur artifacts that become more visible when larger areas are inpainted.

Texture based algorithms fill in damaged or missed regions using similar neighborhoods in an image, i. e. they try to match statistics of damaged regions to statistics of known regions in the neighborhood of a damaged pixels. Papers [6][7][8] comprises exemplar-based inpainting algorithms. Methods in this category try to overcome the drawback exhibited by PDE based techniques, by reconstructing large missing image regions from sample textures.

In [9], the exemplar-based inpainting technique is employed image patches are hand-picked from constant image to reconstruct the missing regions. The goal is to retain the native consistency of the inpainted region by exploring the connection between a group of candidate inpainting patches and also the neighborhood of the missing region. The optimum patches are recovered by increasing the native consistency with relevancy the neighborhood candidates and also the inpainting region boundary pixels so as to settle on the simplest matching patch a confidence term is calculated and maximized.

[10] paper presents the plural non-local exemplars-based propagation. Inspired by collaborative filtering, an effective unknown pixel value prediction method is proposed in exemplar-based propagation for image inpainting. The method utilizes pixels information between exemplar patches and within patch to provide better results in pixel prediction. Paper[10] evaluates sum of squared difference to obtain a best matching patch.

Paper [11] presents a novel and efficient algorithm that combines the advantages of structure and texture approaches. The exemplar-based texture synthesis contains the essential process required to replicate both texture and structure; the success of structure propagation, however, is highly dependent on the order in which the reconstruction proceeds.

Paper [12] presents an exemplar based inpainting method which evaluates a priority term, confidence value and data term that defines the filling order in the image. The algorithm differentiates between patches that have the same minimum mean squared error with the selected patch. This approach is capable of propagating both linear structures and two dimensional textures into the target region.

In paper [13] a decomposition technique is employed to get 2 elements of the image, specifically structure and texture. Reconstruction of every element is performed separately. The missing data within the structure element is reconstructed employing a structure inpainting formula, whereas the texture element is repaired by a texture synthesis technique to get the inpainted image, the 2 reconstructed elements are composed along. Taking advantage of each the structure inpainting ways and texture synthesis techniques, a good image reconstruction technique is employed.

3. MEDIAN DIFFUSION (MEDIAN FILTERING)

In this algorithm [14] the region to be inpainted is marked by the user. Median filtering is applied to the region by using the following equation

$$I(i,j) = median(I(i,j))\ for\ \forall(i,j) \in \Omega$$

Inpainting is interpreted as median filtering, a non linear order statistics filtering. The median is the maximum likelihood estimated value. Median separates higher half of a samples to the lower half in a probability distribution function, Satisfying the criteria

$$P(x \leq m) \geq 0.5\ and\ P(x \geq m) \geq 0.5$$

where m is the median value of the probability distribution function P(x). Hence, the deviation of the neighbors from the median value is never greater than 0.5, i.e., the probability of inpainted pixel is always greater than 0.5. This understanding is important in the context of the current study because it clearly indicates that if median propagation is adopted for the inpainting process then the inpainted pixel will have probability greater than or equal to 0.5. It is important to have larger range of values across the inpainting area to estimate the pixel distribution correctly.

4. DIRECTIOMAL MEDIAN FILTERING

In this algorithm [15] the region to be inpainted is marked by the user. After determining damaged regions (usually manually), direction median filtering is applied by taking the median in all directions as indicated by the fig. finally the damaged pixel is replaced by the median of these medians.

Algorithm .

Step1. Find one pixel thick damaged boundary.

Step2. Determine known pixels in several directions around the current pixel.

Step3. Compute median of these determined pixels in different directions.

Step4. Compute median of obtained values in previous step and past it in current pixel.

Step5. Shrink damaged region one pixel.

Step6.Repeat the above steps until the damaged region is reconstructed

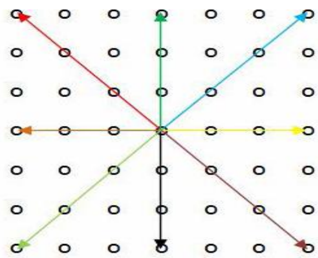

Fig. 2

5. RESULTS

The comparison of proposed algorithm is carried out by implementing in MATLABR2008b. The algorithms are tested on a variety of images to study the performance of inpainting. The original clean images are intentionally damaged by drawing random lines on them. These lines are treated as scratches or areas of inpainting. These degraded images are then inpainted. No standard evaluation algorithm is used in literature hence perceptual quality is considered for evaluation. In our study, the quantitative valuation is performed by calculating peak signal to noise ratio (PSNR) and is defined as

$$PSNR = 20log\,\log_{10} 255/RMSE(u,v)$$

$$RMSE = \sqrt{}(u_{i,j} - v_{i,j})^2/\text{MN}$$

and u is original image, v is inpainted image and M × N is size of u and v. This measure is onlywell-suited for the testing purpose, as original image is damaged and then restored. In practical applications, such a measure is not feasible, because there is no original image. Hence, we have to rely on qualitative evaluation. Output Images for method1(median diffusion) and method 2 (directional median filtering) are as shown below

	image	Method 1	Method 2
PSNR	lina	52.3923	49.3444
PSNR	coins	46.15	42.53
PSNR	cameraman	35.60	35.34

Fig. 3

Fig. 4 PSNR= 52.3923

Fig. 5 PSNR = 49.3444

Fig. 6

Fig.7

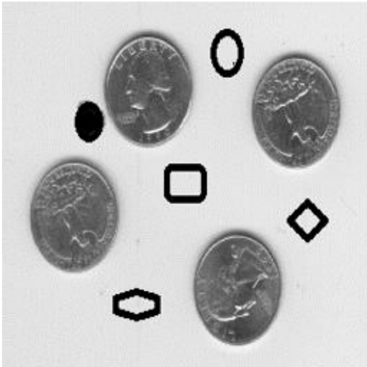

Fig. 8

Fig. 9

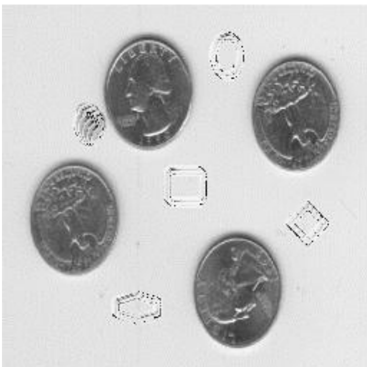

Fig. 10

Fig. 11

Fig. 12

Fig. 13

Fig. 14

Fig. 15

Fig. 16

6. CONLUSION

In this paper we have compared two techniques for image inpainting namely median diffusion (median filtering) and directional median filtering. The techniques are compared based on PSNR. Both the techniques perform well if the region to be inpainted is small. In both the techniques the area to be inpainted is manually selected by the user. Further the work can be extended to larger damaged regions and for colored images.

7. REFERENCES

[1] Marcelo Bertalmio et. al., "Image Inpainting", in International Conference on Computer Graphics and Interactive Techniques, Proceedings of the 27th annual conference on Computer graphics and interactive technique, 2000.

[2] Komal s Mahajan , Prof. M. B. Vaidya, "Image in Painting Techniques: A survey", IOSR Journal of Computer Engineering (IOSRJCE) Volume 5, Issue 4 (Sep-Oct. 2012), PP 45-49 www.iosrjournals.org ISSN: 2278-0661, ISBN: 2278-8727

[3] Tschumperle,D.&Deriche,R.2005.Vector value dimage regularization with PDE's: A common framework for different applications. IEEE Transactions on Pattern Analysis and Machine Intelligence,(27(4)),506–517.

[4] Bornemann,F.& März,T.July 2007.Fast Image Inpainting Based on Coherence Transport. J.Math.ImagingVision,28(3),259–278.

[5] Telea,A.2004. An Image Inpainting Technique Based on the Fast Marching Method. J.GraphicsTools,9(1),23–24.

[6] Criminisi,A.,Pérez,P.,&Toyama,K. Regionfilling and object removal by exemplar-based image inpainting. IEEE transactions on image processing :a publication of the IEEE Signal Processing Society,13(9),1200–12. September2004.

[7] Zhou,J.&Kelly,A.R.2010.Image inpainting based on local optimization, International Conference on Pattern Recognition (ICPR).

[8] Barnes,C.,Shechtman,E.,Finkelstein,A.,&Goldman,D.B .2009.Patchmatch:a randomized correspondence algorithm for structural image editing. ACM Transactions on Graphics (TOG),28(3).

[9] Jun Zhou Antonio Robles-Kelly. "Image Inpainting Based on Local Optimization", IEEE International Conference on Pattern Recognition 2010, pages 4440-4444.

[10] .Xinran Wu, Wei Zeng, Zhenzhou Li, Exemplar-Based Image Inpainting with Collaborative Filtering 2011 Sixth International Conference on Image and Graphics 978-0-7695-4541-7/11 $26.00 © 2011 IEEE DOI 10.1109/ICIG.2011.53

[11] .A.Criminisi*,P. Perezand, K.Toyama "Region Filling and Object Removal by Exemplar-Based Image Inpainting"IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL.13, NO. 9, SEP2004

[12] Anupam, Pulkit Goyal, Sapan Diwakar, "Fast and Enhanced Algorithm for Exemplar Based Image Inpainting"

[13] Somayeh Hesabi, Mansour Jamzad, Nezam Mahdavi-Amiri, "Structure and Texture Image Inpainting", IEEE International Conference on Signal and Image Processing 2010,pages119-125.

[14] RAJKUMARL BIRADAR, and VINAYADATTV KOHIR "A novel image inpainting technique based on median Diffusion

[15] H.Noori, Saeid Saryazdi,"Image Inpainting Using Directional Median Filters", IEEE International Conference on Computational Intelligence and Communication Systems, pages 45-50