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ESTIMATING DAMAGED PIXEL USING NEIGHBORHOOD INFORMATION FOR DIGITAL IMAGE INPAINTING

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Abstract Estimating the value of dead pixels in a damaged image is often desired in image processing. This technique is called as Image In painting. In this paper, two Image In painting techniques based on neighborhood information are compared. In technique one a kernel function of dynamic weights is calculated based on the direction between known pixel and unknown pixel and the Euclidian distance between them. While in technique two the a kernel function is calculated based on gradient of pixels in a neighborhood. The image is unpainted in both the techniques by convolving the damaged region with the kernel function. The two techniques are tested on images and the experimental results confirm the effectiveness of the algorithm.

Keywords—Inpainting, dynamic weights, kernal function, image interpolation, inpainting using convolution.

I. INTRODUCTION

Image in painting is an area of image processing tasks that recover high quality images from incomplete or corrupted data in the image domain or a transform domain. In painting is a name given for image interpolation, which has been used by museum restoration artists to restore old photographs for a long time. Smart digital in painting models, techniques, and algorithms have broad applications in the field of image processing. These applications include image interpolation, photo restoration, zooming and super-resolution, image compression, and error concealment of image transmission, etc. The reconstruction of damaged pixels in an image is performed in such a way that is undetectable for an observer who has not seen the original image. Existing inpainting algorithms require some kind of interaction with the user. The user specifies the area to be inpainted. The performance of algorithm depends on size of the damaged area. The objective of inpainting is to estimate the missing pixels or damaged portions of the image.

Image information may be divided into three parts texture color information and shape/structure. The structure inpainting is used to reconstruct the geometrical structure of an image. The texture to be filled is obtained from the known part of the image. A number of algorithms for image inpainting have evolved due to extensive research and technology advancements, the basic idea of all being to improve the general quality of an image and to achieve better performance in terms of quality of the inpainted images.

Various approaches have been used by the researchers for digital image inpainting which may be classified into the following broad categories: Partial Differential Equation (PDE) based In painting, Texture Synthesis based In painting, and Exemplar based In painting, Hybrid In painting, fast Digital In painting and Convolution Based Methods [1].

The Digital Image In painting performs in painting digitally through image processing in some sense. It automates the process of filling and reduces the interaction with the user. However the user needs to specify where the damage is present in a given image. Ultimately, the only interaction required by the user is the selection of the region to be inpainted which is also called as mask. The user selected region is reconstructed by in painting algorithm.

II. LITERATURE SURVEY

In [2] author has proposed a novel way of Hierarchical Image inpainting using wavelets. In this method advantage of the Exemplar based method is used and the structures are handled separately through wavelets. Wavelets have a multiresolution property and hence makes it suitable for Image In painting. In this method size of the mask is kept smaller and wavelets separately handle the low pass texture and high pass structure information. Four sub bands of the image are formed by applying Discrete Wavelet Transform and then the inpainting algorithm is applied. The proposed algorithm gives the better visual effects but as the number of level increases the overall contrast and brightness of image is changed.

In [3] author has introduced modification to the TV based image inpainting algorithm. In this algorithm the image is first segmented and the edge of damaged zone is identified. Priority of the pixels at the edge is calculated and is sorted according to their priority. Depending upon the threshold value either the pixel is reserved or is discarded. The reserved pixels are stored as a layer according to the order of priority. Then the damaged region is updated and until the corrupted region is zero the above steps are repeated. Inpainting is performed iteratively from outside to inside on the basis of the size of priority. This algorithm makes use of the information available around the corrupted region and hence it makes information diffusion stronger and the speed of the inpainting increases.

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In [4] author has presented a novel approach to the Exemplar based Image Inpainting. In this algorithm firstly the target region is selected then the boundaries of the target region are located. Patch to be inpainted is selected in target region. A patch having close resemblance to the patch to be inpainted is determined by using the NMSE (Normalized Mean square Error). NMSE is used as it determines the overall deviations between the predicted and measured value. Lastly the image is inpainted. This algorithm is capable of eliminating a part of object or the complete object from an image in less time and results in high quality images.

In [5] author has proposed technique for automatic crack detection followed by inpainting. In this method cracks are determined automatically in a image by using bottom hat transform. A thresholding operation is done to distinguish the crack pixels from the background and to produce a binary image. Then to determine the true cracks in image Morphological Area opening process is used. After the cracks are determined a variation median filter is applied which considers only the neighborhood of that crack. The cracks are filled by using the local information provided by the region surrounding the crack. This technique works only on the cracked pixels and keeps the other pixels intact and thus produces better results compared to other techniques.

In [6] author has exploited the spatial redundancy property. In this algorithm the image is loaded and the area to be inpainted is selected. The boundary of the target region is found and the selected portion is burned. To fill the gap starting point is determined and 8 neighborhood pixels of the pixel are found. Median filter is applied from starting point and process is repeated till end point is reached. This method is useful to improve the quality of object and reduce the computational complexity.

Convolution based image inpainting algorithms [7] are very rapid, however in many cases; they don't provide adequate results in sharp details such as edges. In this method the mask coefficients are calculated using the gradient of the image to be inpainted. The algorithm is fast, iterative, simple to implement, and provides very adequate results. Oliveira et al. [8] presents a fast image inpainting algorithm which uses convolution operation. In their algorithm, the regions to be inpainted are convolved with a predefined diffusion mask repeatedly. This model is very similar to isotropic diffusion. In this method, the central weight of the diffusion mask is considered zero, because its related pixel in the original image is unknown. A fast convolution based digital inpainting algorithm is faster than Oliveira algorithm with one iteration rather than 100 iteration and it remove large object in symmetric background images and without blur, but fail or produce poor results when removing large object in natural image.

H. Noori et al. [9] Proposed a new convolution based algorithm. It is adaptive and uses gradient to calculate weights of convolving mask at each position. To assign low weights to pixel near an edge by a predefined function this preserves the edges. The algorithm is fast, iterative, simple to implement and provides as well results as structure algorithms. Convolution based image inpainting algorithms are very rapid, however in many cases; they don't provide adequate results in sharp details such as edges. In this paper a novel convolution based image inpainting algorithm is proposed. The mask coefficients are calculated using the gradient of the image to be inpainted.

Mohiy M. Hadhoud et al. [10] introduced a modified Convolution Based Method. This modification produces fast and good quality with a single iteration without blur and removes large object with symmetric background. The modification achieved the following advantages: Reducing the time of the inpainting process from 100 iterations to one. Producing the result without blur because no repetition in convolution. This algorithm remove large object in symmetric background images and without blur, but fail or produce poor results when removing large object in natural image.

The algorithm introduced by M. Oliveira gives better results when the area to be inpainted is thin and small, although it takes more time as compared to the algorithm introduced by M. M. Hadhoud due to iterations of convolving mask. Though the results of Hadhoud algorithm fills the region faster, it tends to give strokes as it tries to fill the region from the upper left corner and does not takes into consideration the bottom right portion of an image while algorithm by Oliveira fills the region from all the sides. Both the algorithms fail to work on large object removal from asymmetric background. Depending upon the application image, we can use algorithm given by Oliveira if the region to be inpainted is small and contains high frequency components. Algorithm by Hadhoud can be used if the region to be inpainted is small.

Paper [11] uses a unique idea of dynamic weighted kernels. It proposes kernels of different sizes and weights to fill in the damaged regions with different width. We need a kernel size of 4 to compute the missing value, A kernel size greater than 4 may be a good choice. But when we use kernel sizes greater than 8 the interpolated values will not be similar to the neighbors. This is called over cover. Under cover occurs when the size of the kernel is smaller than the size of damaged region. Therefore kernel sizes of different values are used for different sizes of cracks or damage to avoid overflow or underflow. If we just fill in the damaged regions the results might not be pleasing in the places of edges. The human eye detects the structural defects more than the color defects; thus more weight age is given to the edges than the non edge regions.

A weighted average kernel is used to interpolate the missing pixels. The weights are selected in such a way that the edge pixels are weighted double than a non edge pixel

Bilateral filter (BF) is introduced by Tomasi and Manduchi [12], with frame size τ, global space deviation σs and range deviation or which makes surfaces smooth, just as the Gaussian filter, while maintaining sharp edges better than the Gaussian filter .

[13]A bilateral filter is an edge-preserving smoothing filter. Whereas many filters are convolutions in the image domain, a bilateral filter also operates in the image's range (pixel values or gray levels domain). The bilateral filter replaces a pixel's value by a weighted average of its neighbors

in both space and range. This is applied as two Gaussian filters at a localized pixel neighborhood, one in the spatial domain, named the domain filter, and the other in the intensity domain, named the range filter. This approach permits preserving sharp edges. Every sample is replaced by a weighted average of its neighbors:

[14]To compare the quality of different inpainting algorithms, not much research has been done. Initially algorithms were compared based on their capability to handle big fill areas, how good algorithm in curved structures, texture replication capability, time taken and algorithm work for how many images etc. In this paper PSNR (Peak Signal to Noise Ratio) is used for comparing inpainting algorithms [15]. In this paper the results of the algorithms on different types of images and size of region to be inpainted are evaluated.

III INPAINTING USING NEIGHBORHOOD INFORMATION

In technique one the damaged pixels can be reconstructed by determining dynamic weights based on the neighboring pixel values. This algorithm allows estimating a missing pixel value from the available neighborhood information using a weight function depending on local gradient, level set difference and distance. The prediction is iteratively propagated into the missing region.

The damaged region is identified, and the boundary of the damaged region is identified. Then the damaged region is filled by approaching from all four sides of the image. An unknown value of the pixel is obtained by using equation 1

$$I(p) = \frac{\sum_{q \in B_{e(p)}} \mathcal{W}(p,q)[I(q)+\nabla I(q)\cdot(p-q)]}{\sum_{q \in B_{e(p)}} \mathcal{W}(p,q)} \quad (1)$$

Where ∇I (q) is the gradient of I in q and w (p;q) is a weighting function. Standard vector notation is used where (p q) is the difference vector and scalar product. The weighting function is computed as:

$$\mathcal{W}(p,q) = g(p,q)d(p,q)z(q) \quad (2)$$

Where g(p,q) depends on the direction between p and q, d(p;q) is the Euclidean distance between p and q, and z(q) depends on the depth of q. The weighting terms are computes as follows

$$g(p,q) = \frac{(p-q)\cdot N(p)}{\|p-q\|}, \quad (3)$$

$$d(p,q) = \frac{1}{\|p-q\|^2}, \quad (4)$$

$$z(q) = 1 - \frac{\text{depth (q)}}{255} \quad (5)$$

where N(p) is the normal of the edge in p and depth(q) is the standard representation of the depth map at q, i.e. the inverse of the distance from the imaging plane normalized between 0 and 255.Therefore z(q)=0 when depth(q)=255,FG (Foreground) and z(q)=1 when depth(q)=0,i.e.BG (background).

In the second technique an adaptive kernel is evaluated which gives more importance to edge regions. The gradient of known pixels in the neighborhood of a missed pixel is used to compute weights in kernel function. Since gradient values in edge regions are large, and contribution of pixels in adjacent of edges should be less than contribution of pixels in smooth regions, the weights are computed by a predefined function of the image gradient. Small weights are assigned to missed pixels' in the neighborhood of pixels with large local gradients, edges are preserved better. The weights of kernel function changes adaptively with gradient of pixels in a neighborhood. Thus, the algorithm can estimate missed pixels while preserve sharp edges in image.

The gradient of the pixels in a small neighborhood is obtained and a function is defined by the equation

$$F(xk) = 1 - (x/\alpha)〛^2 \qquad \text{if } x \le \alpha/2 \quad (6)$$

$$xk) = (〚(x/\alpha) - 1)〛^2 \quad \text{if } \alpha/2 \le x \le \alpha$$

$$F(xk) = 0 \quad \text{i f } x \ge \alpha$$

The weights of kernel function are defined as

$$w(k) = 1/nF(xk) \quad (7)$$

The damaged pixel is estimated by using the following equation 8

$$f'(p) = (1 - \sum_{k=1}^{n} w((k))f(p) + \sum_{k=1}^{n} w((k) f(k) \quad (8)$$

where f'(p) is estimated value, f(k) is value of a known pixel in the current neighborhood, n is the number of known pixel in the current neighborhood. Where x is gradient value of the current pixel in the image, α is a parameter giving an estimation of the missed pixel gradient and it control the softness of propagation.

IV.ALGORITHM

Technique 1

1. The damaged color image is separated into R G and B components
2. The damaged image is converted to gray scale and by using a threshold value the regions to be inpainted is identified.
3. A mask image is generated with one in the region to be filled and zero in the remaining region.
4. Initialize the region to be inpainted by clearing its color information by making R(x,y) G(x,y) and B(x,y) as zero if mask(x,y) equal to one.
5. If mask(x,y) is equal to one then the corresponding pixel R(x,y) G(x,y) and B(x,y) are to be inpainted.
6. The corresponding pixel value is estimated by using equations 6 to 10.
7. Step 6 is repeated for several iterations or until the pixels belonging to the domain had their values changed by more than a certain threshold during the previous iteration.
8. Alternatively, the user can specify the number of iterations.
9. R G and B planes are combined to reconstruct the inpainted color image.

Technique 2

1. The region of the colored image to be inpainted is identified.
2. The colored image is decomposed into the corresponding RGB components.
3. The gradient of the pixels in a small neighborhood is obtained
4. A kernel function is defined by the equation 6.
5. The weights of convolution mask are calculated by using the equation 7.

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6. The damaged pixel is estimated by using equation 8 in each plane.
7. The colored image is reconstructed by combining the pixels of the corresponding RGB components

IV.RESULTS

The discussed algorithm is tested on a variety of images to investigate the performance of Inpainting. Several images are used to investigate the performance of the proposed method. In order to quantitatively

Compare the results, the Peak Signal-to-Noise Ratio (PSNR) between the original and the inpainted Images are evaluated. The proposed algorithm is implemented in MATLAB 7.7.0.471 R2008b.Evaluation of Inpainting by perceptual quality is subjective in nature. However, this is a difficult task and there is no common method for evaluating Inpainting algorithms. Hence, we have to rely on qualitative evaluation. The contours are well reconstructed and recovered with a good track of the local geometry image and isophotes. Figure 1 and Figure 2 show the input and output image of the algorithm. In Figure 1 we can see that the image is damaged and that region is initialized to zero pixel value. Figure 2 we see that the pixels are filled with the neighboring pixels proceeding in the line of equal intensities.

Fig 1. Damaged Image

Fig 2. Reconstructed Image

Fig 3. Damaged Image

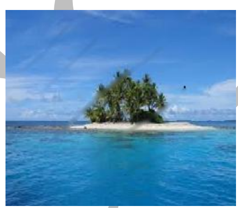

Fig 4.Reconstructed Image

Table 1Results for Technique 1 and 2

	Elapsed time	PSNR
Technique 1	142.23	50.23
Technique 1	242.15	44.96
Technique 2	12.28sec	56.97
Technique 2	18.14 sec	49.13

V.CONCLUSION

In this paper, we have compared two techniques based on neighborhood information. Inpainting based on a dynamic kernel function calculated by using neighborhood information. The unknown damaged pixel is estimated by convolving with the kernel function. Experimental results are very promising in removing the damaged regions. Future work will include Inpainting for different sizes of kernel function based on the size of the damage.

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