

Comparison of Image Inpainting Techniques

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ABSTRACT: Image inpainting is the technique of reconstruction of the damaged image in an undetectable form. The goals and application of this technique are numerous, from the restoration of old damaged paintings and photograph to the removal or replacement of selected object in an image. This paper implements three algorithms for digital image inpainting. In this algorithm user selects the regions to be restored or filled and the algorithm automatically fills in these regions with information surrounding them. In method 1 the pyramids of the image are generated to the level where all the damaged pixels are fully eliminated. Then the damaged pixels are filled in from the bottom of the pyramid to the top. In pyramid image at level i , the damaged pixels are filled in from the expanded pyramid image at level $i - 1$, and so on up to the level 0 pyramid. In method 2 the algorithm is iterative. In the first iteration, median value of known pixels' in each direction is calculated, and then, a damaged pixel is replaced by the median of the obtained values. In latter iterations, median of all pixels' values in each direction is calculated then median of obtained values is copied in place of the damaged pixel. The above algorithms are tested by applying different images and performance compared by using Signal to Noise Ratio (SNR).

Keywords -Image Inpainting, Image Restoration, Image Reconstruction, Median Filter.

I. INTRODUCTION

A lot of significant work carried out in the past (10 years) in the field of inpainting. The algorithm at first sight may seem to be something similar to noise removal from images. Denoising is focused towards modifying individual pixels whereas inpainting aims at modifying larger regions from the image. Denoising also differs from inpainting in the way that in inpainting there is no information about the image in the region to be inpainted as opposed to noise removal where pixels may contain information about both the real data and noise. Thus specific methods are developed to answer this problem. Image Inpainting Most inpainting methods work as follows. As a first step the user manually selects the portions of the image that will be restored. This is usually done as a separate step and involves the use of other image processing tools. Then image restoration is done automatically, by filling these regions in with new information coming from the surrounding pixels (or from the whole image). In order to produce a perceptually plausible reconstruction, an inpainting technique must attempt to continue the isophotes (line of equal gray value) as smoothly as possible inside the reconstructed region. In other words the missing region should be inpainted so that inpainted gray value and gradient extrapolate the gray value and gradient outside the region. The algorithms proposed for inpainting use the information from surrounding portions of image to inpaint the selected region. The algorithms used for film restoration are of little use in the field of image inpainting as those algorithms can use the information present in other frames which is not present in the case of image. Thus for image inpainting, we have to rely on the little information present in the current image to try and reconstruct the image and remove the selected region.

In [1] the image is decomposed using a fast decomposition method to obtain two components of the image, namely structure and texture. Reconstruction of each component is performed separately. The missing information in the structure component is reconstructed using a structure inpainting algorithm, while the texture component is repaired by a texture synthesis technique. To obtain the inpainted image, the two reconstructed components are composed together.

Most image inpainting techniques require a human to identify manually the portion to be inpainted. A detection algorithm which can automatically detect portions in an image, including arbitrary scratches by color ink can be detected based on the characteristics of uniform gray of scratches and structural information of scratches. A top-hat transform and low hat transformation is used to highlight the scratch regions and use erosion- dilation operator in morphology to finalize the regions of arbitrary scratches.[2]

In [3] exemplar-based image inpainting is proposed. By using segmentation-based searching strategy and redefined priority function, this algorithm can solve the problems that would occur in large area's filling regions.

In[4] a novel image inpainting technique based on watermarking and halftoning is proposed. This technique uses LSB method to embed error diffusion halftone image into original image for protecting the image. In image repair process, LSB (Least Significant Bit Substitution) method is used to extract the halftone information, and

the reference image is achieved from LUT (look up table) inverse halftone. Finally the reference image is used to finish the image inpainting work.

In [5], a fully automatic framework for restoration of unknown or damaged picture areas is presented. Diverse causes such as an accident, manual removal, or transmission loss may have lead to the missing visual information. With the assumption that dominant structures are of salient relevance to the human perception the filling process is carried out by using tensor voting, which is a structure inference approach based on the Gestalt laws of proximity and good continuation. A segmentation-based inference mechanism presented in this paper, missing textures crossing dominant structures are robustly recovered. An efficient post-processing step based on cloning via covariant derivatives improves the visual quality of the inpainted textures.

II. ACTUAL IMPLEMENTATION

2.1 Image Inpainting Based on Pyramid

This technique uses the pyramids to restore the damaged regions in digital images. Let I be an image of size $M \times N$. Let Ω be the region in the image to restore. The basic idea in the proposed algorithm is to reduce the given image I up to the levels where all the pixels in region Ω are eliminated or a certain percentage of those pixels is eliminated. Assume there are L levels. Now we replace the values of damaged pixels in pyramid at level $L-1$ from the extended version of pyramid L . Similarly, damaged pixels in pyramid $L-2$ are replaced from the extended version of pyramid $L-1$ and so on. At each level the damaged pixels values are computed from the extended pyramid at its lower level. In general, damaged pixel values in pyramid L are computed from the extended pyramid at level $L - 1$. The proposed algorithm works in two steps: Pyramid Generation and Restoration

2.1.1 Pyramid generation

After user selects the region to restore, the algorithm generates its Gaussian Pyramids. Let g_0 be the given image at pyramid level 0. Level 1 contains image g_1 which is the reduced image of g_0 . In Gaussian Pyramid method, the image is low pass filtered before applying reduction operation which smoothens the image. The technique implemented reduces the image without low pass filtering. This is done to keep the edges and abrupt colour changes as it is. This makes the edges flow into the target region when expand operation is applied. The reduction operation is carried out using the following equations

$$g_1 = \text{REDUCE}(g_0) \tag{1}$$

and g_1 is computed as

$$g_1(i, j) = \sum_{m=-2}^2 \sum_{n=-2}^2 g_0(2 \times i + m, 2 \times j + n) \times w(m, n) \tag{2}$$

where $0 \leq i < m$ and $0 \leq j < n$ and w is Gaussian filter of size 5×5 , given as:

$$\begin{aligned} (0) &= a \\ (-1) &= (1) = 1/4 \\ (-2) &= (2) = 1/4 - a/2 \text{ with } a=0.4. \end{aligned}$$

The size of reduced image g_1 is $1/4$ of the size of g_0 . Fig.1 shows the reduced operation.

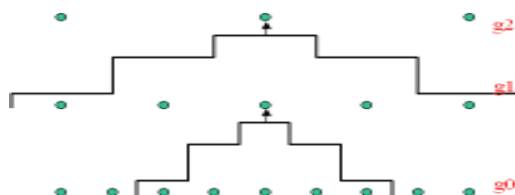


Fig. 1. The bottom row represents the image at level g_0 , given image.

Each value at level g_1 are is weighted average of the level g_0 . Each value at level g_2 are is weighted average of the level g_1 . The size at each step is decreased by $1/4$

2.1.2 Restoration of Damaged Image

Once all the pyramids are generated up to the level k , where all the damaged pixels are fully eliminated or a certain percentage of them is eliminated. We expand the top pyramid g_k and copy the missing pixels values from this pyramid to its lower pyramid g_{k-1} . Then we expand the pyramid g_{k-1} and each value at level g_1 is weighted average of the level g_0 . Each value at level g_2 is weighted average of the level g_1 . The size at each step is decreased by $1/4$ copy the missing pixels values from this pyramid to its lower pyramid g_{k-2} . We repeat this for each pyramid until we reach the bottom level g_0 . The expand operation is done as follows:

$$G_{l,n} = \text{EXPAND}(g_{l,n-1}) \tag{3}$$

$$g_{l,n}(i, j) = \sum_{m=-2}^2 \sum_{n=-2}^2 g_{l,n-1}\left(\frac{i-m}{2}, \frac{j-n}{2}\right) \times w(m, n) \tag{4}$$

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Each damaged pixel (i, j) in $\Omega_{gl}(i, j)$ is computed from its corresponding expanded version $gl,n(i, j)$. The computation is done as follows:

$$\Omega_{gl}(i, j) = gl,n(i, j) \quad (5)$$

2.2 Image Inpainting Based on Median Filter

This algorithm provides very adequate results in both high contrast edges and smooth regions. The algorithm is iterative and, according to experimental studies, it converges at most in 2 or 3 iteration for simple damaged regions. For complex damaged regions, a larger number of iterations will be needed. The proposed algorithm is as follows. After determining damaged regions (usually manually), the algorithm considers one pixel thick boundary of the missed region. For each missed pixel on the boundary, known pixels in different directions are selected, as Fig. 3.3.1 shows. Then, the median value in each direction is determined, and finally, the damaged pixel value is considered to be the median of these medians. Once, all of damaged boundary pixels are reconstructed, the algorithm has finished its first iteration. In next iteration, the new boundary is first calculated. Then in a similar manner, the boundary pixels are reconstructed. The method needs 2 or 3 iterations for an image without complex edges, but for regions with complex edges it will need a larger number of iterations.

Different steps of the algorithm are as follows.

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.

Do all above stages till stopping condition is reached.

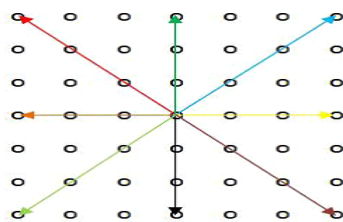


Fig.2 Aspect of a directional median filter.



Fig 3. Considered pixels in directional median inpainting, \circ shows a known pixel, \times shows an unknown pixel, color pixels show considered pixel in different directions.

III. EXPERIMENTS AND RESULTS

The proposed algorithms have been implemented in Matlab and tested for the quality and execution time on a wide variety of images. For each experiment a quality analysis is also carried out by calculating Signal to Noise Ratio (SNR). Results are tabulated in Table 1

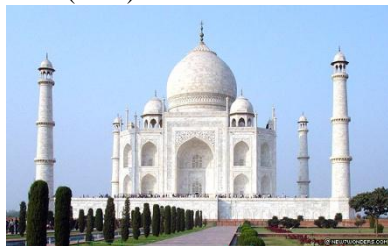


Fig 4. Original Image1.



Fig 5. Original Image2.



Fig 6. Inpainted Image1 Fig 7. Inpainted Image2



Fig 8. Original Image3



Fig 9. Inpainted Image3

Table 1. Results

Method1 Pyramid generation:	SNR	Time elapsed	Method2 Directional Median Filters:	SNR	Time elapsed
Image1	19.52	66.017	Image1	23.78	155.36
Image2	21.25	141.384	Image2	24.56	250.66
Image3	23.78	73.075	Image3	19.52	197.808
Image4	24.56	80.162	Image4	21.25	324.414

IV. CONCLUSION

In this paper two different algorithms for image inpainting are implemented. Each method varies in its complexity, performance and speed. Inpainting using pyramids consumes less time than the median filters but the length and complexity are more than the "median filters method", and the performance is better than median filters. Inpainting using median filters is shorter in length and very is to understand and implement than other method, but the time consumed is more and performance is less than other methods. More experiments can be carried out by changing the value of α and the size of the Gaussian filter in case of median filtering method. The results of pyramid method can be improved by running the program for more number of iterations. Furthermore results can be obtained by applying the algorithms for different types of inpainting problems.

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