Methodology to Recover the Damaged and Degraded Portion of an Image by Image Inpainting

Chetan Biradar

Assistant Professor, Computer Science, Nanded University, Latur, Maharashtra, India

Abstract: ***Inpainting, the technique of modifying an image in an undetectable form, is as ancient as art itself. The goals and applications of inpainting are numerous, from the restoration of damaged paintings and photographs to the removal of selected objects. In this paper, we introduce a novel algorithms for inpainting of images that attempts to replicate the basic techniques used by professional restorators. The algorithms used are Image inpainting using directional median filters, Image inpainting using local binary pattern and Image inpainting based on pyramids. After the user selects the regions to be restored, the algorithm automatically fills-in these regions with information surrounding them. This is done in a fast way, thereby allowing to simultaneously fill-in numerous regions containing completely different structures and textures surrounding backgrounds.***

Keywords: Image Inpainting, Image Restoration, Image Retouch, Image Scratch Removal, Object Removal

1. Introduction

The modification of images in a way that is non-detectable for an observer who does not know the original image is a practice as old as artistic creation itself. Medieval artwork started to be restored as early as the Renaissance, the motives being often as much to bring medieval pictures "up to date" as to fill in any gaps [1, 2]. This practice is called retouching or inpainting. The object of inpainting is to reconstitute the missing or damaged portions of the work, in order to make it more legible and to restore its unity [2]. The need to retouch the image in an unobtrusive way extended naturally from paintings to photography and film. The purposes remain the same: to revert deterioration, or to add or remove elements.

Since an important part of the scientific and cultural heritage of the modern times has been stored in the form of film and photo archive, image processing is a necessary work. A new and very important topic in image processing is image inpainting. Image inpainting is the technique of reconstruction a damaged image in an undetectable form. So far several restoration algorithms have been proposed in the literature, they address the problem of filling in missing data from different points of view. In the following we categorized them in four groups:

1. Partial Differential Equation (PDE) based algorithms.
2. Structure-based restoration.
3. Convolution- and filter based methods.
4. Texture synthesis models.

Partial Differential Equation (PDE) based algorithms are designed to connect edges and discontinuities. In [3,4,5] Bertalmio and others propose complex approaches for joint interpolation of gray levels and gradient/isophotes (line of equal gray values) directions for example Bertalmio et al. pioneered a digital image inpainting algorithm based on PDE. After a user selects the region to be inpainted, the method iteratively propagates information from outside of the area along isophotes. In order to maintain the direction of the isophotes, the direction of the largest spatial change is used. This direction may be obtained by computing a discretized gradient vector, instead of using geodesic curves to connect the isophotes. The prolongation lines are progressively curved while preventing the lines from intersecting each other; this is done by using anisotropic diffusion. Telea [6] proposed a fast marching method that can be considered as the PDE based algorithm. It is faster and simpler to implement than other.

Structure-based restoration: in [7] authors present a sketch guided texture based method. Their approach first generates the sketch (i.e. first it reconstructs edges that separate smooth or texture regions), then guided by the sketch lines the information surrounding sketch lines is restored by patch-based matching algorithm. Finally under constrained of information surrounding sketch lines all of missed regions is reconstructed by exemplar based method. Rares and others [8] present a model very similar to that they use of level lines based algorithm instead of sketch based and apply higher level features extracted from the image.

In convolution- and filter based methods, the inpainting is done by convolving the damaged image with a proper kernel. Oliveira [9] proposed a fast digital image inpainting method which depends on convolution operation. This approach convolves regions to be inpainted with a diffusion mask repeatedly. It is very similar to an isotropic diffusion. In this algorithm, the central weight in convolving kernel is zero. In [10], Hadhoud presents a modification of Oliveira algorithm permitting an implementation time reduction. In this approach, convolving kernel has zero weight at the bottom right corner instead of central weight. Both of above algorithms have provide good result only when damaged regions are thin and image does not have many high contrast edges or high frequency components, however, they have very good speed in compare with other models.

Texture synthesis based algorithms try to fill in the damaged part using a sample of the available image data and such that statistics of neighborhood current pixel matches to statistics of the damaged region. Efros [11] presents nonparametric texture synthesis model based on Markov random field to inpaint textural images. This approach restores pixels based on similarity between their local neighborhood and the surrounding neighborhoods. From candidate neighborhoods one is randomly selected and, the value of central pixel is pasted at the current location. In [12] Criminisi et al. exploit a patch-based algorithm in which the filling order is calculated by a priority function. This guarantees that linear structures are preserved well. The performance of this algorithm is comparable with Efros, while better speed efficiency is obtained.

2. Related Work

2.1 Directional Median Filters

The median filter is one of the best-known order-statistic filters in image denoising topic. Median filters can be applied to reduce significantly the impulsive noise, however, they have poor performance in reducing other kinds of the noise. These filters smooth images while preserving edges and other details in images. They simply replace the value of a pixel by median of the intensity levels in its neighborhood. Applying these filters in several directions - instead of a neighborhood- permits a much better edge preserving. This is main idea behind a directional median filter. Figure 1 illustrates the aspect of a directional median filter. The filter acts as follows. First, it determines the median in different directions. Then, the median of the obtained medians is considered as the output. This permits a better edge preserving than a conventional median filter. In cases where complex edges are included in an image, it is only sufficient to change directions or consider more directions in order to complex edges be preserved. Fig.1 shows the aspect of a directional median filter.

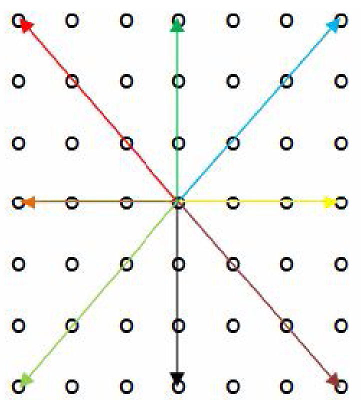

Figure 1: Aspect of a directional median filter

2.2 Local Binary Pattern

Bertalmio had proposed the first known inpainting technique using laplacian diffusion. There are several other methods like FOE; Exemplar based method proposed by Criminasi and so on. Basically image inpainting techniques are divided into two categories: Structure inpainting and Texture inpainting. A structure is a pattern where all the pixels are of same color for example the image of clear sky or a building wall. A texture is however a pattern created by set of pixels where pixels in the blocks have different colors but an overall block represents a definitive pattern. For example an image of our ear or tiles of the floor.

2.3 Using Gaussian Pyramid

It was Bertalmio et al who invented the terminology of inpainting [3]. They proposed the first technique that, after the selection of the damaged region by the user, automatically recovers the target region. This was an impressive technique and was followed by many other methods. This technique is known as BSCB method, after the names of the authors (Bertalmio, Sapiro, Caselles and Ballesterm). BSCB method is based on first order Partial Differential Equation (PDE). After BSCB many techniques were introduced, all based on partial differential equations. After manual selection of the regions to be restored, the BSCB method automatically recovers the damaged pixels from the information in its surroundings. The basic idea of BSCB method is to extend the edges and colors into the target region (region to be restored).

3. Proposed Algorithms

3.1 Using Directional Median Filters

In this section, we propose a new inpainting algorithm based on median filters. The proposed algorithm is explained is fast, very simple to implement and provides very adequate results in both high contrast edges and smooth regions. The algorithm is iterative and, according to our 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 Figure. 2 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.

a) Find one pixel thick damaged boundary.
b) Determine known pixels in several directions around the current pixel.
c) Compute median of these determined pixels in different directions.
d) Compute median of obtained values in previous step and past it in current pixel.
e) Shrink damaged region one pixel.

Do all above stages till stopping condition is reached.

Figure 2: Considered pixels in directional median inpainting, ◦ shows a known pixel, × shows an unknown pixel, color pixels show considered pixel in different directions.

3.2 Using Local Binary Pattern

In this work we will try to implement a simple image inpainting technique which performs both structure as well as texture inpainting based on LBP based texture representation and measurements.

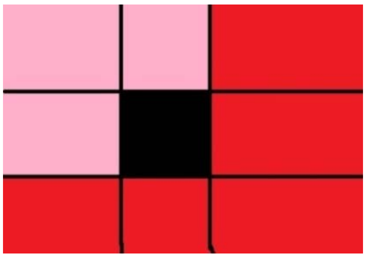

Figure 3: Inpainting Problem in General

From the above figure, Consider that the central pixel needs to be inpainted. How will you do it? You cannot fill it with green or blue color. A human perspective would be to paint it with red color block.

How did you perceive the idea? It is quite simple. You looked around the other pixels in the neighbours and you determined the most frequently appearing pixel and you suggest the same for inpainting.

So from human perspective we can simplify the inpainting problem as:

1. Find the set of pixels to be inpainted. Let us assume image Im be the image of the same size as the original image Is but having 1's at every pixel positions which needs to be filled and 0's otherwise.
2. Loop through every pixel in Im and check if current pixel is 1, if so the pixel in the same position in original image needs to be filled. Define a block of Size N. Observe the first image. Here block size is one. Because there are one pixel at every possible direction from the central pixel.
3. Retrieve a subimage of size (2N+1)*(2N +1) from Is by gathering pixels from all neighbourhood of the pixel to be inpainted. Leave out the defective or inpaint pixel (The centre one).

Now any of these pixels can replace the centre pixel. But the question is which one? So replace one pixel and check homogeneity. Homogeneity can be calculated as mean color distance of all the neighbours from centre when centre is replaced with any of the pixels from the neighbours. One of the simplest form of similarity measure is calculate difference as sum of R,G,B difference of the pixels. But as we defined, a texture may contain pixels of different colors in a definitive way. If you check colors, it is plain and simple structure inpainting. So we will go a step further to define a texture pattern using Local binary pattern. Further this texture representation is extracted from Gray scale image. So we need to convert the image to gray scale first.

Here is the algorithm for LBP:

1. Define a window size W
2. Scan every pixel in an image, extract its WxW neighbourhood.
3. Check if a Neighbour pixel color > Center, if so put 1 in the matrix else 0
4. Thus we get an array of '1' s and '0's . Convert this to binary and subsequently binary needs to be converted to decimal and must replace the center pixel. Remember bigger the value of W, larger will be number. for example for W=4, you will get a binary number of 16 bits. But gray scale image can contain only 8 bit colors. Therefore once entire image's LBP is extracted, it is to be normalized.
5. Normalization is performed as (Image containing local binary pattern)*255/(maximum value in the image)

Important thing is if you take W=1, resultant image will be fine edge detected image. So you can alternatively use this theory to extract edges from images.

Right then, we have a Source image Is, a LBP image Ib and mask image Im.

We will go to our main algorithm and modify third point in that algorithm as below.

Extract a pixel p at position (x,y) from mask, check if it '1' if so , extract a subimage S from Ib around p over area (x-B:x+B,y-B:y+B) where B is Block Size. compare each pixel of S with all other pixel of S. find pixel Ps for which difference is minimum. So pixel Ps is the pixel whose color needs to be put in p.

Map ps in Is, extract Is(ps) and put it in the place of Is(p). Continue this for entire image. You are done!

3.3 Using Pyramid

We propose an inpainting technique that uses the pyramids to restore the damaged regions in digital images. We use Gaussian Pyramids with a little modification for this purpose. Let I be an image of size M × 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. The

International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Impact Factor (2012): 3.358

proposed algorithm works in two step: Pyramid Generation and Restoration.

3.3.1. Pyramid Generation

After user selects the region to restore, the algorithm generates its Gaussian Pyramids. Let g0 be the given image at pyramid level 0. Level 1 contains image g1 which is the reduced image of g0. In Gaussian Pyramid, the image is low pass filtered before applying reduces operation to smooth the image. Our proposed technique reduces the image without low pass filtering. This is done to keep the edges and abrupt color changes as it is. This makes the edges flow into the target region when expand operation is applied. In Gaussian Pyramid reduce operation, each value at gi is computed with an average filter of size 5 × 5. That is and gl is computed as:

$gl = REDUCE(gl-1)$…………….(1)

The size of reduced image gl is 1/4 of the size of gl−1

3.3.2. Restoration of Damaged Regions

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 gk and copy the missing pixels values from this pyramid to its lower pyramid gk−1. Then we expand the pyramid gk−1 and copy the missing pixels values from this pyramid to its lower pyramid gk−2. We repeat this for each pyramid until we reach the bottom level g0. The expand operation is done as follows:

$gl,n = EXPAND(gl,n-1)$……….(2)

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

$\Omega gl\ (i, j) = gl,n(i, j)$……………(3)

Figure 4 shows a damaged image of a historical place in Lahore.

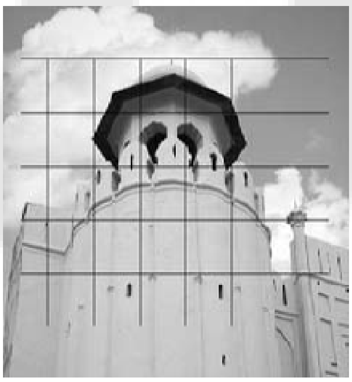

Figure 4: A damaged image of a historical place in Lahore

Fig.5 shows its pyramids up to the level where all the damaged pixels are eliminated and this is achieved at level 5. Figure labeled 1 is the first level image. Figure labeled 2 is the first level pyramid generated by applying the REDUCE operation on image 1. Fig labeled 3 and 4 are the third and the fourth level pyramids. In these figures the damaged pixels are partially eliminated. Fig.5 is the fifth level pyramid, where all the damaged pixels are eliminated.

Figure 6 is obtained by filling in the missing pixels in image 4 from the EXPANDED image of figure 5. Image labeled 7 is obtained by filling in the missing pixels in image 3 from the EXPANDED version of image 6.

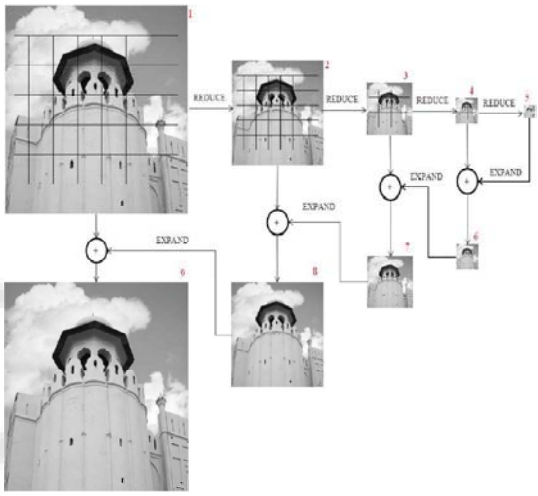

Figure 5 Experiment 1: Figure labeled 1, 2, 3, 4 and 5 are the pyramids generated by REDUCE operation on the damaged image shown in 2. Fig.6 is obtained by filling in the missing pixels in image 4 from the EXPANDED image of figure 5. Image labeled 7 is obtained by filling in the missing pixels in image 3 from the EXPANDED version of image 6, and similarly images 8 and 9 are restored.

Similarly images 8 and 9 are restored. Compare the restored image with the original image shown in figure 6.

Figure 6: The original image of the damaged image shown in 4

4. Experiments and Results

Inpainting using directional median filters evaluate the performance of this proposed method; in this section several comparative experiments are performed. We applied the proposed method and a classical benchmark method (Bertalmio) to several damaged image of different contains. The qualitative results are shown by fig.7. Fig.7-shows an image with a large missed area and three damaged regions. Fig.7-b, c represents the inpainted images obtained by Bertalmio and the proposed algorithm, respectively. As this fore suggests, Bertalmio's algorithm provide good results in small damaged regions, and causes some blurring in large damaged regions, while, the proposed algorithm provides very adequate results in both small and large damaged regions. However, both algorithms provide blurring in texture regions.

Figure 7: From left to right: damaged image, inpainted with Bertalmio's algorithm, restored by proposed algorithm

The proposed algorithm using local binary pattern has been tested for the quality and execution time on a wide variety of images. This section several comparative experiments are performed. We applied the proposed method to several damaged image of different contains.

Figure 8: From left to right: damaged image, inpainted image using local binary pattern method

The proposed algorithm using pyramids has been implemented in Matlab and tested for the quality and execution time on a wide variety of images. Fig. 8 shows a historical photograph of Quaid-e-Azam (left image), that has some red cracks on it. These cracks are successfully removed using the proposed algorithm (middle image). The image on the right is the original image. Signal to Noise Ratio of the restored image is 24.6289 dB.

Figure 9: Image on the left is a historic photograph Quaid-e-Azam with red unwanted cracks. Middle image is the image restored using proposed algorithm and image on the right is the original image

5. Conclusion and Future Scope

This paper presents a new approach for image inpainting by propagating median information of the pixels from exterior of the inpainting area into the inpainting area. The results are better than both Bertalmio in the context of visual appearance and PSNR. In this paper a new algorithm for image inpainting based on median filters is proposed. The proposed method uses the median of known pixels in different directions to inapint a damaged region. The method is simple, iterative, relatively fast, and provides very adequate results. To evaluate the performance of the proposed method, several comparative experiments are performed. The results confirm the efficiency of the proposed method. In this paper a new algorithm for image inpainting based on local binary pattern is proposed. The proposed method uses the LBP of an image to inapint a damaged region.

This paper presents a new and simple approach for image inpainting. The proposed approach uses pyramids to recover the damaged regions. The image is reduced up to the level where all damaged pixels are eliminated. Then the missing pixels are filled in bottom up fashion. The algorithm effectively recovers the broken edges from small damaged regions. For very large damaged regions, the results are not that attractive as the edges at the contour do not flow into the damaged region. The result of the proposed algorithm to recover small damaged regions reviles its efficiency.

It can also be used for restoring old films and photographs. The algorithms can be extended for the video streaming. In conjunction with optical flow data our algorithms could be promising techniques for video inpainting.

References

[1] S. Walden, The Ravished Image, New York, 1985.
[2] G. Emile-Male, The Restorer's Handbook of Easel Painting, New York, 1976.
[3] M. Bertalmio, G. Sapiro, V. Caselles, and C. Ballester,, "Image inpainting", Proceeding of SIGGRAPH, computer graphics processing. pp. 417-424. 47, 2000.
[4] M. Bertalmio, A. Bertozzi, and G. Sapiro, "Navier-stokes, fluid dynamics and image and video inpainting", presented at the *IEEE CVPR,* 2001.
[5] C. Ballester, M. Bertalmio, V. Caselles, G. Sapiro, and J. Verdera, "Filling-in by joint interpolation of vector fields and gray levels", IEEE Trans. on signal processing, pp. 1200-1211, 2001.
[6] A. Telea, "An image inpainting technique based on the fast marching method", journal of graphics tools, vol.9, no. 1, acm press 2004
[7] Y. Chen, Q. Luan, H. Li, O. Au, "Sketch-guided texture-based image inpainting", IEEE trans, pp. 4244-048, 2006.
[8] A. Rares, M. J. T. Reinders, and J. Beimond, "Edge-based image restoration", IEEE trans. On image processing, vol. 14, no. 10, pp 1454-1468, oct. 2005.
[9] M. Oliveira, B. Bowen, R. Mckenna, Y. S. Chang, "Fast digital image inpainting", in proc. VIIP2001, pp. 261-266, [PUB], 2001.
[10] M.M.Hadhoud, Kamel Moustafa and Shenoda. "Digital Image Inpainting using Modified Convolution Based Method", International Journal of Signal Processing, Image Processing and pattern Recognition, 2005.
[11] A. Efros and T. Leung, Texture synthesis by non-parametrics sampling, *proc. IEEE international conference computer vision,* pp. 1033-1038, corfu, Greece, 1999
[12] A. Criminisi, P. P´erez, K. Toyama, Object removal by exemplar based inpainting, *IEEE, Trans. Image processing,* vol. 13, no. 9, pp. 1200-1212, Sept. 2004