Image Inpainting Algorithms: A Survey

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Abstract- With the growth of digital processing of images and film world, the need for assisted or unsupervised restoration requires the development of a series of methods and techniques. Among them, image inpainting is maybe the most impressive and useful. Image inpainting is the method of filling an unknown region of a picture with visual plausible info. Filling this region with info that could be within the image. There is nothing just like the 'perfect' inpainting algorithm, every methodology has its own benefits and disadvantages. Based on partial derivative equations or texture synthesis, many other hybrid techniques have been proposed recently. In this work we have surveyed many papers on image inpainting using different approaches and now work is going on considering these papers as base. For this purpose we studied some papers of 90's too as this is the time when work on it started to gain attraction of researchers. We have also compared the methods in a table on the basis of their merits and demerits.

Keywords: Image Processing, Image inpainiting, Image restore

I. INTRODUCTION

Most problems of any image are often corrupted by noise, scanned old photo paper, dust or stains resting on the scanning glass of a scanner, scratched images or others have logos or stamps. Reconstruction of missing parts or scratches of digital images is an important field used extensively in artwork restoration. The algorithms of image denoising and image deblurring do not apply to image inpainting, because the regions to be inpainting are usually large and the information is distorted, whereas in these algorithms the pixels contain both information about the actual data and noise. Image inpainting finds application in major areas, a diagram is shown in figure 1.1. Applications include image restoration (e.g., scratch or text removal), image coding and transmission (recovery of missing blocks), photo-editing (object removal), virtual restoration of digitized paintings (crack removal), etc.

The restoration can be done by using two approaches, image inpainting and texture synthesis, whereas the meaning of first approach is restoring of missing and damage parts of images in a way that the observer who doesn't know the original image cannot detect the difference between the original and the restored image.

The second approach is filling unknown area on the image by using surrounding texture information or from input texture sample. This technique could be employed to restore digitized photographs especially if a damaged area needs to be filled with some pattern or structure. However texture synthesis usually fails if the area to be reconstructed contains an additional colour or intensity gradient. Most algorithms combine both texture synthesis and inpainting approaches to restores the image. Both are collectively used to fill holes as they remove unwanted features or holes in the image.

The basic requirement for all image inpainting algorithms is that the region to be inpainted should be selected manually by user, because no mathematical equation is capable of detecting or knowing the region to be inpainting without taking desired area. In the inpainting based on partial differential equation, the goal was to maintain the angle of arrival [1].

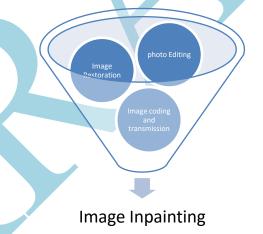


Figure 1.1: Major Application areas of image inpainting The basic idea was the smooth propagation of information from the surrounding areas in the isophotes direction. The drawback of this method was that the CPU time required for inpainting depends on the size of selected region. Therefore, was a time consuming process as it took nearly 8 to 10 minutes for inpainting. In inpainting by total variance and curvature-driven diffusion methods, they used Euler-Lagrange equation and inside the inpainting domain the model simply employs anisotropic diffusion based on the contrast of the isophotes [2]. This was used for inpainting small regions and also good in removing noise but it did not connect broken lines or edges. The CDD model extended the TV algorithm by taking geometric information of isophotes while defining strength of the diffusion process, allowing large area inpainting. A major drawback of the TV inpainting model was that it was unable to restore well a single object when it is disconnected remaining parts were separated far apart by the inpainting domain.

In this paper we have provided a survey of some important papers for almost every diverse algorithms which made a platform for the development of other algorithms. After these algorithms, methods based on heuristic optimisations came into existence for optimal solutions. In this letter further in section 2 we have done a literature review of various papers

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conclusion of the survey followed by a list of references.

LITERATURE REVIEW II.

Image inpainting is an iterative process which ends when any target condition is matched or maximum number of iterations is completed. A general flow chart of image inpainting process is shown in figure 2.1 which is pasted after references.

Bertalmio et al.[2] introduce the term image inpainting to computer science. In the algorithm the region that has to be inpainted will be filled-in by information of the region surrounding the gap. The curves of equal intensity (isophotes) arriving at the boundary are propagated inwards. Because this is the first and one of the most important papers in image inpainting.

Criminisi et al.[1] propose an algorithm inspired by the algorithm by Bertalmio et al.[2] and texture synthesis [3]. In contrast to the paper of Bertalmio et al. the unknown region is inpainted patch by patch. The sequence of patch should be inpainted is based on the isophote information and the amount of known information surrounding the patch. This popular method increased the result of image inpainting a lot. Because of that this method is further explained in chapter 4. In the algorithm of Oliveira et al.[4], the unknown region of the image is convolved with a Gaussian kernel. To prevent edges to be blurred the user manually specifies barriers for the diffusion. This algorithm is much faster than the other algorithms but it can only be used with very small unknown regions and is less accurate. An example of this algorithm is shown in figure 2.2.

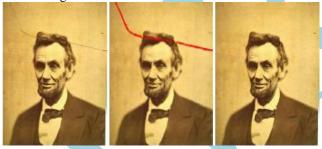


Figure 2.2: Olivera method [4], input, mask and result, note the diffusion barriers near the boundaries of the hair of Abraham Lincoln.

The algorithm of Perez et al.[5] showed how gradient domain reconstruction can be used in image editing applications. The actual pixel values for the unknown pixel values are computed by solving a Poisson equation which locally matches the gradients while obeying the _xed Dirichlet (exact matching) conditions at the seam boundary. Poisson Image Editing can be used best for seamless inserting and local illumination changes but can also be used for image inpainting. The author of [6] proposed a new inpainting algorithm based on propagating the image smoothness estimator along the image gradient. Similar to the algorithm of Bertalmio et al.[2]. The image smoothness is estimated as the weighted average of the known image neighborhood of the pixel to inpaint. The fast marching method (FMM) is used to create a distance function to the initial boundary. The pixels of the unknown region are inpainted in order of the

with their important points listed and section 3 inherits distance to the boundary, proceeding from the smallest to the largest. This method is fast but creates blurry effects with larger unknown regions. An example of this algorithm is shown in Figure 2.3.

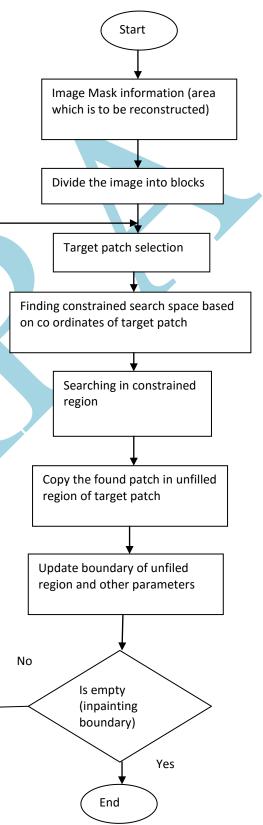


Figure 2.1: A general flow chart of image inpainting process

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Figure 2.3: Telea method [6], input plus mask and result.

Texture synthesis

Texture synthesis is the process of algorithmically constructing the large digital image from a small digital sample image by taking advantage of its structural content [3][7]. Texture synthesis can be also used to all in unknown regions in images, the algorithm of Criminisi et al.[1] is partially based on these algorithms. An example of the algorithm by Efros et al.[3] is shown in Figure 2.4.

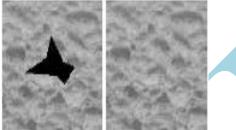


Figure 2.4: Texture Synthesis by Efros et al.[3], input plus mask and result.

Guided method

Sun et al.[8] introduces a new direction in image inpainting. In the authors algorithm the user is also able to specify support lines. These support lines specify where important lines in an image should be continued. This algorithm first alls in the unknown information around the support lines by dynamic programming or belief propagation, depending on the structure of the support lines. After that the rest of the image is filled in by texture propagation. The result of this algorithm is good but we can not compare these with others because this algorithm requires extra input. An example of this algorithm is shown in Figure 2.5.

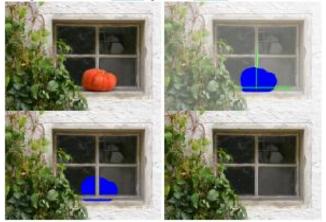


Figure 2.5: Sun method [8], input, mask, first stage and result.

Multiple images

Hays et al.[9] developed a total different way of image completion, instead of searching in the input image, the algorithm searches throughout a whole database of images to and information to all the missing region. The new area is paste in using Poisson blending [5]. The authors state that their results look better then the algorithm of Criminisi et al.[1] but the algorithm needs a database of two million images for only three scenes. This algorithm gives visual pleasing results but is very slow and is unpractical because it needs the large dataset. An example of this algorithm is shown in Figure 2.6.



Figure 2.6: Hays method [9], input, mask, first stage and result

Video inpainting

Image completing methods can also be used for videos, because a video is a set of multiple images. Naively inpainting each frame will not result in the best result important information about the current frame can be found in the adjacent frames. Patwardhan et al.[10] presented an algorithm for video inpainting of a scene taken from a static camera. This method is an extension of the paper of Criminisi et al.[1]. It extends the idea from a single image to a set of images but also taken in to account the adjacent frames. In this algorithm the frame is separated into a background and a foreground in which the foreground is first inpainted. After this step the background is inpainted, each patch is copied to every frame to get a consistent background. This technique has some nice results but it has some restrictions, it requires a fixed camera position and a stationary background with some moving foreground. Wexler et al.[11] have proposed a method for space-time completion of large damaged areas in the video sequence. They pose the problem of video completion as a global optimization problem with a welldefined objective function. In the algorithm every local patch should be found in the remaining part of the video and globally all these patches must be consistent with each other spatially and temporally. An example of this algorithm is shown in Figure 2.7.



Figure 2.7: Wexler method [11], input, mask and result sequence.

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III. CONCLUSION

To gain an insight about image inpainting algorithms we studied various research paper which worked on it using different algorithms. We have noticed that work based on contrast mapping or considering the difference of contrast in

mask and original image performs well and widely accepted by many researchers. So in our future work too, we will develop the algorithm based on it.

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