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Image Inpainting Using Total Variation Algorithm

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Abstract: *This paper presents Total Variation (TV) regularization has evolved from an image denoising method for images corrupted with Gaussian noise into a more general technique for inverse problems such as deblurring, blind deconvolution, and inpainting, which also encompasses the Impulse, Image is usually statistically corrupted with noise ,hence removal of the noise is another necessary objective of this paper. These ways are going to be applied to grey scale and RGB pictures. Compared to existing approaches, some enhancements are done .The inpainting of a rough version of the input image permits to scale back the machine complications, to be less vulnerable to noise and to figure with the dominant orientations of image structures.*

Key Word: *Inpainting, Denoising, Total variation, regularization, image restoration.*

I. INTRODUCTION

For inpainting a broken image or associate ancient painting with missing regions is to guess and fill within the lost image data in such an identical manner that the restored image or painting appears as natural as its original version. Applications of digital inpainting are:

(a)Restoration of ancient paintings for conservation functions
(b) Restoring aged or broken images and films
(c) Object removal and text removal in pictures for computer graphics
(d)Digital zooming and edge-based image cryptography

Mathematically, what makes the inpainting drawback thus difficult is that the quality of image functions. In contrast to several ancient interpolation or boundary worth issues, the target image functions to be inpainted usually lie outside the Sobolev class. Structure complexities of image functions force researchers to develop inpainting schemes targeted at specific categories of pictures. As a result, these inpainting models are of low levels. The last word goal, of course, as within the blueprint of vision and computing, is eventually to be ready to mix and integrate all the low-level inpainting parts into a perfect program which will well approximate human inpainters.

Image inpainting is that the method of filling in missing components of broken pictures supported data gathered from close areas. Additionally to issues of image restoration, inpainting can even be utilized in wireless transmission and compression applications. during this project, we'll developed associate automatic digital in painting system that allows the user to settle on between 2 complementary approaches. The primary relies on the answer of partial equation of isophote intensity to reliever missing parts within the region into account, whereas the second relies on texture inpainting. The filling-in method is mechanically worn out regions containing utterly completely different structures, textures, and close backgrounds.

II. MATERIAL AND METHODS

2.1. Input damaged images.

There are different types of images *i.e.* gray scale image and RGB (color) image. The image inpainting works on gray scale and RGB images also repairs the scratches on gray scale photograph and image Figure 2.1.1 is shows a gray scale damaged image. In where figure there are many scratches on images. When the inpainting algorithm is applied on that image and filled the missing pixel and removes the scratches from that image. Creates the output images *i.e.* figure 2.1.2 with maximum pixel repairs

Figure 2.1.1: Penguin: Original Damaged Image

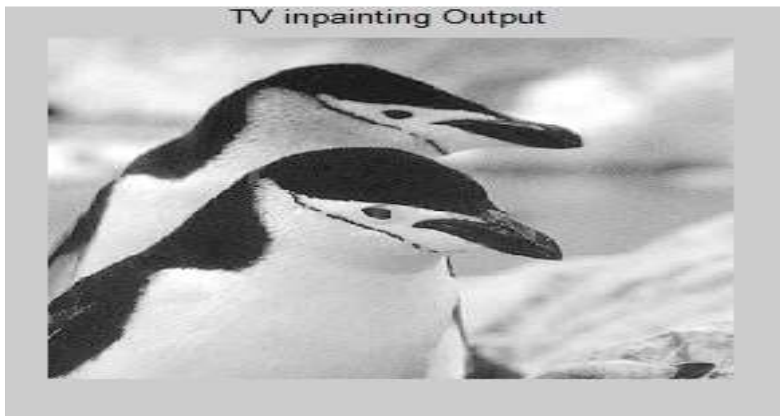

Figure 2.1.2: Penguin Total Variation Inpainting Output

Table 2.1 : Results for Sample 1 Penguin

Inpainting method	PSNR
Total variation inpainting	11.67

2.2. Identify input image type.

Removal of labeled text like dates, subtitles, or publicity Figure 2.2.1 show a color damaged image .It is damaged by the image label like image create dates, image create time, image name or *etc.* Apply the inpainting algorithm on that images and creates the output images i.e. figure 2.2.2 remove that label.

Figure 2.2.1. Damaged image by text.

Figure 2.2.2. Output Image.

Table 2.2 : Results for Sample 2 Damaged

Inpainting method	PSNR
Total variation inpainting	28.9426

2.3. Implement Inpainting Method: this method repairs the scratches on RGB photograph and image Figure 2.3.1 show a color damaged image by scratches. Apply the inpainting algorithm on that image and filled the missing pixel and remove the scratches from that image. It takes nearest pixel values of an image. Creates the output images i.e. figure 2.3.2 with repair maximum pixels.

Figure 2.3.1. Damaged colour image by scratch.

Figure 2.3.2. Output Image.

Table 2.3: Results for Sample 3 Damaged

Inpainting method	PSNR
Total variation inpainting	14.367

There are shows the all possible damaged images and that are recovered by after image inpainting algorithm. All input images are figure 2.1.1, 2.2.1, 2.3.1 and output images are figure 2.1.2, 2.2.2,2.3.2 respectively .

Procedure methodology

Image Inpainting

As discussed earlier there exist various inpainting algorithms in literature: The two widely used algorithms are viz; Total Variation. The description of each is presented in forthcoming section.

Total Variation

It is based on texture inpainting. The filling-in process is automatically done in regions containing completely different structures, textures, and surrounding backgrounds The Total Variation (TV) inpainting model uses an Euler-Lagrange equation and inside the inpainting domain the model simply employs anisotropic diffusion based on the contrast of the isophotes. This model was designed for inpainting small regions. Image with painted data has to be removed by using two new proposed algorithm *i.e.*,CDD inpainting and Total Variation image inpainting.

- Design a function to solve the Total Variation inpainting problem

$$min\, TV(X)\ subject\ to\ \parallel X(Ic) - B(Ic) \parallel F \leq delta$$

where B is a noisy image with missing pixels, Ic are the indices to the intact pixels, X is the reconstruction, and delta is an upper bound for the residual factor. The Total Variation function is the 1-norm(factor) of the gradient magnitude, computed with help of neighbouring pixel differences. At the image borders, we imposed reflexive boundary conditions for the gradient computations.

- The information regarding the intact and missing pixels is given in the form of mask M which is a matrix of the same size as that of B, whose non-zero elements indicate missing pixels.
- The parameter delta should be of the same size as the norm of the image noise. If the image is m-times-n, and sigma is the standard deviation of the image noise in a pixel, then we recommend to use *delta* = tau*sqrt(*m***n*)**sigma*, where tau is slightly smaller than one, say, *tau* = 0.85.
- The function must return an epsilon-optimal solution X, meaning that if , X^* is the exact solution, then our solution$X$satisfies
  $TV(X) - TV(x^*) \leq \epsilon = \max\big(B(Ic)\big) * m * n * esp\_rel$
  where eps_rel is the specified relative accuracy; the default is eps_rel $=10^{-3}$.
- After ever iteration number of iteration is decremented by 1.
- Delta is given by the formula $delta = \tau$ sqrt $(mn)\ \sigma$. $\tau = 0.85$.
- If the Total Variation solution is less than or equal to delta then the algorithm will again calculate the difference between the noisy image pixel and original image pixel $X(Ic)$-$b(Ic)$ or it will go to next step.
- The next step includes the actual inpainting process.
- *IC* gives the pixel locations i.e. the intact pixels.
- The Total Variation function gives the noise free inpainted image as output.

III. DISCUSSION

Image inpainting is a large area for the research. It is expected that our developed algorithm should reproduce texture and at the same time keep the structure of the surrounding area of the inpainted region. In future the algorithm is automatically finding the damaged pixel from the image. It is so easy to generate mask on that images. Developed the new algorithm for image inpainting for better output. Compare the different method for improve the PSNR ratio for inpainting. Apply better inpainting method for different types of image extensions

IV. CONCLUSION

This paper presents a detailed study of image in-painting using total variation algorithm and literature existing on image inpainting. Different techniques such as Total Variation, CDD(Curvature Driven Diffusion), PDE (Partial Differential Equation), FMM (Fast Matching Method), and Hybrid. In this paper we presented a comparative analysis of Total Variation for different categories of damaged images. In this project, we developed a digital in-painting system for Total Variation algorithms. For any input damaged image first static mask was created for the damaged portion and then the created static mask has been used as the input for Total Variation algorithms for in-painting process. Using the static mask, the filling-in process has been done in regions containing completely different structures, textures, and surrounding backgrounds. The Total Variation has been evaluated on 3 odd damaged images with different complexities. The performance of the Total Variation is evaluated using PSNR ratio.

From the experimental results it has been observed that Total Variation is more effective to those damaged images that consist of texture and curve distortion. It has also been analyzed that time required for the inpainting process depends on the size of the image and the regions to be inpainted, and it ranges from few seconds to several minutes for large images.

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