Novel Approach for Image Inpainting

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Abstract--- This presents a novel and efficient examplar-based inpainting algorithm through investigating the sparsity of natural image patches. Two novel concepts of sparsity at the patch level are proposed for modeling the patch priority and patch representation, which are two crucial steps for patch propagation in the examplar-based inpainting approach. First, patch structure sparsity is designed to measure the confidence of a patch located at the image structure the sparseness of its nonzero similarities to the neighboring patches. The patch with larger structure sparsity will be assigned higher priority for further inpainting. Second, it is assumed that the patch to be filled can be represented by the sparse linear combination of candidate patches under the local patch consistency constraint in a framework of sparse representation. Compared with the traditional examplar-based inpainting approach, structure sparsity enables better discrimination of structure and texture, and the patch sparse representation forces the newly inpainted regions to be sharp and consistent with the surrounding textures.
Keywords: Patch, Inpainting, Taylor Series, color image processing

I. 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. 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. 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 (e.g., cracks in photographs or scratches and dust spots in film), or to add or remove elements (e.g., removal of stamped date and red-eye from photographs, the infamous “airbrushing” of political enemies. Digital techniques are starting to be a widespread way of inpainting, ranging from attempts to fully automatic detection and removal of scratches in film all the way to software tools that allow a sophisticated but mostly manual process.

II. ALGORITHM

An image the missing region Ω and the known region Ω, the task of image inpainting is to fill in the target region (i.e., the missing regionΩ) using the image information in the source region (i.e., the known region W). The boundary of the target region is denoted by ∂Ω, which is called the fill-front in the examplar-based inpainting algorithm
Points of the proposed Scheme

Step 1: Input image (RGB or Gray Scale)

Step 2: If Grayscale Image then
Take only one band and go to step 3
Else
Divide RGB image into three
different band R’ , G’ , B’

Step 3: Process each band as follows:
Required Parameters for each band image
For Taylor Expansion using
Tmax- The length of time to run the simulation
nt -The number of timesteps to take
nx-The number of points in x axis
of the "mesh"
alpha -Diffusion coefficient
H -The height of our domain (y)
L-The width of our domain (x)
leftPix -The two pixels on the left boundary
rightPix-The two pixels on the right boundary

Step 4: Initialize IMG as black image
Initially image (0,1)

Step 5: Update pixel by Pixel using
Taylor series method for each band
dy = H /(ny-1);
dx = L /(nx-1);
dt = tmax/(nt-1);
t=0;
img=zeros(ny,nx);
img(i,j)=imgold(i,j)+alpha*(dt)*((imgold(i+1,j)+imgold(i-1,j) - 2 *imgold(i,j))/dy^2 + (-2* imgold(i,j) + imgold(i,j+1) + imgold(i,j-1))/dx^2);

Step 6:If Convergence level
(IMG,IMGold) >0.0001 then repeat
Step 5 for each band
Else
Go Step 7

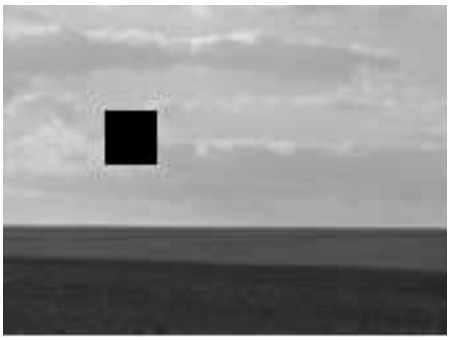
Step 7: if Image is RGB then combine
Those 3 bands and create RGB image.

Step 8: Resultant Inpainted image as output.

III. RESULT

A collection of color image and gray scale images with generic themed content, downloaded and chosen at random from a much larger dataset used for training and validation. All images used in the undergo color and grayscale conversion prior to any experiment. The motivation and mechanics behind this simple pre-processing step. Presents some statistics regarding the types of patches extracted from the images.

(a) Original Image



(b) Unproccessed Image

(c) Result

(d)Original Image

(e) Unprocessed Image

(f) Result

Fig. 1: Examples of patch types, presents a distribution over image-patch types.

IV. ADVANTAGES

The exemplar based approach is used removing large objects from digital photographs.

The technique is capable of propagating both linear structure and two-dimensional texture into the target region with a single, simple algorithm.

Structure sparsity enables better discrimination of structure and texture.

The patch sparse representation forces the newly inpainted regions to be sharp and consistent with the surrounding textures.

Also, patch-based filling helps achieve:

1) Speed efficiency
2) Accuracy in the synthesis of texture(less garbage growing).
3) Accurate propagation of linear structures.

CONCLUSION & FUTURESCOPE

A. Conclusion

This paper proposed novel patch propagation based inpainting algorithm to be implemented in removal and missing block completion. The major novelty of this work is that two types of patch sparsity were proposed and introduced into the examplar-based inpainting algorithm. This was inspired from the recent progress of the research in the fields of image sparse representation and natural image statistics. Structure sparsity was designed by measuring the sparseness of the patch similarities in the local neighborhood. The patch with larger structure sparsity, which is generally located at the structure, tends to be selected for further inpainting with higher priority. On the other hand, the patch sparse representation was proposed to synthesize the selected patch by the sparsest linear combination of candidate patches under the local consistency constraint. The proposed examplar-based patch propagation algorithm on a variety of natural images. Apply algorithm to the applications of scratch/text removal, object removal and block completion. Algorithm with the previous diffusion-based, examplar-based, and sparsity-based inpainting algorithms. With the help of Comparisons,The proposed examplar-based patch propagation algorithm can better infer the structures and textures of the missing region, and produce sharp inpainting results consistent with the surrounding textures.

B. Future Scope

1) Using above method we can recover damaged image. But we cannot deform the objects of an image, which is removed fully due to damage of the image
2) We can combine this proposed algorithm with object deformation algorithm to get inpainted image.
3) The present work can be extended to image inpainting for convert to video data.

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