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Hierarchical Super-Resolution-Based Inpainting

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Abstract— This introduces a new structure of exemplar-based inpainting. In this we combine both, inpainting method and super resolution method. With the help of this approach that high resolution image is converted to low-resolution image and inpainted then again converted into high-resolution image. This makes it easy both in terms of computational complexity and visual quality and work with the border of image structures.

In Hierarchical Super-resolution method first select the area of image which has to be edited.Selected area within boundary will be filled by different colour. If image is in the form of high resolution then convert it into low resolution image. The low-resolution input picture is divided in patch of small size and inpainted one by one with the nearest neighbour pixel value. Patch will select accordingly the patch priority now the Inpainting outcome is again converted to high resolution image efficiently recovered by a single-image super-resolution algorithm.

Index Terms—Examplar-Based Inpainting, Single-Image Super-Resolution.

I. INTRODUCTION

Inpainting the procedure of reconstructing lost or damage parts of images and videos. It used to remove unwanted elements present in the image. In photography and cinema, it is used for film restoration; to reverse the deterioration cracks in photographs or scratches is also used for removing red-eye, the stamped date from photographs and remove by objects to creative effect.

Since the wide applications of the digitalization of old photos, inpainting is an automatic process that is performed on digital images and also applied to object removal, text removal and other automatic modifications of images. Furthermore, it can used in applications like image compression and super resolution. Three groups of image inpainting algorithms can be found in this. The first is structural inpainting, the second one is texture inpainting and the last is a combination of that techniques. All these inpainting methods have one thing in common they use the information of the known or undestroy image areas in order to fill the gap.Image in-painting is the art of filling the missing pixel in an image.

The purpose of inpainting is to reconstruct missing region in a visually plausible manner so that it seems realistic to the human eye. There several approaches proposed for the same. In the digital world, inpainting also known as Image Interpolation refers to complicated algorithms to replace corrupted part of the image.

A. Structural Inpainting

Structural inpainting uses geometric for filling in the missing information in the region which should be inpainted. These algorithms centre on the uniformity of the geometric structure.

B. Textural Inpainting

Tthe structural inpainting methods are not able to restore texture. Texture has a repetitive pattern so a missing portion cannot be restored by systematic the level lines into the gap.

C. Combined Structural And Textural Inpainting

structural and textural inpainting approaches try to perform texture and structure filling in regions of missing image information. The boundaries between image regions build up structural information which is a complex. when blending different textures together. That is why, inpainting method attempts to combine structural and textural inpainting.

The goal of super resolution is to create a high resolution image from one or more low resolution image. Methods of super resolution can be broadly classified into two methods:

D. Exemplar Based Image Inpainting

Exemplar-based image inpainting preform computerize the duplicate tool process. It fills holes in the image by searching for similar patches in a close source region of the image, and copying pixels from the mainly similar patch into the hole.

The proposed method builds upon the super-resolution-based inpainting method proposed in which is based on examplar-based inpainting (in particular Criminisi-like approach) and single-image examplar-based super-resolution. Proposed algorithm is the combination of multiple inpainted versions of the input picture. The basis of this approach is to handle with the sensitivity of examplar-based algorithms to parameters such as the patch size and the filling order. Different combinations have been tested and compared. Different adjustments about examplar-based inpainting described.

The paper is prepared as follows. In Section II, a general idea of the proposed examplar-based inpainting algorithm is pre-sented. In Section III, the details of the inpainting algorithm as well as the combination of the inpainted pictures are given. Section IV presents the super-resolution method. Experiments and comparisons are performed in Section V. Finally we conclude this work in Section VI.

II. THE PROPOSED EXAMPLAR-BASED INPAINTING

Existing methods can classified into following categories. The first category is a diffusion-based approaches tend to introduce some blur when the hole to be filled-in is large. The second approaches is exemplar-based methods which sample and copy best matches texture patches from the known image neighbourhood. These methods have been inspired from texture synthesis techniques are known to work well in regular or repeatable textures. To use differential equations such as the Laplace's equation with Dirichlet boundary conditions for continuity. This works well if missing information lies within the homogeneous portion of an object area.

III. INPAINTING ALGORITHM

Existing issue Diffusion-based approaches some blur when the hole to be filled-in is large

A. Algorithm steps:-

1.Initialize the target region
This is performed by marking the target region in some particular colour
2.Detect Boundary of the target region.
3.Patch analysis
4.Computing patch priorities
Compute priority values that are assigned to each patch
Using Mean square analysis
Update the image information according to the patch
5.Propagate texture and structure Synthesis
Compute the patch P with highest priority
Propagate pixel-value information via diffusion which leads to image smoothing
6.Filling Order
Find data pattern & confident for each boundary point
Find the pixel on boundary point having highest priority
Find highest priority matched window then replace the patch window
7.Updating confidence values
Update confidence C(p) After the patch p has been filled with new pixel values.

IV. SUPER-RESOLUTION ALGORITHM

Once the low-resolution inpainted pictures is completed, a hierarchical single-image super-resolution approach is used to rebuild the high resolution details of the image.Tthe single-image SR method is applied only when the input picture has been downsampled for the inpainting purpose.

A. Process:-

If the input picture of resolution *(X, Y)* has been down-sampled by four in both directions, the SR algorithm is applied twice: a first time to recover the resolution and a second time to recover the native resolution.

a). Patch Priority
The filling order computation defines a measure of priority for each patch in order to distinguish the structures from the textures. The priority of a patch centered on $p\mathbf{x}$ is just given by a data and confidence term.Thi term is based on a structure tensor

$$J=\sum_{i=1}^{m} \nabla^{li} \nabla^{IiT}$$

The sparsity-based priority In a search window, a template matching is performed between the current patch $\psi p\mathbf{x}$ and neighbouring patches $\psi p\mathbf{j}$ that belong to the known part of the image similarity weight $wp\mathbf{x},p\mathbf{j}$ **.**

i.e. proportional to the similarity between the two patches centered on $p\mathbf{x}$ and $p\mathbf{j}$ is computed. The sparsity term is defined as:

$$D(p\mathbf{x}) = \|\mathbf{w}p\mathbf{x}\|^{*}\sqrt{\frac{|Ns(p\mathbf{x})|}{(|N(p\mathbf{x})|)}}$$

Where Ns and N represent the number of valid patches having all its pixels known and the total number of candidates in the search window. When $\|\mathbf{w}p\mathbf{x}\|$ is high, it means larger sparseness whereas a small value indicates that the current input patch is highly predictable by many candidates

b). Texture Synthesis
The filling process starts with the highest priority patch. To fill in the unknown part of the current patch $\psi uk\ p\mathbf{x}$, the most similar patch located in a local neighbourhood W centred on the current patch is sought. A similarity metric is used for this purpose. The chosen patch $\psi{*}p\mathbf{x}$ maximizes the similarity between the known pixel values of the current patch to be filled in $\psi^{k}p\mathbf{x}$ and co-located pixel values of patches belonging to W: $\psi^{*}_{p\mathbf{x}}= \arg\min_{\psi_{p\mathbf{j}}\in W} d(\psi^{k}_{p\mathbf{x}},\psi^{k}_{p\mathbf{j}})$

$$\text{s.t } Coh\ (\psi^{uk}_{p\mathbf{x}}) < \lambda\text{coh}$$

$$Coh(\psi^{uk}_{p\mathbf{x}}) = \min_{p\mathbf{j}\in S}(dSSD(\psi^{uk}_{p\mathbf{x}},\psi^{uk}_{p\mathbf{j}}{}^{u})$$

where dSSD is the sum of square differences. The coherence measure Coh indicates the degree of similarity between the synthesized patch $\psi^{uk}_{p\mathbf{x}}$ and original patches.

Most of existing approaches, the setting such as thepatch size and the filling order, to name the most importantfactors, may dramatically impact the quality of results. To overcome this issue, we combine inpainted pictures obtained when different settings are used.

B. Combining Multiple Inpainted Images

To obtain the final inpainted picture, three types of combination have been considered. The first two methods are either the average or the median operator

$$I^*(P_x) = 1/M \sum_{i=1}^{M} I^i(Px)$$
$$I^*(P_x) = \text{med} \sum_{i=1}^{M} I^i(Px)$$

The advantage of these operators is their simplicity. They have two main drawbacks they does not consider the neighbours of the current pixel to take a decision. Result may be blurring.

Using a global minimization that would solve exactly the problem, we use a Loopy Belief Propagations the problem is to be solved.

a). Loopy Belief Propagation

The problem is toassign a label to each pixel $p\mathbf{x}$ of the unknown regions T of the picture. The major drawback of the belief propagation is that it is slow specially when the quantity of labels is high. This problem can be formalized with a Markov Random Field (MRF).

Defined over the target region T. Total energy E of the MRF is minimized we denote by $l\ p$ the label of pixel

$$E(l) = \sum_{\mathbf{p}\in v} Vd\,(l\ p) + \sum_{(n,m)\in N4} Vs(ln, lm)$$

where, $Vd\ (l\ p)$ is called the label cost or the data cost. This represents the cost of assigning a label $l\ p$ to a pixel px . This is given by:

$$Vd\,(l\ p) = \sum_{n\in L} \sum_{\mathbf{u}\in v} \{ I^l(\mathbf{x} + \mathbf{u}) - I^n(\mathbf{x} + \mathbf{u})\}^2$$

V. EXPERIMENTAL RESULTS

A. Perform image Inpainting

User will select portion(target region) of image which he want to remove from image that selected portion is particular object itself or unwanted region of image .Target region must be complete object it must not be part of particular object contain in image.

Fig1. Target Region

B. Object Separation Module

In this module the target region which is selected by user will be displayed separately.The target region will be the object itself.

Fig2. Object Separation

C. Output Image

The algorithmic steps will be performed on input original image and processed output image will be shown to user which does not have portion (target region) selected by user and that image will be saved to user specified directory.

Fig 3. Output

D. Super-Resolution of Image

The output image after performing image Inpainting is a final output

Fig 4. Super-Resolution

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State-of-the-art inpainting methods are used for comparison purposes. The first one is the well known method proposed by Criminisi *et al*..We have used a third part implementation available on http://www.cc.gatech.edu/ sooraj/inpainting/ (we use a patch's size of 9 × 9.

The second one is the PatchMatch method which is a fast algorithm for computing approximate nearest neighbour between patches of two image regions. This is available in Adobe Photoshop CS5.

The shift-map method is the third algorithm considered in the test. This approach is treating inpainting as a global optimization in a multi-scale scheme. The goal is to shift pixel values from the known part of the picture to the missing part.

A graph cut optimization allows finding the best mapping. Inspired by, He and Sun recently proposed a new method. The idea is to find the most important 2D offsets (displacement) in the picture.

a). Parameter Analysis

- At Plain Background

First we taken a one single colour image and name it as d1.jpeg.at second stage we edit that image add a shape of diamond as d11.jpeg. After that by using The Hierarchical Super Resolution Based Inpainting remove the shape of (unwanted object).

Compare the original single colour image and our inpainted image.

Using MatLab we calculate the MSE & PSNR of original image and inpainted image.

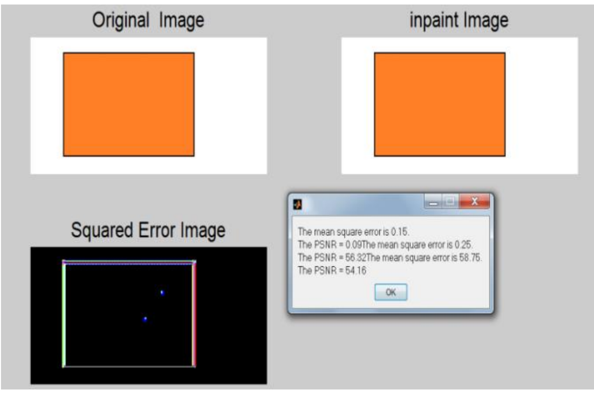

Fig 5. Plain Image

- At Sample Image

we taken a one sample image and name it as d2origi.jpeg. we edit that image add an object of another image as d2.jpeg. After that by using The Hierarchical Super Resolution Based Inpainting remove that object of image (unwanted object).

Compare the original sample image and our inpainted image.

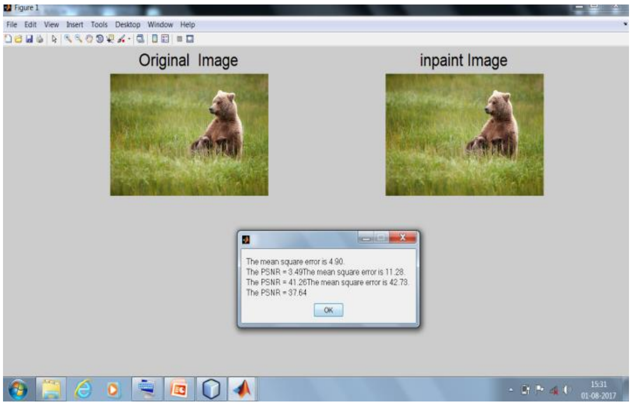

Fig 6. Sample Image

The mean square error is 4.77. The PSNR = 3.40The mean square error is 10.67. The PSNR = 41.38The mean square error is 42.84. The PSNR = 37.88.

E. Mean Opinion Score

Mean opinion score (MOS) is a measure used in the Quality of Experience representing overall quality of a system. "values on a predefined scale that a subject assigns to his opinion of the performance of a system quality".

The MOS is expressed as a single rational number, typically in the range 1–5, where 1 is lowest perceived quality, and 5 is the highest perceived quality.

Rating	Label
5	Excellent
4	Good
3	Fair
2	Poor
1	Bad

Table 1:

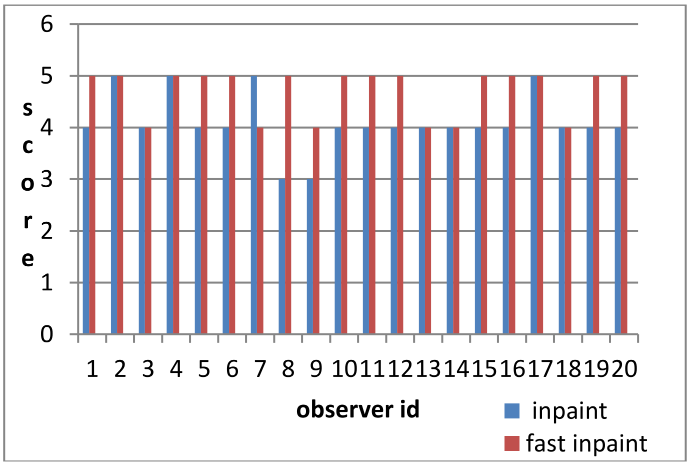

Fig: 7 Opinions Score (MOS)

F. Running Time:-

Name	Inpaint time	selected area	Fast inpaint	selected area	Resolution
Engle	1m 38 sec	141w X 122h	1m 11sec	145w X 131h	259 X194
Cow	1m 38 sec	61w X 63h	52 sec	59w X 71h	640 X427
Desert	3m 24 sec	66w X 63h	1m 34 sec	62w X 58h	1024X 768
water mark	4 m24 sec	458w X 49h	1 m 50sec	459w X 45h	480 X315

Table 2: Comparism Between Original Image and Inpaint

G. Using Inpainting:-

Name	PSNR	MSE
D2	34.89	2.09
Lip	31.80	1.17
Watermark	35.76	5.89
Cow	33.09	4.59
Desert	36.88	5.38
Sample	37.16	5.67

Table 3

H. Using Fast Inpainting:-

Name	PSNR	MSE
D2	34.16	1.59
Lip	32.19	0.82
Watermark	33.50	4.91
Cow	32.96	3.43
Desert	35.30	6.61
Sample	37.19	5.57

Table 4

VI. RESULT DISCUSSION

Fig. 8

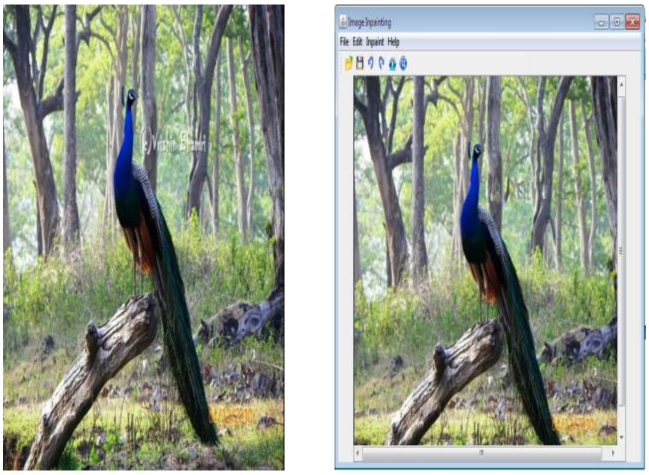

Fig. 9

VII. CONCLUSION

A renew inpainting approach has been presented. The input picture is first down sampled and several inpaintings are performed. The low-resolution inpainted pictures are combined by globally minimizing an energy term. Once the combination is completed, a hierarchical single image super resolution method is applied to recover details at the native resolution.

The super resolution process is the most time-consuming step; It is due to the template matching which is not simultaneous. To improve the performance, the template matching could be replaced by an approximate nearest neighbour search.

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