IMAGE INPAINTING USING TEXTURE SYNTHESIS AND OBTAIN HIGH RESOLUTION IMAGES FOR PROFESSIONAL RESTORATIONS

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Abstract: Inpainting is the process of filling the missing regions in an image. The main aim of this paper is to fill the missing areas using examplar based inpainting and to recover the missing areas and improve the quality of the image using super resolution algorithm. The performance of the algorithm is evaluated using PSNR. The damaged image is first down sampled. Then the image is inpainted a number of times using examplar based approach. The inpainted images are combined using loopy belief propagation. The image is finally up sampled and the image quality is improved using a super resolution algorithm.
Keywords: examplar based inpainting, mean square error, super resolution.

I. INTRODUCTION

Image inpainting refers to methods which consist in filling in missing regions in an image [1]. Existing methods can be classified into two main categories. The first category concerns diffusion-based approaches which propagate linear structures or level lines (so-called isophotes) via diffusion based on partial differential equations and variational methods [3]. The diffusion-based methods tend to introduce some blur when the hole to be filled in is large. The second family of approaches concerns examplar-based methods which sample and copy best matches texture patches from the known image neighbourhood. Two types of methods (diffusion- and examplar-based) can be efficiently combined, e.g. by using structure tensors to compute the priority of, the patches to be filled in as in [4]. A recent approach [5] combines an examplar-based approach with super-resolution. It is a two-steps algorithm. First a coarse version of the input picture is inpainted. The second step consists in creating an enhanced resolution picture from the coarse inpainted image.

Although tremendous progress has been made in the past years on examplar-based inpainting, there still exists a number of problems. We believe that the most important one is related to the parameter settings such as the filling order and the patch size. This problem is here addressed by considering multiple inpainted versions of the input image. To generate this set of inpainted pictures, different settings are used. The inpainted pictures are then combined yielding the final inpainted result. Notice that the inpainting algorithm is preferably applied on a coarse version of the input image; this is particularly interesting when the hole to be filled in is large. This provides the advantage to be less demanding in terms of computational resources and less sensitive to noise and local singularities. In this case the final full resolution inpainted image is recovered by using a super-resolution (SR) method. SR methods refer to the process of creating one enhanced resolution image from one or multiple input low resolution images. The proposed method builds upon the super-resolution based inpainting method proposed in [10] which is based on examplar-based inpainting and single-image examplar-based superresolution. The main novelty of the proposed algorithm is the combination of multiple Image inpainted versions of the input picture. The rationale behind this approach is to cope 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. Besides this major point, different adjustments regarding examplar-based inpainting and SR methods are described such as the use of the coherence measure to constrain the candidate search.

II. LITERATURE SURVEY

[1] D. Tschumperlé and R. Deriche,: A new algorithm is proposed for removing large objects from digital images. The challenge is to fill in the hole that is left behind in a visually plausible way. In the past, this problem has been addressed by two classes of algorithms:(i) “texture synthesis” algorithms for generating large image regions from sample textures, and (ii) “inpainting” techniques for filling in small image gaps. The former has been demonstrated for “textures” – repeating two-dimensional patterns with some stochasticity; the latter focus on linear “structures” which can be thought of as one-dimensional patterns, such as lines and object contours.

[2] Drori, D. Cohen-Or, and H. Yeshurun: The algorithm patches up holes in images by finding similar image regions in the database that are not only seamless but also semantically valid. Our chief insight is that while the space of images is effectively infinite, the space of semantically differentiable scenes is actually not that large. For manyimage completion tasks we are able to find similar scenes which contain image fragments that will convincingly complete the image. Our algorithm is entirely data-driven, requiring no annotations or labeling by the user.

[3] S. Dai, M. Han, W. Xu, Y. Wu, Y. Gong, and A. Katsaggelos: Designing effective image priors is of great interest to image super-resolution (SR), which is a severely under-determined problem. An edge smoothness prior is favored since it is able to suppress the jagged edge artifact

effectively. However, for soft image edges with gradual intensity transitions, it is generally difficult to obtain analytical forms for evaluating their smoothness.

[4] D. Glasner, S. Bagon, and M. Irani: There are lots of Super resolution methods developed recently. Each has its own pros and cons and behavior. Even, this is not truefor SR because of one to many mappings between Low Resolution and High Resolution patches .To minimize the problem for NE-based SR reconstruction, an advanced Neighbor Embedding based method for Super resolution used in which combine learning technique used to train two projection matrices simultaneously and to map the original Low Resolution and High Resolution feature spaces onto a unified feature subspace. Reconstruction weights of the k-Nearest neighbour of Low Resolution image patches is found by performing operation on those Low Resolution patches in unified feature space. To handle a large number of samples, combine learning use a coupled constraint by linking the LR–HR counterparts together with the k-nearest grouping patch pairs. The Advanced NE algorithm gives better resolution and outperforms NE method for image super resolution.

III. METHODOLOGY

Image completion of large missing regions is a challenging task. In this project, we propose a new inpainting framework relying on both the combination of low-resolution inpainting pictures method and a single-image super-resolution algorithm. In the following sections, we briefly present the main ideas of this paper and the reasons why the proposed method is new and innovative. The proposed method is composed of two main and sequential operations. The first one is a non-parametric patch sampling method used to fill in missing regions. The inpainting algorithm is preferably applied on a coarse version of the input picture. Indeed a low-resolution picture is mainly represented by its dominant and important structures of the scene. We believe that performing the inpainting of such a low-resolution image is much easier than performing it on the full resolution. A low-resolution image is less contaminated by noise and is composed by the main scene structures. In other words, in this kind of picture, local orientation singularities which could affect the filling order computation are strongly reduced. Second, as the picture to inpaint is smaller than the original one, the computational time is significantly reduced compared to the one necessary to inpaint the full resolution image. To give more robustness, we inpaint the low-resolution picture with different settings (patch's size, filling order, etc.). By combining these results, a final low-resolution inpainted picture is obtained. Results will show that the robustness and the visual relevance of inpainting is improved. The second operation is run on the output of the first step. Its goal is to enhance the resolution and the subjective quality of the inpainted areas. Given a low-resolution input image, which is the result of the first inpainting step, we recover its high-resolution using a single-image super-resolution approach. Illustrates the main concept underlying the proposed method namely:

1) A low-resolution image is first built from the original Picture.
2) An inpainting algorithm is applied to fill in the holes of the low-resolution picture. Different settings are used and inpainted pictures are combined.
3) The quality of the inpainted regions is improved by using a single-image super-resolution method.

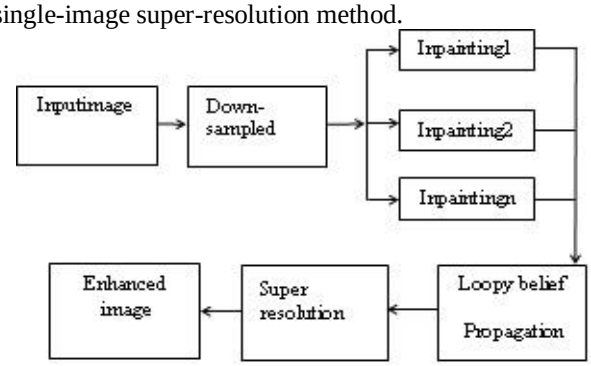

Fig. 1: The Block diagram of the proposed method.

A. EXAMPLAR BASED INPAINTING:

The first step in image inpainting is to convert the high resolution image into low resolution image into low resolution image. For this converting process a Gaussian pyramid decomposition is performed. A low pass filtering operation is performed on the image pixels. Down sampling is necessary because the low resolution images are easier to inpaint. Low resolution images are contaminated by noise. Local orientation singularities which affect the filling process are strongly reduced if low resolution images are used. After converting into low resolution images, mark the target region to be filled using region of interest. The remaining part of the image is the source region from which the neighbouring patches are selected. A Boolean matrix is constructed which stores a binary value 1 for pixel to be inpainted and binary value 0 for the other pixels. This matrix is called fill region. The next step is to find the boundary of marked region $\delta\Omega$ by convolving the fill region with laplacian filter. The next step is to find the priority of the patch which is to be filled first. Texture synthesis is performed which copies the samples from the neighbourhood and replaced in the missing region.

B. FIND PATCH PRIORITY:

The missing patch which has the highest priority is to be found. Priority is the patch which has less unknown regions. The patch priority is given by the product of data term and confidence term. Data term can be either a tensor based or sparsity based data terms. Tensor based priority term is given by

$$J=\Sigma\nabla Ii\nabla Ii^{T} \quad (1)$$

Where J is the sum of structure tensors of each scalar image channels. The scalar structure tensor undergoes smoothing operation be

$$J\sigma=J\times G\sigma \quad (2)$$

Where $G\sigma$ is the Gaussian distribution with standard deviation$\boldsymbol{\sigma}$. A similarity weight is measured between the known patches and the unknown patch. For any selected

patch, a collection of neighbouring patches with highest similarities are distributed in the same structure or texture. The confidence values of structure for a patch are measured by the sparseness of its non-zero similarities to the neighbouring patches. The patch which is more sparsely distributed with non zero similarities is placed on the fill front due to more structure sparseness. For a patch located at the fill front $\delta\Omega$, a neighborhood window N (p) is set with centre p.

C. TEXTURE SYNTHESIS:

Texture synthesis is the process of algorithmically constructing a large digital image by taking advantage of the structural content. Texture synthesis is used for filling the missing parts. The patch which has the highest priority is filled first. To fill a patch, the most similar patch from the remaining part of the image is taken. A similarity metric is used to find the best matching patch. Texture synthesis is of two types. Pixel based texture synthesis and patch based texture synthesis. In pixel based method, a texture is synthesized in scan line order by finding and copying pixels with most similar local neighborhood as the synthetic texture. This method is very useful for image completion. In patch based texture synthesis, a new texture is created by copying and stitching the textures at various offsets. This method is more effective and faster than pixel based texture synthesis. The chosen patch should have maximum similarity between the known pixel values of the current patch to be filled and the co-located pixel values.

Coherence measure is given by

$Coh\ (\psi px) = minpj\epsilon s\ (dSSD\ (\psi px, \psi pj,))$ (3)

dSSD - sum of square differences

Ψpx - current patch

Ψpj – neighbouring patch

Coherence measure is the degree of similarity between the synthesized patch and the original patch. The chosen neighbor should lie within (1+α) dmin where dminis the minimum distance between the current patch and the closest neighbor. If the selected patch does not satisfy this condition, then the filling process is stopped and the priority of the current patch is decreased. Again the patch with highest priority is chosen. The unknown parts are pasted using the best matching patch by direct sampling. Alpha blending is used to combine the known part and the source patch. Alpha blending is the process which displays a bitmap which has or semitransparent pixels. The image is made transparent and the known part and unknown part are combined together. Patch size and filling order must be considered.

D. LOOPY BELIEF PROPOGATION:

LBP is a message passing algorithm. A node is used to pass a message to the adjacent node only when it has received all the messages, eliminating the message from the destination node to itself. In the same way, all the inpainted images are combined together using loopy belief propagation. A label is assigned to each pixel of the unknown regions T of the image. A major drawback of belief propagation is that it is slow when the number of labels is high. So loopy belief propagation is used to avoid this complexity. To solve the problems like blur and spatial consistency, there is a need to minimize the objective function. The number of labels assigned must be equal to the number of patches in the source region. In loopy belief propagation, the number of labels is small. Label is the index of the inpainted image from which the patches are extracted.

E. SUPER RESOLUTION ALGORITHM:

After combining all the inpainted images, a super resolution algorithm is used to recover back the high resolution image from the low resolution image. The down sampled image is up sampled. It is also used to improve the quality of the image. In low resolution image, the pixel density within an image is small. Hence it offers fewer details. In a high resolution image, the pixel density is larger. Hence it offers more details. Super resolution is the process of obtaining a high resolution image to low resolution image. To increase the image resolution, the pixel size is reduced by increasing the number of pixels per unit area. But the amount of light available per pixel also decreases. The chip size can be reduced but the increase of capacitance leads to storage problem. SR image reconstruction is computationally effective and cost is less.

IV. PROPOSED WORK

Fundamentals: Given an input image I with a missing orunknown region Ω and its contour/fill front is denoted as dΩ. The task of image completion is as follows:

1. The global picture determines how to fill in the gap, the purpose of inpainting being to restore the unity of the work;
2. The structure of the area surrounding Ω is continued into the gap, contour lines are drawn via the prolongation of those arriving at dΩ.
3. The different regions inside Ω, as defined by the contour lines, are filled with colour, matching those of dΩ.

The Ω is progressively shrunk by propagating structure and texture information from the contour dΩ. Target/missing region Ω is filled up patch wise with the similar patches from source region F. Next, the size of patch to be filled on fill front is defined, assuming the probability distribution of brightness values for a pixel given the brightness values of its spatial neighbourhood is independent of the rest of the image. The neighbourhood of a pixel is modeled as a square window around that pixel. More specifically, if the texture is presumed to be mainly regular at high spatial frequencies and mainly stochastic at low spatial frequencies, the size of the window should be on the scale of the biggest regular feature i.e., slightly larger than the largest distinguishable texture element in the source region F.

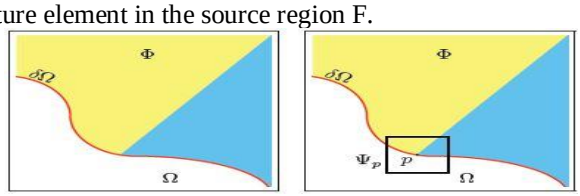

Fig 2: Original image with target region Ω and its boundary ∂Ω and source region ϕ. (b) ψp marks the area which we wants to remove.

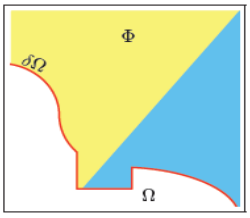

Fig 3: Copied data from nearby region of the image.

A. Overview of region filling algorithm

- Taking an input for the inpainting image.
- Calculating the number of rows, number of columns and number of frame.
- Selecting the region which is to be removed.
  - Calculate number of rows of selected region.
  - Calculate number of columns of selected region.
- On the values of rows and columns, we will get the number of total count.
  - Total count: gives last point of processing.

Repeat until done the following steps:

- Check for pixel which needs to be inpainted.
- If found, Check pixel in previous row, next Column and next row for replacing the matched pixel.
- If not found, increases the window length.
- Replacing the current pixels with the found pixel.

V. RESULT

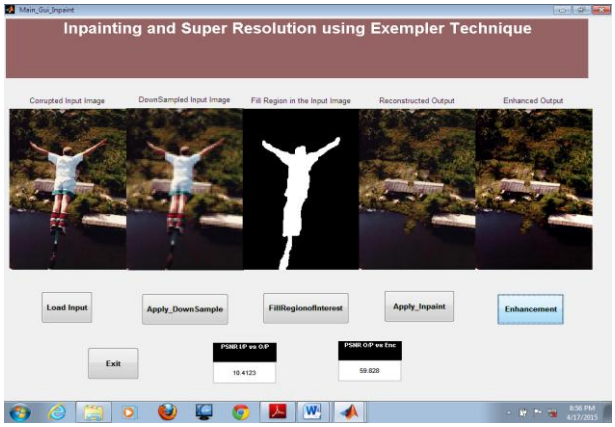

Fig 4: input image and enhanced output

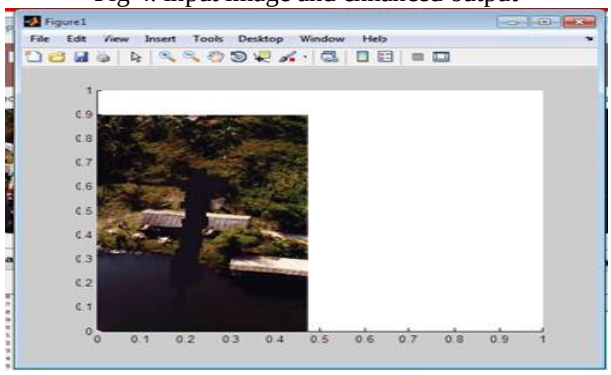

Fig 5: inpainting image

VI. CONCLUSION

The input picture is first down sampled and several inpainting 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. Experimental results on a wide variety of images have demonstrated the effectiveness of the proposed method.

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