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Exemplar Based Super-Resolution Technique for Image Inpainting

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Abstract: Image Inpainting is the art of filling in missing data in an image. The purpose of inpainting is to reconstruct missing regions in a visually plausible manner so that it seems reasonable to the human eye. There have been several approaches proposed for the same. In this paper, we present an algorithm that improves and extends a previously proposed algorithm and provides faster inpainting. Using our approach, one can inpaint large regions (e.g. remove an object etc.) as well as recover small portions (e.g. restore a photograph by removing cracks etc.). The inpainting is based on the exemplar based approach. The basic idea behind this approach is to find examples (i.e. patches) from the image and replace the lost data with it. We obtained good quality results quickly using our approach.Image Inpainting is the process of reconstructing lost or deteriorated part of images based on thebackground information.This paper introduces a novel framework for exemplar-based inpainting. It consists in performing first the inpainting on a coarse version of the input image. A super-resolution algorithm is then used to recover details on the missing areas. The advantage of this approach is that it is easier to inpaint low-resolution pictures than high-resolution ones. The gain is both in terms of computational complexity and visual quality. However, to be less sensitive to the parameter setting of the inpainting method, the low-resolution input picture is inpainted several times with different configurations. Results are efficiently combined with loopy belief propagation and details are recovered by a single-image super-resolution algorithm. Experimental results in a context of image editing and texture synthesis demonstrate the effectiveness of the proposed method.

Keywords: Image inpainting, super resolution inpainting, Low-resolution, High Resolution, exemplar-based inpainting.

I. INTRODUCTION

In real world, many people need a system to recover the damaged photographs, artwork, designs, drawings etc. Damage may be due to various reasons like scratches, overlaid text orgraphics, scaled image etc., This system could enhance and return a good looking photographusing a technique called inpainting or retouching. The observer does not know the originalimage. Traditionally, inpainting has been done by professional artists. But we could not expectthe accuracy and quality if it was done by human and time consuming process. The objective of inpainting is to reconstitute the missing or damaged portions of the work, in order to make itmore legible and to restore its unity. The need to retouch the image in an unobtrusive wayextended naturally from paintings to photography and film. Digital techniques are ranging fromattempts to fully automatic detection and removal of scratches in film, all the way to softwaretools that allow a sophisticated but mostly manual process [1].

Image inpainting refers to methods which consist in filling in missing regions (holes) in an image. The goal of image inpainting is to restore parts of an image, in such a manner, that aviewer cannot detect the restored parts. One application of image inpainting is to retouch damaged parts of a digital picture. Before the inpainting process is started, the user denes abinary mask for the image, which marks the region that should be restored [2].

Inpainting is the art of restoring lost parts of an image and reconstructing them based on the background information. This has to be done in an undetectable way. The term inpainting is derived from the ancient art of restoring image by professional image restorers in museums etc. Digital Image Inpainting tries to imitate this process and perform the inpainting automatically. Figure 1 show an example of this technique where a building (manually selected as the target region) is replaced by information from the remaining of the image in a visually plausible way. The algorithm automatically does this in a way that it looks “reasonable” to the human eye. Details that are hidden/ occluded completely by the object to be removed cannot be recovered by any mathematical method. Therefore the objective for image inpainting is not to recover the original image, but to create some image that has a close resemblance with the original image.

Such software has several uses. One use is in restoring photographs. Ages ago, people were preserving their visual works carefully. With time, photographs get damaged and scratched. Users can then use the software to remove the cracks from the photographs.

Another use of Exemplar Based Super-resolution image inpainting is in creating special effects by removing unwanted objects from the image. Unwanted objects may range from microphones, ropes, some unwanted person and logos, stamped dates and text etc. in the image. During the transmission of images over a network, there may be some parts of an image that are missing. These parts can then be reconstructed using image inpainting. There have also been a few researches on how to use image inpainting for super-resolution and zooming of images [13].

II. LITERATURE SURVEY

Existing methods can be classified into two main categories. The first category concernsdiffusion-based

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approaches which propagate linear structures or level lines (isophotes) via diffusion based on partial differential equations and variational methods [3]. Thediffusion-based methods tend to introduce some blur when the hole to be filled in is large. Thesecond family of approaches concerns exemplar-based methods which sample and copy best matching texture patches from the known image of
Neighborhood. These methods havematching texture patches from the known image neighborhood. These methods have been inspired from texture synthesis techniques [4] and are known to work well in cases ofregular or repeatable textures.
The first attempt to use exemplar-based techniques for object removal has been reportedin [5]. The authors in [13] improve the search for similar patches by introducing an a priori rough estimate of the inpainted values using a multi-scale approach which then results in an iterativeapproximation of the missing regions from coarse-to-fine levels. The two types of methods (diffusion and exemplar-based) can be efficiently combined, e.g. by using structure tensors tocompute the priority of the patches to be filled in as in.

A. Diffusion based Inpainting
Diffusion based Inpainting was the first digital Inpainting approach. In this approach missing region is filled by diffusing the image information from the known region into the missing region at the pixel level. Basically these algorithms are based on theory of variation method and Partial Differential equation (PDE). The diffusion- based Inpainting algorithm produces superb results or filling the non-textured or relatively smaller missing region. The drawback of the diffusion process is it introduces some blur, becomes noticeable when filling larger regions. All the PDE based in painting models are more suitable for completing small, non-textured target region [16].

B. Texture Synthesis Based Inpainting
Texture synthesis based algorithms are one of the earliest methods of image Inpainting. And these algorithms are used to complete the missing regions using similar neighborhoods of the damaged pixels. The texture synthesis algorithms synthesize the new image pixels from an initial seed. And then strives to preserve the local structure of the image. All the earlier Inpainting techniques utilized these methods to fill the missing region by sampling and copying pixels from the neighboring area. For e.g. Markov Random Field (MRF) is used to model the local distribution of the pixel. And new texture is synthesized by querying existing texture and finding all similar neighborhoods. Their differences exist mainly in how continuity is maintained between existing pixels and Inpainting hole. The main objective of texture synthesis based inpainting is to generate texture patterns, which is similar to a given sample pattern, in such a way that the reproduced exture retains the statistical properties of its root texture [13].

C. PDE based Inpainting
This algorithm is the iterative algorithm. The main idea behind this algorithm is to continue geometric and photometric information that arrives at the border of the occluded area into area itself [15]. This is done by propagating the information in the direction of minimal change using isophotes lines. This algorithm will produce good results if missed regions are small one. But when the missed regions are large this algorithm will take so long time and it will not produce good results. Inspired by this work proposed the Total Variational (TV) Inpainting model [6]. This model uses Euler-Lagrange equation and anisotropic diffusion based on the strength of the isophotes. This model performs reasonably well for small regions and noise removal applications. But the drawback of this method is that this method neither connects broken edges nor greats texture patterns. These algorithms were focused on maintaining the structure of the Inpainting area. And hence these algorithms produce blurred resulting image. Another drawback of these algorithms is that the large textured regions are not well reproduced.

D. Exemplar based Inpainting
The exemplar based approach is an important class of inpainting algorithms [14]. And they have proved to be very effective. Basically it consists of two basic steps: in the first step priority assignment is done and the second step consists of the selection of the best matching patch. The exemplar based approach samples the best matching patches from the known region, whose similarity is measured by certain metrics, and pastes into the target patches in the missing region. Exemplar- based Inpainting iteratively synthesizes the unknown region i. e. target region, by the most similar patch in the source region. According to the filling order, the method fills structures in the missing regions using spatial information of neighboring regions. This method is an efficient approach for reconstructing large target regions.

E. Sparse Representation Method
This method is based on single-image super resolution, which is based on sparse signal representation. Researchers in imaging field suggest that image patches can be well represented as a sparse linear combination of elements from an appropriately chosen over-complete dictionary. Learning an over-complete dictionary capable of optimally representing broad classes of image patches is a difficult problem [8]. It is difficult to learn such a dictionary or using a generic set of basis vectors (e.g., Fourier), so for simplicity one can generate dictionaries by simply randomly sampling raw patches from training images of similar statistical nature. Researchers suggest that simple prepared dictionaries are already capable of generating high-quality reconstructions, when used together with the sparse representation prior [9].

III.RELATED WORK

The algorithm performs the synthesis task through a best-first filling strategy that depends entirely on the priority values that are assigned to each patch on the fill front. The priority computation is biased toward those patches which: (i) are on the continuation of strong edges and (ii) are surrounded by highconfidence pixels. Given a patch p centred at the point p for some P(n) we define its priority P(p) as the product of two terms:

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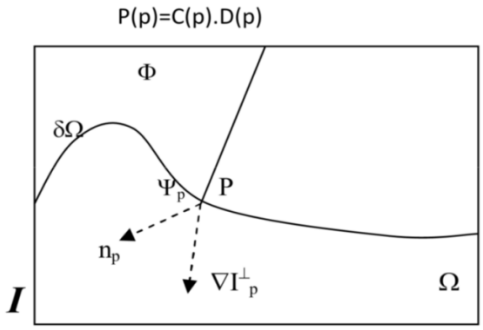

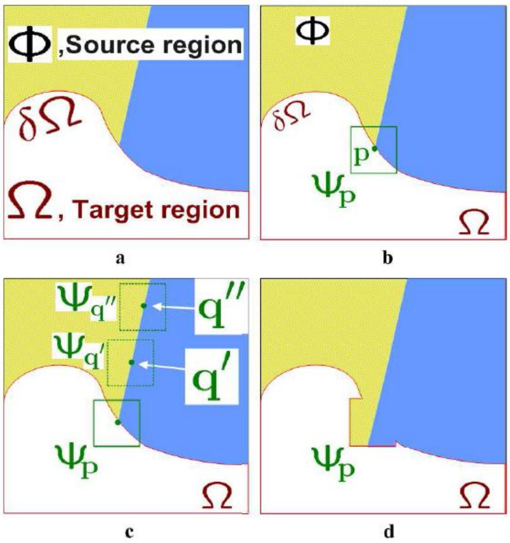

Fig1.Structure propagation by exemplar-based texture synthesis.

(a) Original image, with the target region Ω, its contour ∂Ω, and the sourceregion Φclearly marked.
(b) We want to synthesize the area delimited by the patch Ψp centred on the point p є∂Ω.
(c) The most likely candidate matches for Ψp lie along the boundary between the two textures in the source region, e.g., Ψ_q' and Ψ_q'' .
(d) The best matching patch in the candidates set has been copied into the position occupied by Ψp, thus achieving partial filling of Ω. Notice that both texture and structure (the separating line) have been propagated inside the target region. The target region Ω has, now, shrank and its front ∂Ω has assumed a different shape.[12]

A. Texture Synthesis:
Once all priorities on the fill front have been computed, the patch p with highest priority is computed. We then fill it with data extracted from the source region. In traditional inpainting techniques, pixel-value information is propagated via diffusion. As noted previously, diffusion necessarily leads to image smoothing, which results in blurry fill-in, especially of large regions. On the contrary, we propagate image texture by direct sampling of the source region.

B. Filling order:
Exemplar based filling may be capable of propagating both texture and structure information. This section demonstrates that the quality of the output image synthesis is highly influenced by the order in which the filling process proceeds. As it can be observed, the ordering of the filled patches produces the horizontal boundary between the background image regions to be unexpectedly reconstructed as a curve. A concentric-layer ordering, coupled with a patch-based filling may produce further artefacts. Another desired property of a good filling algorithm is that of avoiding "over-shooting" artefacts that occur when image edges are allowed to grow indefinitely.

C. Super-Resolution Technique
Once the inpainting of the low-resolution picture is completed, a single–image super-resolution approach is used to reconstruct the high resolution of the image. The idea is to use the low-resolution inpainted areas in order to guide the synthesis at the higher resolution. As in [8], the problem is to find a patch of higher-resolution from a database of examples. The main steps are described below:

1) Dictionary building: it consists of the correspondences between low and high resolution image patches. The unique constraint is that the high-resolution patches have to be valid, i.e. entirely composed of known pixels. In the pro-posed approach, high-resolution and valid patches are evenly extracted from the known part of the image. The size of the dictionary is a user-par ammeter which might influence the overall speed/quality trade-off. An array is used to store the spatial coordinates of HR patches$_D{}^{HR}$and those of LR patches are simply deduced by using the decimation factor;
2) Filling order of the HR picture: the computation of the filling order is similar to the one described in Section B. It is computed on the HR picture with the sparsity-based method. The filling process starts with the patch $\Psi_p{}^{HR}$having the highest priority and which is composed of known and unknown parts. Compared to a raster-scan filling order, it allows us to start with the structures and then to preserve them.
3) For the LR patch corresponding to the HR patch having the highest priority, its best neighbor in the inpainted images of lower resolution is sought. This search is performed in the dictionary and within a local neighborhood. Only the best candidate is kept. From this LR candidate, a HR patch is simply deduced. Its pixel values are then copied into the unknown parts of the current HR patch$\Psi_p{}^{HR}$.

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

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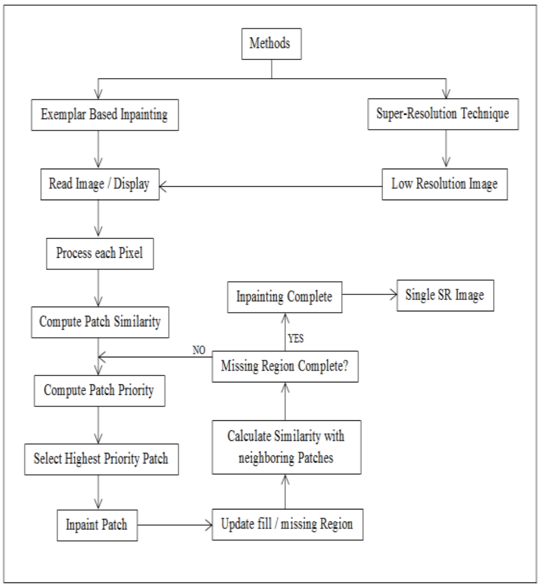

Fig 2.Flowchart of Proposed System

the origin alone, the computational time is significantly reduced comparedto the one necessary to inpaint the full resolution image. The second operation isrun on the output of the first step. Its goal is to enhance theresolution and the subjective quality of the inpainted areas; we recover its high-resolution using asingle-image super-resolution approach. Fig. 1 illustrates themain 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.

IV. RESULTS AND COMPARISONS

Here we apply our algorithm to a variety of images, ranging from purely synthetic images to full-colour photographs that include complex textures. Where possible, we make side-by-sidecomparisons to previously proposed methods. In other cases, we hope the reader will refer to the original source of our testimages (many are taken from previous literature on inpainting nd texture synthesis) and compare these results with the results of earlier work.[12]

(a) **(b)**

Fig 3.Example of object removal from photographs.

(a) Original image. (b) After object removal. Objects and people are removed by Exemplar Based Super resolution Technique in the selected target regions.

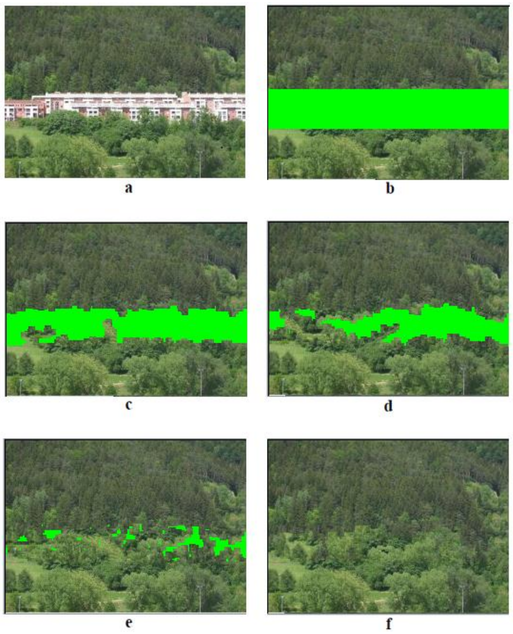

Fig 4.Removing large objects from photographs.

Fig 5.Removing multiple objects from photographs.

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(a) Original image. (b) The target region (25% of the total image area) has been blanked out. The (c: d: e) Intermediate stages of the filling process. (f) The target region has been completely filled and the selected object removed. The source region has been automatically selected as a band around the target region.

(a) Original photograph of Kirkland. (b,c,d) Several objects are sequentially removed.Notice how well the shore line and other structures have been reconstructed.

A. Comparison with Concentric-layer filling approach

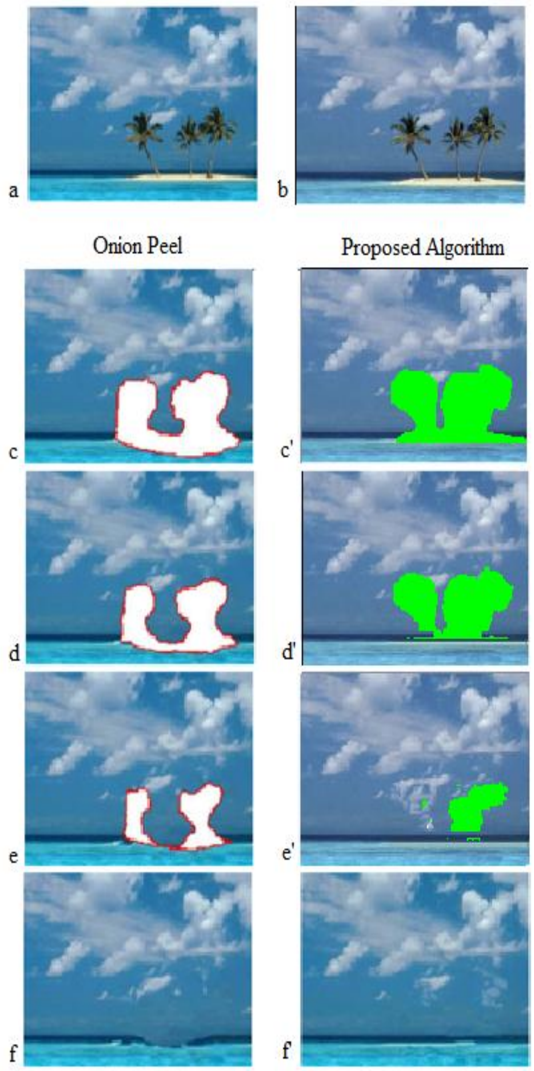


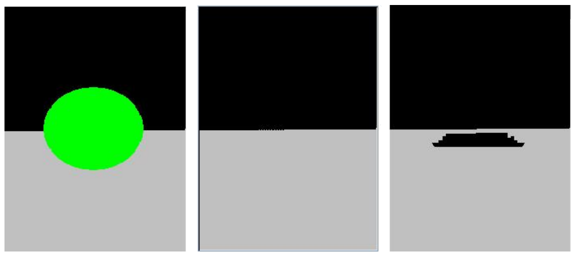
Fig 6.Comparison withConcentric-layer filling approach

(a) Original image (b) The manually selected target region (20% of the total image area) has been marked in Green boundary.The (c, d, e, f) Intermediate stages in the concentric-layer filling. The deformation of thehorizon is caused by the fact that in the concentric-layer filling sky and seagrow inwards at uniform speed.

Thus, the reconstructed sky-sea boundarytends to follow the skeleton of the selected target region. The (c', d', e', f') Intermediate stages in the filling by the proposed algorithm, where the horizonis correctly reconstructed as a straight line.

B. Comparison with Criminisi's approach [12]

Now we present the comparison of our approach with the one presented by Criminisi et al. in [12]. The image in Figure 7 (a) was given as input to the inpainting process that used our approach as well as to implementation of the Criminisi's approach. The results using Criminisi"s approach were not that promising whereas proposed algorithm achieved better results. The difference in the results occurred while searching for the best exemplar patch. In Criminis's approach, nothing is described about which patch to select if we get two patches with same minimum error. During our implementation of Criminis's algorithm, we assumed that we would choose the patch that was found earlier and got the results as shown. Using our approach, however, the best exemplar process was well defined and therefore it selected a better patch as shown in Figure 7.



(a) **(b)** **(c)**

Fig 7.Comparison with Criminisi's approach.

(a) Image to be inpainted, (b) Result using proposed algorithm, (c) Result using implementation of Criminisi's approach.

(a) **(b)**

(c)

Fig8.Comparison with Criminis's approach on givenImage

(a) Image to be inpainted (b) Result using proposed algorithm. (c) Result using implementation of Criminis's approach [12].

V. CONCLUSION AND FUTURE WORK

In this paper we have introduced a new inpainting framework which combines non-parametric patch sampling method with a super-resolution method. We first propose an extension of a well-known exemplar-based

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method (improvements are sparsity-based priority, K-coherence candidates and a similarity metric adapted from [6] and compare it to existing methods. Then, a super-resolution method is used to recover a high resolution version. This framework is interesting for different reasons. First the results obtained are within the state- of-the-art for a moderate complexity. Beyond this first point which demonstrates the effective-ness of the proposed method, this framework can be improved.

For instance, one interesting avenue of future work would be to perform several inpainting of the low-resolution images and to fuse them by using a global objective function.First, different kinds of inpainting methods (patch based or PDE-based) could be used to fill-inthe missing areas of a low-resolution image. Second, for a given inpainting method, one can envision to fill-in the missing areas by using different settings e.g. for the patch size in order tobetter handle a variety of textures and to better approach the texture element sizes.

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