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An Algorithm For Object Removal And Image Completion Using Exemplar-Based Image Inpainting

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Abstract—
A new method is proposed for removing large objects from digital images and filling up the hole by using background information in a visually plausible way. This problem tried to guess the leftover region from the remaining part of whole image. Previously, this problem is solved by two different methods 'Texture synthesis' method to fill large portion of image by using sample textures and 'Inpainting' technique for filling small gaps in image. This paper presents a robust algorithm that combines these two methods in a single, efficient manner. The main motto of Exemplar-based texture synthesis is to replicate both texture and structure and hence the success of this method is highly dependent on the order in which the feeling proceeds. This method is computationally efficient as we are using block-based sampling process instead of pixel-based one. This method works successfully on both real life and synthetic images. We get good results compare to those obtained by using existing technique.
Index Terms— Object removal, Image Inpainting, Exemplar, Image restoration, filling priority

I. INTRODUCTION

Object removal is a technique for removing large objects from digital image and filling the lacuna by using the left over portion of complete image. The goal is to produce a modified image in which the inpainted region is merged into the image so seamlessly that a typical viewer is not aware that any modification has occurred. Image Inpainting is the art of restoring lost portion of an image and reconstructing them. The term inpainting is derived from the ancient art of restoring images by professional image restorers in museums. The terminology 'Digital image inpainting' was firstly put forward at the international conference in Singapore in 2000.

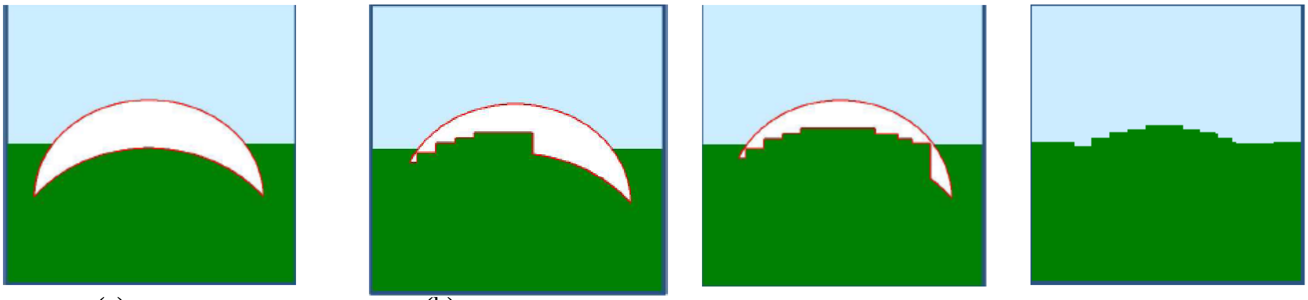
The problem can be solved by using three different methods. The first method is diffusion based inpainting which uses parametric models or partial differential equations (PDEs) for propagating local structures from known region to unknown region. This method works well for completion of lines, curves, and for recreating small regions. We cannot use this method to recover the texture of large areas as it

The second method is proposed by Efros and Leung [10]
which is based on image statistics and self-similarity priors. Here statistics of image textures are assumed to be homogeneous or stationary. The texture to be synthesized is sampled from similar regions in known part of the image. These samples that are used to copy is known as exemplars and the corresponding techniques are known as exemplar-based methods. This method synthesizes entire patches by learning from patches in the known part of the image. This method is faster than pixel-based approach since they synthesize entire patches at once.

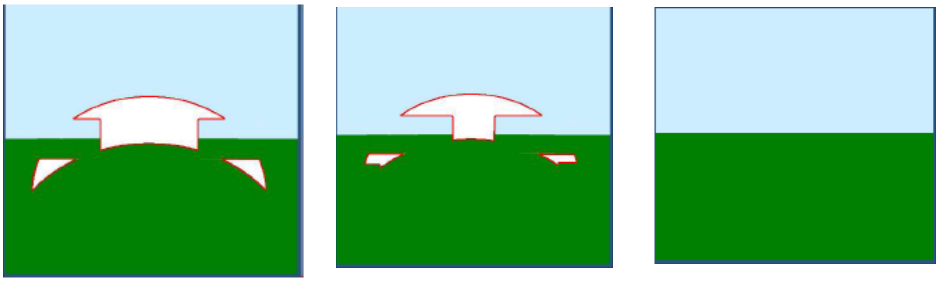
The third method uses sparse priors to solve the inpainting problem. In this case the image is considered as sparse in a given basis e.g. discrete cosine transforms (DCT) or wavelets. Exemplar-based and sparse based methods perform well than diffusion-based methods when we have to fill the large portion of image.

In previous work, two separate methods are used for object removal problem. Texture synthesis algorithm is used to reconstruct textures by repetitively coping two dimensional patterns with some stochasticity and inpainting method is used to complete linear structures which can be seen as one dimensional pattern such as horizontal lines in real world images. If we consider the region to be filled, pixel-based texture synthesis methods [8] reconstruct one pixel at a time. For a simple texture images, pixel-based texture synthesis algorithms always gives better result. But the serious problem of pixel-based texture synthesis algorithm is that it takes too much time for computation and it also cannot reconstruct the feature of structures properly. Hence patch-based texture synthesis algorithms are proposed to maintain the overall feature of texture [1]-[2].

The notion of digital image inpainting was firstly presented by Bertalmio et al [9] which uses third order Partial Differential Equations (PDE).This method recreates the missing regions by transferring information along the direction of isophote. One of the first attempts to use exemplar-based synthesis method to remove the large object from the given image was by Harrison [11]. Here level of "texturedness" of pixel's neighborhood is used for object removal. In past, many researchers used pure texture synthesis to remove the object



(a) (b)



(C)

Fig. 1 The importance of the filling order. (a) A figure showing an image and a selected target region is shown in white. (b) results obtained with onion peel strategy (c) desired results obtained by using edge-driven strategy. (ref.[2])

[3,4]. Among all methods Exemplar-based method is cheap and effective in generating new texture by sampling and copying color values from the source region. Though these methods are effective but they can't produce good results for real life images as it contains linear structures and highly composite textures. Method in [6] uses diffusion for propagating linear structures into target region. But this introduces blur which is dominated when we have to fill large regions.

The method presented in this paper combines the advantages of both approaches into a single and more efficient algorithm. Using inpainting, we pay special attention to linear structures.

II. THE IMPORTANCE OF THE FILLING ORDER

We know that exemplar-based filling is capable of propagating both texture and structure information. But the quality of the output image synthesis is highly influenced by the order in which the filling process proceeds. A comparison between the standard concentric filling strategy also known as onion peel strategy and desired filling behavior is shown in fig.1. The white portion in fig. 1(a) is selected as a target region which lies on the continuation of line. Fig. 1(b) shows the progressive filling of a concave target region using an anti-clockwise onion-peel strategy. We can easily see that ordering of the filled patches produces the horizontal boundary between the background image regions to be unexpectedly reconstructed as a curve. A concentric-layer strategy when used with patch-based filling produces further artifacts.

Fig. 1(c) shows the better filling algorithm where the patches on the continuation of the line are given higher priority and hence filled first. Hence using this method the horizontal line is reconstructed properly.

III. PROPOSED OBJECT REMOVAL ALGORITHM

First select the region to be removed from the entire image. The region to be filled is known as target region and the remaining portion of image is known as source region. Initialize confidence values of all pixels. It is 0 for pixels in the target region while 1 for pixels in source region. In next step find the boundary of target region.

A. Assigning patch priorities

The target region generally composed of textures & structures. For getting good results it is observed that these two

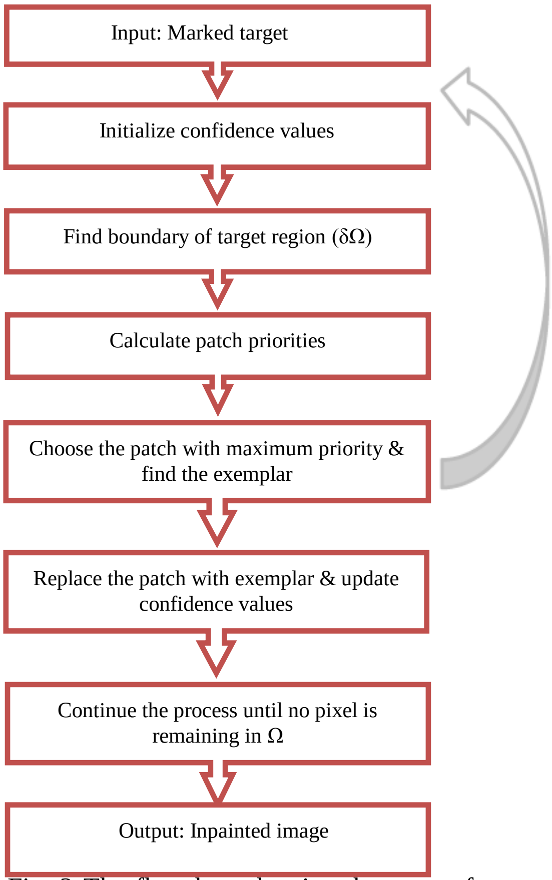


Fig. 2 The flowchart showing the steps of exemplar-based object removal algorithm

components should be separated and hence the structure should be recovered first.

This led to assign patch filling order which is given by product of two terms i.e. confidence term and data term. The confidence term gives the amount of known pixels versus unknowns in the given patch. Data term shows the presence of some structure in the patch.

Here we are using gradient-based data term which gives higher priority to those patches in which the isophote is perpendicular to the front line at a central pixel of given patch. Isophotes are line of constant intensity within an image. The data term is given by following equation

$$D(p) = \left| \frac{\nabla I_p^{\perp} . n_p}{\alpha} \right| \qquad (1)$$

Where $\nabla I_p^{\perp}$ the isophote at point p. n_p is a unit vector orthogonal to boundary at point p. $\perp$ denotes orthogonal operator. A is a normalization factor which is 255 for typical gray-level image. In this way calculate patch priorities for each and every patch on the boundary. Choose the patch with maximum priority and find the most appropriate exemplar to copy. These exemplars are obtained from source region by finding the distance between the given patch and all other patches from source region. There exist several metrics for measuring the similarity between images or between image patches. One of the available metrics to measure the similarity is pixel-based metrics measuring the similarity in terms of difference or cross-correlation between pixel color values. Another one is statistics-based metrics measuring the similarity between probability distributions of pixel color values in patches. In our algorithm we use sum of square difference (SSD) which is given by equation no. 3 as a similarity measure which is a most widely used pixel-based metric. Replace the patch with most similar exemplar and update the confidence value of that patch. Continue this process until there is no unfilled pixel in target region.

$$\Psi \hat{q} = \min_{\Psi q \in \phi} d(\Psi \hat{p}, \Psi q) \qquad (2)$$

$$\bar{d}_{SSD}(\Psi_p, \Psi_q) = \sum [(\bar{R}_{\Psi p} - \bar{R}_{\Psi q})^2 + (\bar{G}_{\Psi p} - \bar{G}_{\Psi q})^2 + (\bar{B}_{\Psi p} - \bar{B}_{\Psi q})^2] \quad (2)$$

Now let us consider the fig. 3 given below. It shows how the exemplar-based texture synthesis algorithm is use to propagate the structure from source region into target region. Hence in this manner we are going to reconstruct both structure and texture within target region without employing two ad-hoc strategies.

For easy understanding, we use similar notations as of inpainting literature. The target region is a region to be filled, and is denoted by Ω and its contour by δΩ .The contour proceeds inward as the algorithm progresses, and hence it is known as the “fill front”. The source region is denoted by ϕ_p which provides samples used in the filling process and remains fixed throughout the algorithm. Let us consider the single iteration of the algorithm to show how structure and texture are properly reconstructed by using only single method i.e. exemplar based synthesis method. Suppose that the square template ψ_p centered at the point p (fig. 1(b)), is to be filled. The best-match sample i.e. most similar patch is found from the source region by calculating sum of square differences (SSD).

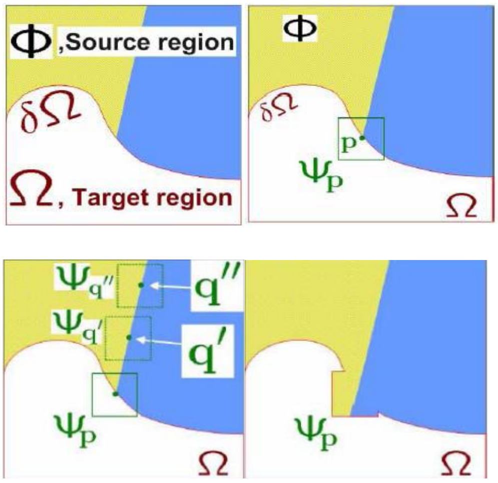


Fig.3 Structure propagation using Exemplar-based texture synthesis. (ref.[2])

From the example in fig. 1, we see that if ψ_p lies on the continuation of an image edge, the most similar best matches will lie along the same or a similarly colored edge. Hence the color values of most similar patch are copied to the respective positions of the target patch. In this manner both structure and texture properties of the image are preserved in newly inpainted region of the image.

IV. RESULTS

We propose an improved exemplar-based image inpainting method for removing objects in digital images. Here we apply our algorithm to standard color images and some real life images. Every time we use patch size as 5*5. The results that we obtained are given below. The bird flying in the sky is removed from fig. 4.we can easily see that the inpainted image is visually plausible which is our ultimate

aim of this algorithm. The middle boat in fig.5 occupies a large portion of image. We apply our algorithm to remove it and we get good result for removal of large region of image. One of the applications of exemplar-based method is structure completion. We obtain the results shown in Fig. 6 and 7 which proves the success of our algorithm. In fig. 4 the bird sitting on the horizontal wire is selected as a target region. As we can see from this figure the bird is removed but the wire gets completed which fullfill the connectivity principle. Hence the risk of “broken-structure” artefacts is eliminated.

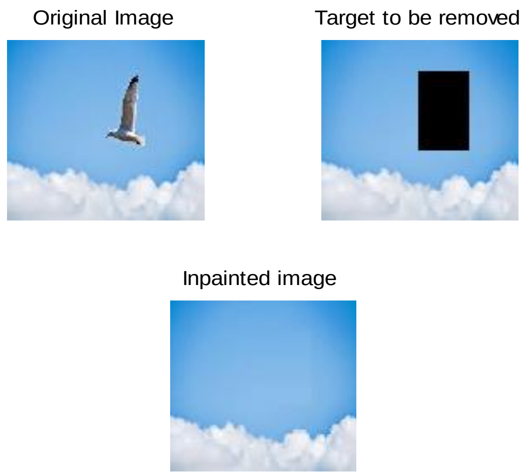


Fig.4 Inpainted image

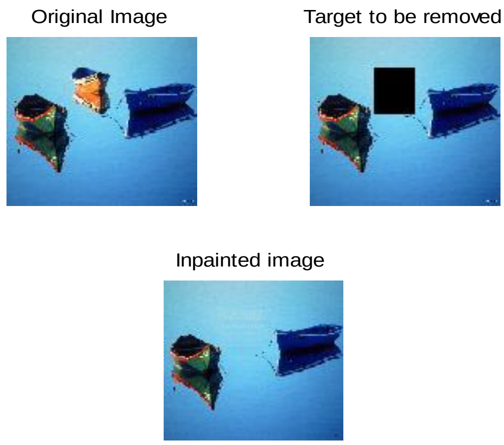


Fig. 5 Results showing object removal with large area

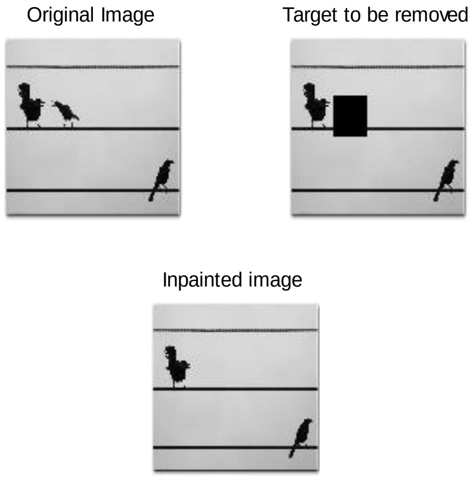


Fig. 6 Inpainted region showing structure completion

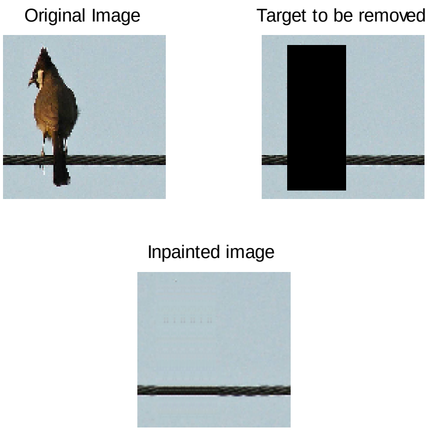


Fig. 7 Structure completion with large inpainting region

V. CONCLUSION

In the past few years Image inpainting has received a lot of attention. Different algorithms have been proposed having various applications in restoration, object removal, disocclusion, and in texture synthesis. This paper has presented a robust algorithm for removing large objects from digital photographs. The result is an inpainted image which looks so natural that the ordinary observer cannot find that any changes have been made in the image. Our method employs an Exemplar-based texture synthesis method to fill the hole created due to object removal. Determining the quality of inpainted images is another open and difficult issue as there is no quantitative metrics to judge the inpainted image. For most of inpainting applications, the ground truth is generally unknown. One has to rely on a subjective assessment to evaluate whether the inpainted images are visually plausible. Our method works well as compare to previous already existing methods. Computational efficiency is improved as we used block-based filling approach instead of pixel-based filling strategy.

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