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Exemplar Based Super-Resolution Technique for Image Inpainting: A Review

Abhijit L. Rakshase[1], S. N. Gite[2]

Department of Computer Science Engineering, M.S.S. College, Jalna, India [1]

Abstract: Image Inpainting is the process of reconstructing lost or deteriorated part of images based on the background 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 ofinpainting 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 retouchdamaged 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].

II. LITERATURE SURVEY

Existing methods can be classified into two main categories. The first category concernsdiffusion-based 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 [3]. 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 examplar-based techniques for object removal has been reportedin [5]. The authors in [6] improve the search for similar patches by introducing an a priori roughestimate 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 [7].

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 variational 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, which becomes noticeable when filling larger regions. All the PDE based in painting models are more suitable for completing small, non-textured target region.

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 neighbourhoods 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 [3]. All the earlier Inpainting techniques utilized these methods to fill the missing region by sampling and copying pixels from the neighbouring area. For e.g, Markov Random Field (MRF) is used to

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model the local distribution of the pixel. And new texture is synthesized by querying existing texture and finding all similar neighbourhoods. 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 [4].

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 [5]. This is done by propagating the information in the direction of minimal change using isophote 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 [1]. 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.

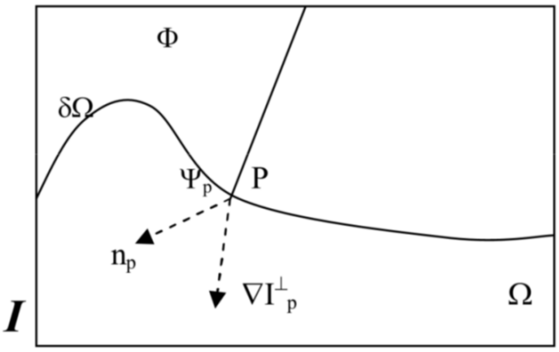
F. Sparse Representation Method

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. FRAMEWORK

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:

$$P(p)=C(p).D(p)$$



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-resolutioninpaintedareas in order to guide the texture synthesis at the higher resolution. As in

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[11], 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 3. It is computed on the HR picture with the sparsity-based method. The filling process starts with the patch Ψ_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 patchΨ_p^{HR}.

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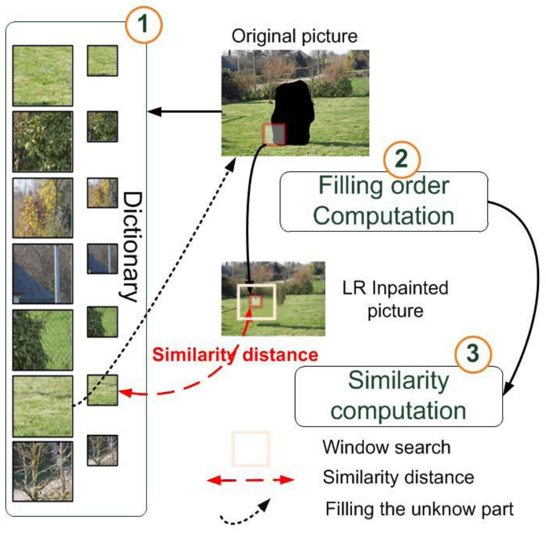

IV. CONCLUSION

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 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.

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