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A Novel Framework for Examplar-Based Inpainting

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KEYWORDS :

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ABSTRACT

In recent years inpainting has an important role in Humors, Entertainment and Improving aesthetic quality of images and video. This research introduces a novel framework for examplar-based inpainting. It can perform by inpainting on a rough version of the input image. A hierarchical super-resolution algorithm is used to recover 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. A data term is used to improve the patch propagation. Here also introducing a new coefficient β for propagating structure components accurately.A video can also be inpainted using this approach.

I. INTRODUCTION

In recent years inpainting has an important role in Humors, Entertainment and improving visual quality of images and video. Inpainting is the process of reconstructing lost or damaged parts of images and videos [1] .The Existing methods are classified into two categories, diffusion-based approaches and examplar-based methods. These two methods work well in repeatable or regular textures, and can be combined by using structure tensors to compute the patch priorities.

Current approach combines exampler based approach with super resolution. This is a two step process. First a raw version of the input picture is inpainted , second step is to create high resolution picture from the inpainted image. Enormous progress has been made in past years on examplar-based inpainting, that have some problems. The main challenge is related with the parameter settings such as the filling order and the patch size. The inpainting algorithm is applied on a coarse version of the input image. The proposed SR-aided inpainting method is a single-image SR.

In this approach, the image is inpainted at once, multiple inpainting can be possible but it is time consuming.

A new coefficient β is introduce here for propagating structure components accurately .An analysis study has been done between the two approaches of inpainting , i.e, with β coefficient and without β coefficient.

In summary, the proposed method improves quality of the images and video by proposing a new framework involving single image inpainting of the input picture followed by a single-image examplar-based SR method. The SR method is used only when the inpainting method is applied on a low resolution of the input picture.

The paper is structured as follows. Section II describes the related works .The III part gives a brief description of the proposed algorithm. Section IV describes the single image super-resolution method. Finally we conclude this work in Section V.

II RELATED WORKS

In [3] A novel and efficient algorithm for removing large objects from digital photographs is introduced. This algorithm combines the advantages of two approaches “texture synthesis” algorithms and “inpainting” techniques. Here an image, in which the selected object has been replaced by the surrounding regions. The advantage of this approach is that it preserves the edge sharpness. There is no dependency on image segmentation and there is a balanced region filling to avoid over- shooting artefacts. The limitation of this approach is that, the algorithm is not designed to handle curved structures and it does not handle depth ambiguities. In [4] it addresses the problem of generating a super resolution (SR) image from a single low-resolution input image. This problem can be viewed from the perspective of compressed sensing. The drawback of this approach is that the number of raw sample patches required generating a dictionary satisfying the sparse representation prior. The method proposed in [5] introduces a framework for single-image super-resolution. The idea is to learn a map from input low-resolution images to target high-resolution images based on example pairs of input and output images. Kernel ridge regression (KRR) is adopted for this purpose which reduces time complexity.The disadvantage of this approach is difficulty in artefact removal of JPEG encoded images. A novel patch propagation based inpainting algorithm is proposed in [6] which deals with scratch or text removal, object removal and missing block completion. The Two main concepts of sparsity is patch structure sparsity and patch representation .The advantage of this approach is that it can better infer the structures and textures of the missing region and produce sharp inpainting results consistent with the surrounding textures. The main limitation of this approach is that it does not deal with the sparsity of natural images at multiple scales and orientations and it does not incorporate with the human-labelled structures to recover the totally removed structures. The [6] proposes an algorithm that can remove objects from the image and also restores old photographs the limitation of this algorithm is that computational complexity is not reduced efficiently. The paper [8] suggested a novel approach toward single image super-resolution based on sparse representations in terms of high- low resolution image patch pairs.The main drawback of this paper is in difficulty to obtain high-low resolution image patch pairs. In [9] a novel inpainting algorithm is proposed it combines the advantages of PDE-based schemes and examplar-based approaches but it is not suitable for inhomogeneous textures, for which repetitions of structure are absent. The author in [10] suggests that digital inpainting is automatic filling of user-selected regions in digital images. It refers to removal of image defects, removal of disturbing objects and restoring the same with information surrounding them. But it depends on the size of the inpainting region. This approach can use only for small regions and also computation time is large.

III ALGORITHM OVERVIEW

This paper, propose a new inpainting framework relying on both the combination of low-resolution inpainting picture method and a single-image super-resolution algorithm. From the following section we can understood that why we using this method. The proposed method is consisting of two important and linear operations. The first operation is a non-parametric patch sampling method used to fill lost regions. The inpainting algorithm is applied on a raw version of the input image. A low-resolution picture represents its prominent structures of the scene. The low resolution images can better Inpainting on low resolution images than the high resolution one .The main reason for this is that, a low-resolution image is less corrupted by noise and is also composed by the main scene structures

.The local orientation singularities which could affect the filling order computation are strongly reduced. Second, the computational time is drastically reduced because of the low reolution image. The low-resolution picture is inpainted with different settings (patch's size, filling order, etc) to give more robustness. The second step which use the output of the first and improves the resolution and quality of the inpainted image into its original one. This can be done using a single image super resolution algorithm. Fig. 1 illustrates the main idea of the proposed method. They are:

1) A low-resolution image is first built from the original image;
2) An inpainting algorithm is applied to fill lost regions.
3) The visual relevance of the inpainted image can be improved using single image super resolution.

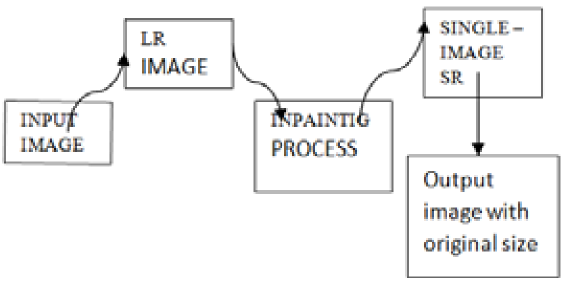

Fig.1.main concept

A) Examplar-Based Inpainting

This algorithm is based on patch propagation by inwardly propagating the image patches from source region into the core of the target region patch by patch [6].

The proposed examplar based inpainting consists two important steps: first step is to compute the priority of patches and second one is the texture synthesis.

1) Patch Priority: The presence of structure can be identified by using patch priority. A high priority indicates the presence of structure. The priority of a patch centered on *p***x** is calculated from a data and confidence term. Based on the data term, a tensor-based and a sparsity-based [11] data terms have been used. The proposed approach uses only sparsity –based data term.

The sparsity-based priority has been proposed recently by Xu et al. [6]. We use a graph-based segmentation algorithm [12].A segmentation is produced which is a set of properly refined regions through iterative merging process. A graph is refined as a segmentation map that provides relevant structural information of the input image. Segmentation maps are labeled with gray-scale value. The user selected region is represented using white. The appropriate parameter values that represent the features of each segment can be selected by applying difference of Gaussians (DoG) [13].

The priority function is the product of confidence term and data term.

$P_{(P)} = C_{(p)} . D_{(p)}$ ……………………(1)

Where p is center pixel of a patch. The priority decreased when the number of iterations increases due to the dropping effect. The dropping effect can be avoided in future work by using a β value in the data term.

To determine the weighting parameters DoG values is used in this approach. The data term is more important in propagating structure components. Structure components are propagating accurately with the help of a coefficient β in data term. The target image is a binary image, in which 0(black) indicates source region and 1(white) indicates target region.

In search window, a template matching is performed between the current patch and neighbouring patches that belong to the known part of the image. By using a non-local means approach a similarity weight *wp***x**,*p***j** (i.e. proportional to the similarity between the two patches centered on *p***x** and *p***j**) is computed for each pair of patches. The sparsity term is:

$$D(p_x) = \| w_{px} \| 2 \times \sqrt{\frac{|N_{s(px)}|}{|N_{(px)}|}} \quad \text{…………(2)}$$

Ns: the number of valid patches (having all its pixels known)

N: total number of candidates in the search window. If 2 is high, it means larger sparseness .The small value indicates that the current input patch is highly predictable by many candidates.

2) Texture Synthesis: The highest priority patches have the fill order priority. The unknown part of the selected patch can be filled using the most similar patch located in a local neighborhood *W* .A similarity metric is used for selecting the nearby patches. The selected similar patch maximizes the similarity between the known pixel values of the current patch to be filled in and nearby pixel values of patches belonging to *W*:

$$\varphi^*_{px} = \arg \min_{\varphi_{pj} \in w} d(\varphi^k_{px}, \varphi^k_{pj})$$

$$\text{s.t } Coh(\varphi^{uk}_{px}) < \zeta_{coh} \quad \text{………………(3)}$$

Where *d(.)*:weighted Bhattacharya [14]

Coh(.):coherence measure initially proposed by Wexler *et al.*[5]:

$$Coh(\varphi^{uk}_{px}) = \min_{pj \in s} (d_{SSD}(\varphi^k_{px}, \varphi^k_{pj})) \qquad (4)$$

Where *d*SSD : sum of square differences.

The coherence measure *Coh* indicates the degree of similarity between the unknown patch and original patches.It prevents pasting a texture into an unknown region that would be too different from original textures. If none of the candidates satisfy the constraints (3), the filling process is stopped and the priority of the current patch is decreased. The process restarts by selecting the next highest priority patch. To fill the missing region only best similar patches are used. A linear combination of the *K* most similar patches is generally performed to compute the patch .In these case the computed patch becomes

$$\varphi^*_{px} = \sum_1^k w_{px,pj} \times \varphi^k_{pj} \quad \text{…………. (5)}$$

Where *K* is the number of candidates which is chosen by locally. The similarity of chosen neighbors is in the range *(1+α)* ×*d*min, where *d*min is the distance between the current patch and its nearest neighbors. Different techniques can be used to compute the weights. For most of existing approaches, the patch size is chosen between 5 × 5, 7 × 7, 9 × 9 and 11 × 11. The filling order is computed by using the sparsity-based method.

original image

inpainted image(using β)

Original image

inpainted image(without β)

IV SUPER-RESOLUTION ALGORITHM

Once the process of inapinting on low resolution image is completed, a hierarchical single-image super resolution algorithm is used to reconstruct the high resolution of the input image. The single-image SR method is applied only when the input picture has been down sampled for the inpainting process. Finding a high resolution patch from the given example database is a difficult task.

The main idea to get the original resolution of the input image is illustrated bellow:

I) Building a Dictionary: Dictionary consist of low and high resolution patch pairs. The high-resolution patches have to be valid, this is one and only one constraint used here i.e. high resolution patches consist only known pixels. From the known parts of the image we can quote the high-resolution and valid patches .The dictionary size is a user-parameter which affects the overall speed and quality reciprocity. An array is used to store the spatial coordinates of HR patches (*DHR*). The LR patches can obtain by gathering he decimation factor equal to 2

II) Filling order of the HR picture: Filling order is computed on the High Resolution picture with the sparsity-based method [6]. The highest priority patches are filled priorly .The highest priority patches are composed of known and unknown parts. Compared to a raster-scan filling order, we can start with the structures and then to purview them.

III) Similarity computation: The highest priority low resolution and high resolution pairs the best matching inpainted images of lower resolution is found out. The search for the best match is performed in the dictionary and with in local neighbourhood. The dictionary contains only best matching samples. A high resolution patch can be obtained by deducing from the low resolution patch. The pixel values o f the HR patches are then pasted into the unknown parts of the current HR patch.

After filling of the current patch, the priority value is promulgated and the above-mentioned steps are repeated while there exist unknown areas.

The hierarchical SR method is applied. If the input picture of resolution *(X, Y)* has been down-sampled by four we should have to apply the SR algorithm twice: first to recover the resolution *(X/*2, *Y/*2) and second, to recover the original resolution.

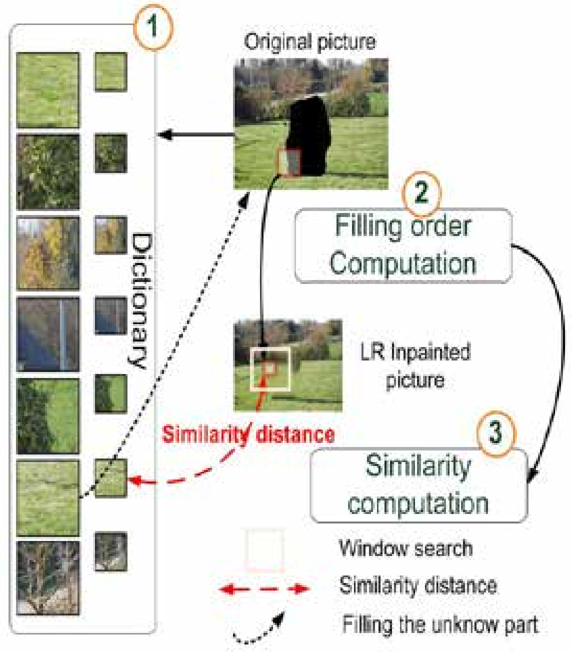

Fig.2. Flow chart of the super-resolution algorithm.

V CONCLUSION AND FUTURE WORK

A novel inpainting approach has been presented in this paper. The input picture is first down sampled.

The proposed approach uses a coarse version of the inpainted image and applying a single step inpainting. The inpainting algorithm works well in low resolution images. Here only a single step inpainting is performed, we can perform multiple inpainting steps with different configuration if necessary, but it is a time consuming task. The high resolution of the inpainted image can obtain by using single image super resolution. Some inbuilt dictionaries are used here. Here again using sparsity based method to compute the filling order priority. A new coefficient β is introduced for propagating structure components accurately. This approach can work well on video also. The damaged video can be inpainted frame by frame.

Simulation has been performed on a laptop with an Intel Core i3 2.40GHz and 4Go RAM. As the proposed approach is not multithreaded, it just uses one core. In addition, no optimization was made.

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