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HIERARCHICAL SUPER-RESOLUTION-BASED INPAINTING USING IMAGE PROCESSING.

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Abstract- This paper give the novel introduction of framework for exemplar-based inpainting. Firstly its perform the inpainting on a coarse version of the input image, then hierarchical super-resolution algorithm is used to recover details on the missing areas. It is easier to inpaint low-resolution pictures than high-resolution ones, Hence that is the advantages of this approach. 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 in painted several times by using different configurations. Results are efficiently combined with a 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: Diffusion, Computation, In painting, Exemplar Based, Super-resolution.

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INTRODUCTION

Image inpainting refers to methods which consist in filling in missing regions (holes) in an image . these methods can be classified into two main categories. The first is concerns diffusion-based approaches which propagate linear structures via diffusion based on partial differential equations as well as variational methods .It is known as isophotes. The diffusion-based methods tend to introduce some blur when the hole to be filled in is large. The second category is concerns exemplar-based methods which sample and copy best matching texture patches from the known image neighbourhood. These methods have been inspired from texture synthesis techniques, this are known to work well in cases of regular or repeatable textures. The authors in improve the search for similar patches by introducing an a priori rough estimate of the in painted values using a multi-scale approach which then results in an iterative approximation of the missing regions from coarse-to-fine levels. The two types of methods diffusion- and exemplar based can be efficiently combined by using structure tensors to compute the priority of the patches to be filled in as in. A recent approach combines an exemplar-based approach with super-resolution. It is a two-steps algorithm. First a coarse version of the input picture is in painted. 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 exemplar-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 similarly to. SR methods refer to the process of creating one enhanced resolution image from one or multiple input low resolution images. These problems are then referred to as single or multiple images SR, respectively. In both cases, the problem is of estimating high frequency details which are missing in the input image(s). The proposed SR-aided inpainting method falls within the context of single-image SR. The SR problem is ill-posed since multiple high-resolution images can produce the same low-resolution image. Solving the problem hence requires introducing some prior information. The prior information can be an energy functional defined on a class of images which is then used as a regularization term together with interpolation techniques. This prior information can also take the form of example images or of corresponding LR-HR (Low Resolution - High Resolution) pairs of patches learned from a set of un-related training images or from the input low resolution image itself. This latter family of approaches is known as exemplar-based SR methods. An exemplar-based super-resolution method embedding K nearest neighbors found in an external patch database has also been described. Instead of constructing the LR-HR pairs of patches from a set of un-related training images,the authors in extract these correspondences by searching for matches across different scales of a multi resolution pyramid constructed from the input low-resolution image. The proposed method builds upon the super-resolution based inpainting method proposed in which is based on exemplar-based inpainting like approach and single-image exemplar-based super-resolution. The main novelty of the proposed algorithm is the combination of multiple inpainted versions of the input picture. The rationale behind this approach is to cope with the sensitivity of exemplar-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 exemplar-based inpainting and SR methods are described such as the use of the coherence measure to constrain the candidate search.

III. SUPER-RESOLUTION ALGORITHM OVERVIEW

Image completion of large missing regions is a challenging task. As presented in the previous section, there are a number of solutions to tackle the inpainting problem. In this paper, 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 like patch's size, filling order. 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. Fig. 1 describes the main concept underlying the SR 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.

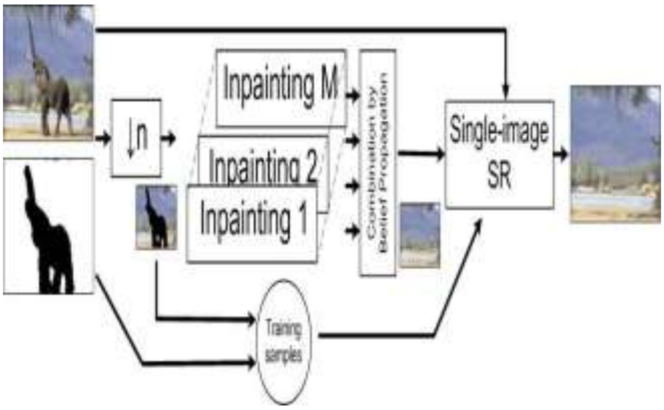

Fig. 1. The framework of the SR method.

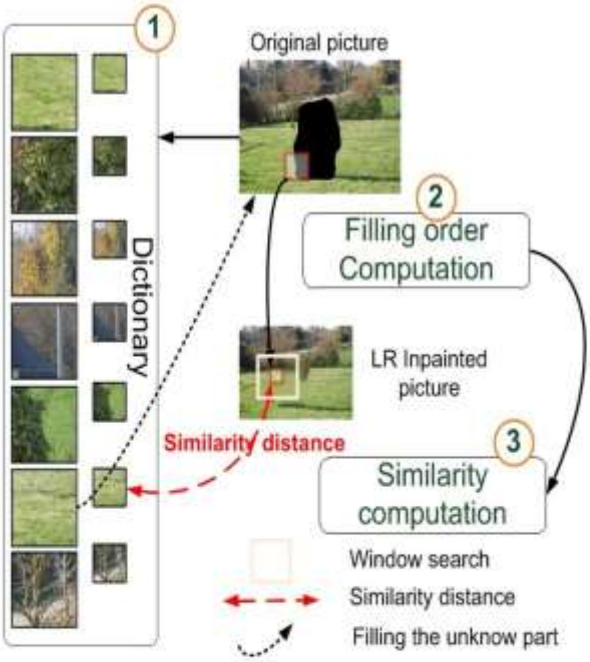

Fig.2. Flowchart of the super-resolution algorithm. (b)

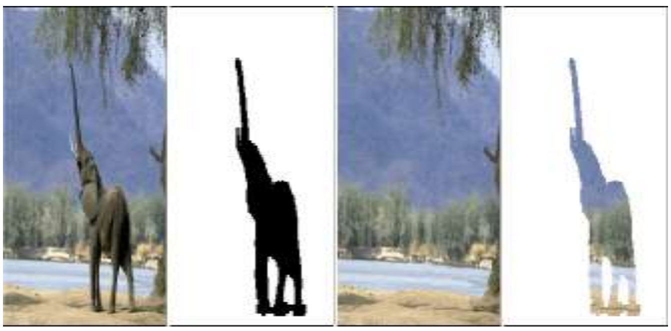

Fig. 3. Output of proposed method (SR based inpainting method)

IV. CONCLUSION

A novel inpainting approach has been presented in this paper. The input picture is first down sampled. then several inpaintings 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. One interesting avenue of future work would be to extend this approach to the temporal dimension. Also, we plan to test other SR methods to bring more robustness to the method. But the main important improvement is likely the use of geometric constraint and higher-level information such as scene semantics in order to improve the visual relevance.

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