SUPER RESOLUTION BASED INPAINTING

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ABSTRACT

This paper introduces a new exemplar-based in painting frame-work. A coarse version of the input image is first in painted by a non-parametric patch sampling. Compared to existing approaches, some improvements have been done (e.g. filling order computation, combination of K nearest neighbors). The in painted of a coarse version of the input image allows to reduce the computational complexity, to be less sensitive to noise and to work with the dominant orientations of image structures. From the low-resolution in painted image, a single-image super-resolution is applied to recover the details of missing areas.

Keywords -- Exemplar-Based In Painting, Super-Resolution

I. INTRODUCTION:

Image in painting refers to methods which consist in filling-in missing regions (holes). Existing methods can be classified into two main categories. The first category concerns diffusion-based approaches which propagate linear structures or level lines (so-called isotopes) via diffusion based on partial differential equations and vibrational methods. Unfortunately, the diffusion-based methods tend to introduce some blur when the hole to be filled-in is large. The second family of approaches concerns exemplar-based methods which sample and copy best matches texture patches from the known image neighbourhood. These methods have been inspired from texture synthesis techniques and are known to work well in cases of regular or repeatable textures. The first attempt to use exemplar-based techniques for object removal has been reported. Authors 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 combined efficiently, e.g. by using structure tensors to compute the priority of the patches to be filled.

Although tremendous progress has been made in the past years on in painting, difficulties remain when the hole to be filled is large and another critical aspect is the high computational time in general required. These two problems are here addressed by considering a hierarchical approach in which a lower resolution.

II. SUPER-RESOLUTION (SR)

Refers to the process of creating one enhanced resolution image from one or multiple input low resolution images. The two corresponding 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 in painting method falls within the context of single-image SR on which we thus focus in this section.

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 de-fined 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 corresponding LR-HR (Low Resolution - High Resolution) pairs of patches learnt from a set of un-related training images in an external database or from the input low resolution image itself. This latter family of approaches is known as example-based SR methods. An example-based SR method embedding K nearest neighbors found in an external patch database has also been described in . Instead of constructing the LR-HR pairs of patches from a set of un-related training images in an external database, 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.

III. METHODOLOGY

The method thus builds upon earlier work on exemplar-based in painting in particular on the approach, as well as upon earlier work on single-image exemplar-based super-resolution. However, since the quality of the low-resolution in painted image has a critical impact on the quality at the final resolution, the in painting algorithm is first improved by considering both a linear combination of K most similar patches (K-NN) to the input patch rather than using simply the best match by template matching and K-coherence candidates. The impact of different patch priority terms on the quality of the in painted images is also studied, leading to retain a sparsely-based priority term. In addition, a new similarity measure based on a weighted Bhattacharya distance is introduced. In a second step, the patches to be filled within the input HR image are processed according to a particular filling order. The algorithm thus proceeds by searching for K nearest neighbours to the input vector concatenating the known HR pixels of the patch and the pixels of the corresponding in painted LR patch. The K-NN patches are searched in a dictionary composed of LR-HR patches extracted from the known part of the image. since the inpainted HR patches are overlapping, a seam is searched throughout the overlapping region, and the initially overlapping patches are thus pasted along this seam.In summary, the proposed method further advances the state-of-the-art in exemplar-based in painting methods by proposing:

- A new framework which combines in painting and super-resolution in a two-step approach improving the trade-off between quality and complexity;
- Improvements concerning the use of priority terms, the set of candidates (K-NN and K-coherence candidates) and distance metrics.

A. 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 in painting problem. In this paper, we propose a new in painting method using a single-image SR 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.

B. MOTIVATIONS

This 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. However, rather than filling in missing regions at the original resolution, the in painting algorithm is applied on a coarse version of the input picture. There are several reasons for performing the in painting on a low-resolution image. First, the coarse version of the input picture could be compared to a gist representing dominant and important structures. Performing the in painting of this coarse version is much easier since the in painting would be less contingent on local singularities (local orientation for instance) or even noise. Second, as the picture to in paint is smaller than the original one, the computational time to in paint it is significantly reduced compared to the one necessary to in paint the full resolution image.

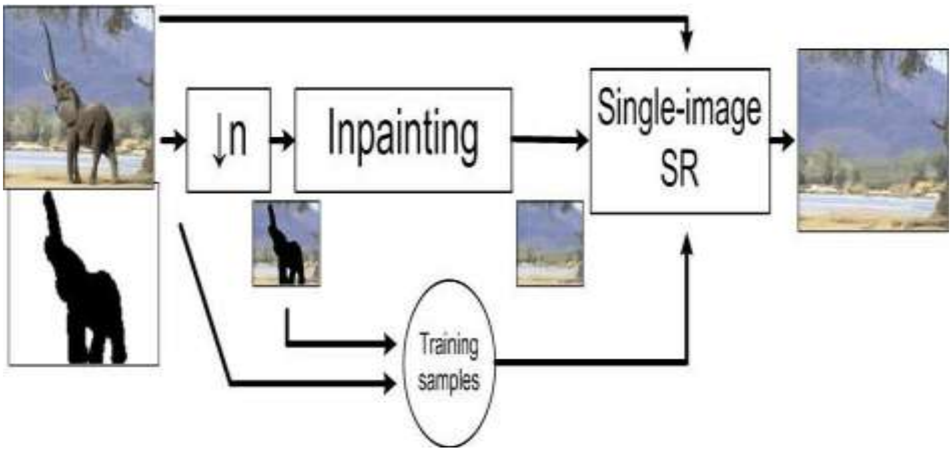

Fig 1. The Framework

This new method is generic since there is no constraint on both the number and the type of in painting methods used in the first pass. The better the in painting of low-resolution images, the better the final result should be. Regarding the number of methods, one could imagine using different settings (patch size, search windows etc.) or methods to fill-in the low-resolution images and to fuse results. We believe that it would increase the robustness and the visual relevance of in-painting. They have indeed shown that the best in painting results are obtained by a combination of three different methods. In this paper, due to the limited space

IV. PRINCIPLE

The main concept underlying the proposed method. The two main components are the in painting and the super-resolution algorithms. More specifically, the following steps are performed:

1. a low-resolution image is first built from the original picture;
2. An in painting algorithm is applied to fill-in the holes of the low-resolution picture.
3. The quality of the in painted regions is improved by using a single-image SR method.
4. Exemplar-based in painting of low-resolution images

This section presents the in painting method which is used in this paper to fill in the low-resolution images. This is an adaptation of the Criminisi et al method. The influence of different priority terms on the quality of the in painted images is first studied. A similarity metric based on a weighted Bhattacharya distance is proposed. The resulting in painting algorithm is compared against two state-of-the-art methods. The first one is also based on a non-parametric patch sampling whereas the second one is based on partial derivatives equations. We have chosen these two methods because of their relevance and because the code is available. The proposed exemplar-based method follows the two classical steps as described: the filling order computation and the texture synthesis. These are described in the next sections.

A. PATCH PRIORITY AND FILLING ORDER:

The filling order computation defines a measure of priority for each patch in order to distinguish the structures from the textures. Classically, a high priority indicates the presence of structure. The priority of a patch centered on p is just given by a data term. Three different data terms have been tested: gradient-based priority, tensor-based and sparsity-based.

The sparsity-based priority has been proposed recently by Xu et al. In a search window, a template matching is performed between the current patch ψ_p and neighbouring patches $\psi_{p,pj}$ that belong to the known part of the image. By using a non-local means approach, a similarity weight $w_{p,pj}$ (i.e. proportional to the similarity between the two patches centered on P and P_j) is computed for each pair of patches.

Fig 2. In painting of LR pictures with deferent gradient-based priority (first row), tensor-based priority(second row) and sparsity-based priority (third row).

The sparsity-based priority is more robust and visually improves the final result compared to the gradient and tensor-based priority. In the following, we adopt this method to compute the filling order.

B. TEXTURE SYNTHESIS

The filling process starts with the patch having the highest priority. Two sets of candidates are used to fill in the unknown part of the current patch. A first set is composed of the K most similar patches located in a local neighbourhood centered on the current patch. They are combined by using a non-local means approach.

A major problem of local neighbourhood search is its tendency to get stuck at a particular place in the sample image and to produce verbatim copying. This kind of regions is often called garbage region. This problem can be addressed by introducing some constraints in terms of spatial coherence. The idea is based on the fact that patches that are neighbours in the input image should be also neighbours in the output image.

Fig 3. K-Coherence Algorithm

C. OTHER STATE-OF-THE-ART METHODS

- Diffusion-based method: diffusion-based methods prop-agate the structures into missing regions.
- Patch Match: the Patch Match method is a fast algorithm for computing dense approximate nearest neighbour correspondences between patches of two image regions. This algorithm is available in Adobe Photoshop CS5 and works well. We will systematically compare our results to Patch Match ’ones.

Note that we have also tested a method called tensor completion. However, when the missing area is too large, the in painting quality is low. We then put aside this method.

V. SUPER-RESOLUTION ALGORITHM:

Once the in painting 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 in painted areas in order to guide the texture synthesis at the higher resolution; 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-parameter which might influence the overall speed/quality trade-off. An array is used to store the spatial coordinates of HR patches. 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 having the highest priority. This improves the quality of the in painted picture compared to a raster-scan filling order;

4. For the LR patch corresponding to the HR patch having the highest priority, its K-NN in the in painted images of lower resolution are sought. The number of neighbors is computed as described in the previous section. The similarity metric is also the same as previous;

5. Stitching: the HR patch is then pasted into the missing areas. However, as an overlap with the already synthesized areas is possible, a seam cutting the overlapped regions is determined to further enhance the patch blending. The minimum error boundary cut is used to find a seam for which the two patches match best. The similarity measure is the Euclidean distance between all pixel values in the overlapping region. More complex metrics have been tested but they do not substantially improve the final quality. At most four overlapping cases (Left, Right, Top and Bottom) can be encountered. There are sequentially treated in the aforementioned order. The stitching algorithm is only used when all pixel values in the overlapping region are known or already synthesized. Otherwise, the stitching is disabled.

6. After the filling of the current patch, priority value is recomputed and the afore-mentioned steps are iterated while there exist unknown areas.

VI. EXPERIMENTAL RESULTS

In order to assess the performance of the proposed approach, the parameters of the algorithm are kept constant for the tests presented in this paper.

A. IMPLEMENTATION DETAILS AND PARAMETERS:

Reproducible research: It is possible to reproduce results by using the executable software, the masks and pictures available on authors' web page. Parameters: Two versions of the proposed method are evaluated. One uses a down sampling factor of 4 in both directions (the patch size is equal to 5×5) whereas this factor is set to 2 for the second version (the patch size is equal to 7×7). For both versions, the size of the dictionary is the same and can contain at most 6000 patches evenly distributed over the picture. The LR patch size is 3×3 and the HR patch size is 15×15.

Line front feathering: in spite of the use of stitching method, the front line which is the border between known and unknown areas can still be visible. It is possible to hide this transition by feathering the pixel values across this seam. A Gaussian kernel is used to perform the filtering.

VII. CONCLUSION

In this paper we have introduced a new in painting 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 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 in painting of the low-resolution images and to fuse them by using a global objective func-tion. First, different kinds of inpainting methods (patch-based or PDE-based) could be used to fill-in the missing areas of a low-resolution image.

(a) Criminisi (b) PatchMatch (c) Proposed method

Fig 4. Comparison of the proposed method with state-of-the-art approaches: (a) Cri-minisi et al; (b) Patch Match; (c) proposed method (N = 4), (N = 2) .

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