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Removing Unwanted Objects From An Image Using Image Inpainting

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ABSTRACT

This project introduces a new examplar-based inpainting frame-work. A coarse version of the input image is first inpainted 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 inpainted 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 inpainted image, a single-image super-resolution is applied to recover the details of missing areas. Experimental results on natural images and texture synthesis demonstrate the effectiveness of the proposed method.

Keywords: **Exemplar-based; Image Inpainting; texture synthesis; object removal; region filling.**

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I. INTRODUCTION

This method is used for solving single-image super-resolution problems. Given a low resolution image as input, objective is to recover its high-resolution counterpart using a set of training examples. In a recent neighbor embedding method based on Semi-nonnegative Matrix Factorization (SNMF) only nonnegative weighs are considered. In LLE the weights are constrained to sum up to one, but no constraints are specified for their sign. This might explain the unstable results, since possible negative weights can lead to having subtractive combinations of patches, which is counterintuitive. This method is based on assumption that small patches in the low- and high-resolution images form manifolds with similar local geometry in two distinct spaces. In this method each low- or high-resolution image is represented as a set of small overlapping image patches. Each patch is represented by a feature vector. The feature may be contrast, correlation, entropy, variance, sum of average, sum of variance, homogeneity, variance of difference, sum of entropy, difference of entropy, change of luminance. Image inpainting refers to methods which consist in filling-in missing regions (holes) in an image. 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 isophotes) via diffusion based on partial differential equations and variation 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 neighborhood. These methods have been inspired from texture synthesis technique 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 in. Authors in improve the search for similar patches by introducing an a priori rough estimate of the inpainted 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 as in. Although tremendous progress has been made in the past years on inpainting, difficulties remain when the hole to be filled is large and other critical aspects the high computational time in general required. These two problems are here addressed by considering a hierarchical approach in which a lower resolution of the input image is first computed and inpainted using a K-NN (K Nearest Neighbors) examplar-based method. Correspondences between the K-NN low-resolution and high-resolution patches are first learnt from the input image and stored in a dictionary. These correspondences are then used to find the missing pixels at the higher resolution following some principles used in single-image superresolution methods. 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).

Image inpainting refers to methods which consist in filling-in missing regions. 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. However, rather than filling in missing regions at the original resolution, the inpainting algorithm is applied on a coarse version of the input picture. There are several reasons for performing the inpainting 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 inpainting of this coarse version is much easier since the inpainting would be less contingent on local singularities (local orientation for instance) or even noise. Second, as the picture to inpaint is smaller than the original one, the computational time to inpaint it is significantly reduced compared to the one necessary to inpaint the full resolution image. The proposed SR-aided inpainting 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. The proposed method thus builds upon earlier work on examplar-based inpainting in particular on the approach proposed in, as well as upon earlier work on single-image examplar-based super-resolution. However, since the quality of the low-resolution inpainted image has a critical impact on the quality at the final resolution, the inpainting algorithm in 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 as proposed in. The impact of different patch priority terms on the quality of the inpainted 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 neighbors to the input vector concatenating the known HR pixels of the patch and the pixels of the corresponding inpainted LR patch. The K-NN patches are searched in a dictionary composed of LR-HR patches extracted from the known part of the image.

II. BACKGROUND

1. 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 variation method and Partial Differential equation (PDE). The diffusionbased 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.

2. 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. 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. Then inspired by this work proposed the total variation (TV) inpainting model. 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.

3. Exemplar based Inpainting. The exemplar based approach is an important class of inpainting algorithms. 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.

4. 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 neighborhoods 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. All the earlier Inpainting techniques utilized these methods to fill the missing region by sampling and copying pixels from the

neighboring area. For e. g, Markov Random Field (MRF) is used to model the local distribution of the pixel. And new texture is synthesized by querying existing texture and finding all similar neighborhoods. 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.

5. Non-uniform Interpolation SR Technique The basis of non-uniform interpolation super-resolution techniques is the nonuniform sampling theory which allows for the reconstruction of functions from samples taken at non-uniformly distributed locations. Early super-resolution applications used detailed camera placement to allow for accurate interpolation, because this method requires very accurate registration between images. The advantage of this approach is that it takes relatively low computational load and makes real-time applications possible. However, in this approach, degradation models are limited they are only applicable when the blur and the noise characteristics are the same for all LR images.

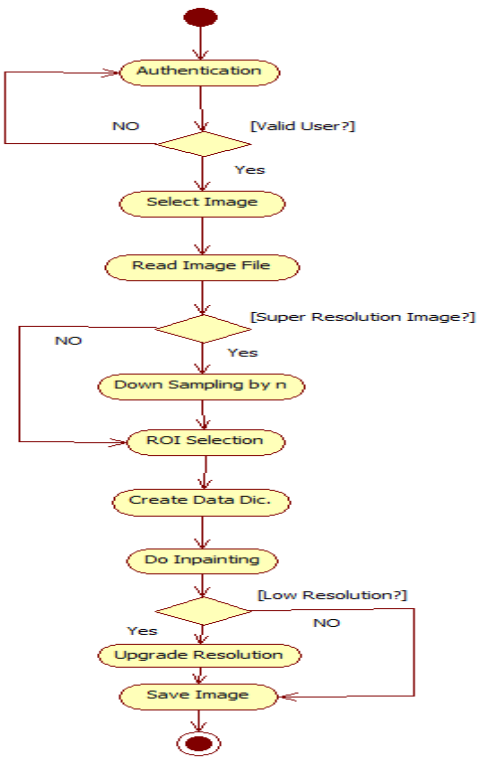

Fig 1. Flowchart of the fast and simple exemplar-based image inpainting algorithm

III. 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 (the confidence term proposed in is not used here since it does not bring about any improvement). Three different data terms have been tested: gradient-based priority, tensor-based and sparsely-based. In a search window, a template matching is performed between the current patch p and neighboring patches p, pj that belong to the known part of the image. By using a non-local means approach, a similarity weight wp,pj (i.e. proportional to the similarity between the two patches centered on p and pj) is computed for each pair of patches. The sparsity term is defined as: D(p) = ||ωp||2 ×s|Ns(p)| |N(p)| Where Ns and N represent the number of valid patches (having all its pixels known) and the total number of candidates in the search window. When kwpk2 is high, it means larger sparsity whereas a small value indicates that the current input patch can be efficiently predicted by many candidates.

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 neighborhood centered on the current patch. They are combined by using a non-local means approach. The weighting factors are classically defined as follows:

$$\omega p,pj = \exp(-d(\psi p,\psi p,pj)\ h)$$

Where d() is a metric indicating the similarity between patches, and h is a decay factor. These weights are then normalized as wp,pj /Pk wp,pk . The number of neighbors is adapted locally so that the similarity of chosen neighbors lies within a range, where dmin is the distance between the current patch and its closest neighbor, that is equal to 0.75. As mentioned by, a major problem of local neighborhood 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 neighbors in the input image should be also neighbors in the output image this process. With a 8-connexity neighborhood centered on the current patch(noted C on figure 3 a)), Ki patches are used as candidates and compared to the best candidate obtained by the local neighborhood search. show the influence of the k-coherence method on the quality of the low-resolution inpainted image. The use of k-coherence candidates improves locally the quality on many parts of the pictures. Concerning the similarity measure, we have considered two metrics: the classical Sum of Squared Differences (dSSD) and a weighted Bhattacharya distance as the one proposed in [16] (d(SSD,BC)). The last metric is defined as follows:

$$d(SSD)(\Psi P,\Psi P,Pj) = dSSD(\Psi P,\Psi P,Pj)\times(1 + dBC(\Psi P,\Psi P,Pj))$$

Where, dBC(p, p,pj) is a modified version of the classical Bhattacharya distance as described in

$$dBC(\Psi P,\Psi P,Pj) = q1-\Sigma kpp1(k)p2(k)$$

Where p1 and p2 represent the histograms of patches p, p,pj , respectively). This is not exactly the same formulation as in: indeed Bugeau et al. directly multiply the SSD distance with dBC. This presents a drawback: for two patches having the same distribution, no matter how the rotation the value dBC is null, leading to a null distance d(SSD,BC). With the proposed metric, the distance is equal to the SSD distance.

IV. RESULTS

V. CONCLUSION

The proposed method improves on the state of-the-art exemplar-based inpainting methods by proposing a new framework involving a combination of multiple inpainting versions of the input picture followed by a single-image exemplar-based SR method. As different methods of super-resolution have been developed using models with unequal assumptions of the existing problem, and because the results provided have been primarily based on subjective measurements, it is difficult to find an unbiased comparison on what super resolution methods are more appropriate for a given task.

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