Super Resolution Based Image Inpainting

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***Abstract*— A new algorithm is proposed for removing large objects from digital images. The challenge is to fill in the hole that is left behind in a visually plausible way. This has been addressed by two classes of algorithms one is the "inpainting algorithms" for filling in small image gaps, and second is the "super resolution" techniques" for creating one enhanced resolution image. This paper presents a novel and efficient algorithm that combines the advantages of these two approaches. We first note that exemplar-based texture synthesis contains the essential process required to replicate both texture and structure; the success of structure propagation, however, is highly dependent on the order in which the filling proceeds. We propose a best-first algorithm in which the confidence in the synthesized pixel values is propagated in a manner similar to the propagation of information in inpainting.**

***Index Terms*— exemplar-based inpainting framework, non parametric patch sampling.**

I. Introduction

Inpainting is the process of reconstructing lost or deteriorated parts of images or videos. Image inpainting consists in recovering the missing or corrupted parts of an image so that the reconstructed image looks natural. Image inpainting refers to methods which consist of filling-in missing regions (holes) in an image.

The first category concerns diffusion-based approaches which propagate linear structures or level lines (so-called isophotes) via diffusion based on partial differential equations[1], [2] and variational methods [3]. The diffusion based methods tend to introduce some blur when the hole to be filled in is large. The second family of approaches concerns examplar-based methods which sample and copy best matching texture patches from the known image neighbourhood [4]. These methods have been inspired from texture synthesis techniques [8] and are known to work well in cases of regular or repeatable textures. The first attempt to use examplar-based techniques for object removal has been reported in [6].The two types of methods (diffusion- and examplar based) can be efficiently combined, e.g. by using structure gradient to compute the priority of the patches to be filled. A recent approach [10] combines an examplar based approach with super-resolution. It is a two-steps algorithm. First a coarse version of the input picture is inpainted. 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 examplar-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 .

First method is the inpainting algorithm. Consider a region in the image to be inpainted. Algorithm starts from the boundary of this region and goes inside the region gradually filling everything in the boundary first. It takes a small neighbourhood around the pixel on the neighbourhood to be inpainted. This pixel is replaced by normalized weighted sum of all the known pixels in the neighbourhood. Selection of the weights is an important matter. More weight age is given to those pixels lying near to the point, near to the normal of the boundary and those lying on the boundary contours. Once a pixel is inpainted, it moves to next nearest pixel using weighted Battacharya Method. This ensures those pixels near the known pixels are inpainted first.

Super-Resolution (SR) is a class of techniques which refers to the process of creating one enhanced resolution image from one or multiple input low resolution images in an imaging system. 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 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 examplar based SR methods. An examplar-based super-resolution method embedding K nearest neighbours 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, extract these correspondences by searching for matches across different scales of a multi-resolution pyramid constructed from the input low resolution image.

There are many objectives and applications of inapaiting techniques. In photography and cinema, inpainting is used for restoration, to reverse the deterioration (e.g., cracks in photographs or scratches and dust spots in film) .It is also used for removing red-eye, the stamped date from photographs and removing objects to creative effect.

II. METHODOLOGY

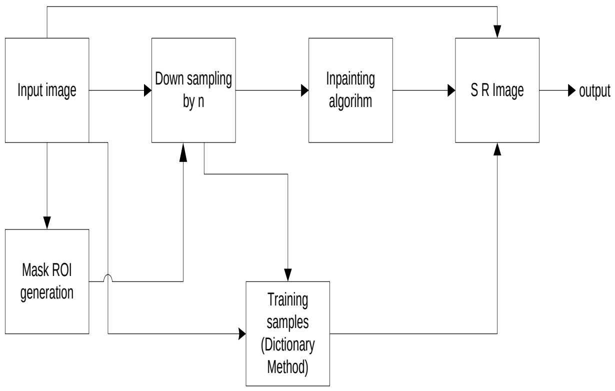

Figure 1: Block Diagram of the Proposed System

Figure1 illustrates the main concept underlying the proposed method. The two main components are the inpainting 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 inpainting algorithm is applied to fill-in the holes of the low-resolution picture;
3. The quality of the inpainted regions is improved by using a single-image SR method.

The features used in this system are described as follows:

A. Image Inpaintng

In painting is the process of reconstructing lost or deteriorated parts of images and videos. For instance, in the museum world, in the case of a valuable painting, this task would be carried out by a skilled art conservator or art restorer. In the digital world, in painting refers to the application of sophisticated algorithms to replace lost or corrupted parts of the image data.

B. Region of Interest

A region of interest (ROI) is a selected subset of samples within a dataset identified for a particular purpose. For example: on a waveform (1D dataset), a time or frequency interval, on an image (2D dataset), the boundaries of an object etc. A ROI is a specification structure that allows for the definition of arbitrarily shaped regions within a given image, often called sub images (although a ROI can encompass the entire image if so defined). A ROI contains no image data. It is not an image itself, but a place holder that remembers a defined location within an image. ROIs can be irregular shapes, not necessarily the rectangle or square that our camera supplies. ROIs can be rectangles or squares (a square is often called an area of interest, or AOI), circles, annuluses, polygons and freehand shapes. Secondly, we may want to perform different image processing routines on different areas of an image, when we are only interested in a few small parts of it. Another reason for ROIs is that we can dynamically define and change them. We can draw a ROI over a portion of an image at run time, selecting their particular region of interest.

C. Down sampling

Down sampling is the process of reducing the sampling rate of a signal. This is usually done to reduce the data rate or the size of the data. The down sampling factor is usually an integer or a rational fraction greater than unity. This factor multiplies the sampling time or, equivalently, divides the sampling rate. The down sampled value is 4. (M=4)

Down sampling by an integer factor, M can be explained as a 2-step process, with an equivalent implementation that is more efficient:

- Reduce high-frequency components with a digital low pass filter.
- Decimate the output sequence, keeping only every M^{th} output sample.

Decimation causes high-frequency signal components to be misinterpreted by subsequent users of the data, which is a form of distortion called aliasing. The first step, if necessary, is to suppress such components to an acceptable level of distortion. In this application, the filter is called an anti-aliasing filter.

D. Image restoration

Image restoration is the operation of taking a corrupted/noisy image and estimating the clean original image. Corruption may come in many forms such as motion blur, noise, and camera miss focus.

E. Super Resolution

Super resolution (SR) is a class of techniques that enhance the resolution of an imaging system. In some SR techniques—termed optical SR—the diffraction limit of systems is transcended, while in others—geometrical SR—the resolution of digital imaging sensors is enhanced.

F. 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.

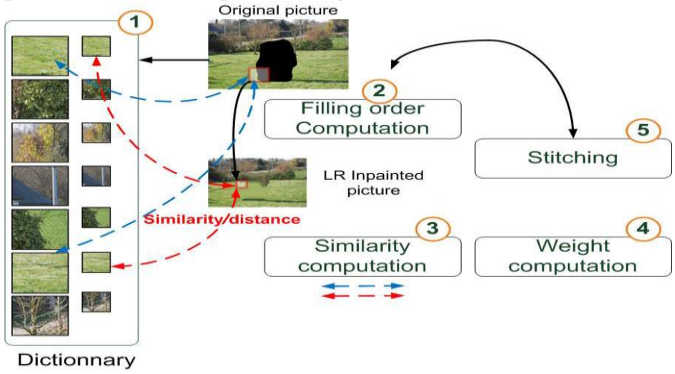

Figure 2: Flowchart of the super-resolution algorithm. The missing parts of the red block is filled by a linear combination of K HR-candidates (green arrows). The weights are computed using the similarity distance between LR and HR patches (green and red arrows, respectively). The top image represents the original image with the missing areas whereas the bottom one is the result of the low-resolution inpainting.

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 (DHR). 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 earlier. It is computed on the HR picture with the gradient-based method. The filling process starts with the patch having the highest priority. This improves the quality of the in painted picture compared to a raster-scan filling order;
3. 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 neighbours is computed using the nearest neighbouring pixels.
4. Weights w_p, p_j are calculated by using a non-local means method as if we would like to perform a linear combination of these neighbours. However, the similarity distance used to compute the weights is composed of two terms: the first one is classical since this is the distance between the current LR patch and its LR neighbours. The second term is the distance between the known parts of the HR patch HRp and the HR patches corresponding to the LR neighbours of LRp. Say differently, the similarity distance is the distance between two vectors composed of both pixels of LR and HR patches. The use of pixel values of HR patches allows to constraint the nearest neighbour search of LR patches.
5. A HR candidate is finally deduced by using a linear combination of HR patches with the weights previously computed

$$\psi_p^{HR} = \sum_{p_j \in \mathcal{D}^{HR}} w_{p,p_j} \times \psi_{p,p_j}$$

6. 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.

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

G. Masking of region

The basic idea is simple. We are going to choose an area which are completely connected components, inside region we will fill that with 0's and that region we will call as mask region. Selection of mask can be random or regular. In random selection based we are creating how the object shape is and there by seeing that we will create that area. In matlab if we do this masking there is one function called as getpixel. In this it will start to pick the pixel co ordinates and then at last one closed loop will be formed and then that closed loop inner part we will fill with 0's then we will get a mask region then that region we will start filling and for this we want gradient direction.

H. Image Gradient calculation

An image gradient is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images. Image gradients can be used to extract information from images. Gradient images are created from the original image (generally by convolving with a filter, one of the simplest being the Sobel filter) for this purpose. Each pixel of a gradient image measures the change in intensity of that same point in the original image, in a given direction. To get the full range of direction, gradient images in the x and y directions are computed. One of the most common uses is in edge detection. After gradient images have been computed, pixels with large gradient values become possible edge pixels. The pixels with the largest gradient values in the direction of the gradient become edge pixels, and edges may be traced in the direction perpendicular to the gradient direction. One example of an edge detection algorithm that uses gradients is the Canny edge detector.

Image gradients can also be used for robust feature and texture matching. Different lighting or camera properties can cause two images of the same scene to have drastically different pixel values. This can cause matching algorithms to fail to match very similar or identical features. One way to solve this is to compute texture or feature signatures based on gradient images computed from the original images. These gradients are less susceptible to lighting and camera changes, so matching errors are reduced.

The gradient of an image is given by the formula :

$$\nabla f = \frac{\partial f}{\partial x}\hat{x} + \frac{\partial f}{\partial y}\hat{y}$$

where :

$\frac{\partial f}{\partial x}$ is the gradient in the x direction.

$\frac{\partial f}{\partial y}$ is the gradient in the y direction.

$x^{\wedge}$ and $y^{\wedge}$ represent the number of valid patches.

The gradient direction can be calculated by the formula :

$$\theta = \operatorname{atan2}\left(\frac{\partial f}{\partial y}, \frac{\partial f}{\partial x}\right).$$

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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 [4] 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 inpainted images is also studied, leading to retain a gradient based priority term. In addition, a new similarity measure based on a weighted Battacharya 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. The similarity metric is again the weighted Battacharya metric. Similarity weights are also computed between the input and K-NN vectors formed by the LR and known pixels of the HR patches. Finally, 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 examplar- based inpainting methods by proposing a new framework which combines inpainting and super-resolution in a two step approach improving the trade-off between quality and complexity and improvements concerning the use of priority terms, the set of candidates (K-NN and K-coherence candidates) and distance metrics.

J. 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 [4] 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 sparsity-based. The sparsity-based priority has been proposed recently by Xu et al. [9]. 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 [8], a similarity weight w_p,p_j (i.e. proportional to the similarity between the two patches centered on p and p_j) is computed for each pair of patches. In this project the gradient based priority method is used.

K. 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 neighborhood centered on the current patch. They are combined by using a non-local means approach [8]. The weighting factors are classically defined as follows: $w_{p,pj}$=exp(-d($\psi_{p,}\psi_{p,pj}$))

$$w_{p,p_j} = exp\left(-\frac{d(\psi_p, \psi_{p,p_j})}{h}\right)$$

where d($\psi_{p,}\psi_{p,pj}$)) is a metric indicating the similarity between patches, and h is a decay factor. The number of neighbors is adapted locally so that the similarity of chosen neighbors lies within a range (1 + α) × d_{min}, where d_{min} is the distance between the current patch and its closest neighbour, α is equal to 0.75.

III. 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) (b) (c) (d)

Figure 3: (a) low-resolution pictures with missing areas in black; (b) Criminisi et al.'s results; (c) Patch Match results; (d) Gradient -based results and Proposed method (the down sampling factor is set to n = 4; patch size is 11×11).

IV. CONCLUSION

In this paper I 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 gradient-based priority, K-coherence candidates and a similarity metric 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 effectiveness of the proposed method, this framework can be improved. For instance, one interesting avenue of future work would be to perform several inpainting of the low-resolution images and to fuse them by using a global objective function. 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. Second, for a given inpainting method, one can envision to fill-in the missing areas by using different settings e.g. for the patch size in order to better handle a variety of textures and to better approach the texture element sizes. Finally, we believe that the proposed framework will be appropriate for video completion. This application is indeed very time-consuming. The use of the proposed framework could dramatically reduce the computational time.

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