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Processing an Image using Inpainting and Super-Resolution Algorithm

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Abstract **–A coarse version of the input image is first inpainted by a non-parametric patch sampling. This inpainting process allows to reduce the computational complexity, to be less sensitive to noise and to work with the dominant orientation of image structure. After the process of inpainting a single-image super-resolution algorithm is applied to recover the details of missing areas.**

Index Terms – inpainting, single-image super resolution.

I. INTRODUCTION

The missing region in an image is filled by using a method called image Inpainting . The lower resolution image is first inpainted and then it is again inpainted using a K-NN(K Nearest Neighbours)examplar-based methods. This will be helpful to fill the holes in the image when the hole to be filled is large and the high computational time is also reduced. Correspondences between the K-NN low- resolution and high-resolution patches are first learnt from the input image and stored in a dictionary. This is used to find the missing pixel at the higher resolution image.

An enhanced resolution image is created from one or multiple input low resolution image is done by a process known as Super-Resolution.

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 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 neighbours found in an external patch database has also been described in.

II. ALGORITHM OVERVIEW

A. SR Algorithm

A new image inpainting method using the super-resolution algorithm is used for the retrieval of the image.

B. Motivations

Two major operations are used as a motivation. They are non-parametric patch sampling method and the inpainting method. The non-parametric patch sampling is used to fill in the missing region. Rather than the non-parametric patch sampling method the inpainting algorithm is also done in order to fill the missing region more accurately. The inpainting method is easy to perform and it is less contingent on local singularities or even noise. As the image to inpaint is smaller than the original one, the computational time si reduced.

C. Principle

The two main components are:

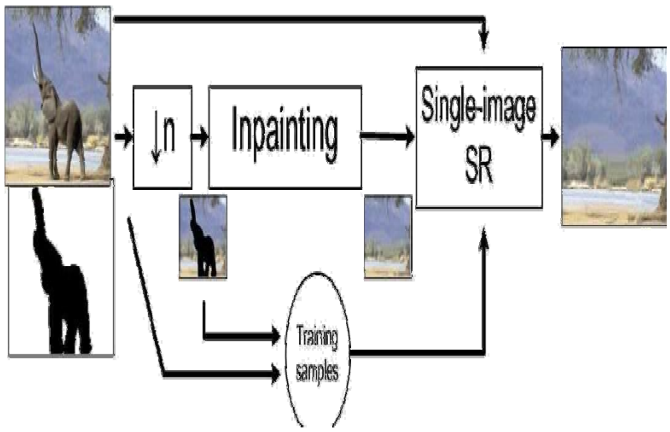
1. Inpainting
2. Super-Resolution Algorithm

The below steps are followed:

1. A low resolution image is built from the original picture.
2. To fill the holes in the low resolution image inpainting method is adopted.
3. Single-image Super-Resolution algorithm is applied to improve the quality of the inpainted region.

D. Framework

The framework explains that the image is cropped and then the image is converted into a low resolution image. After that the inpainting method is being implemented on the low resolution image. Then the single image super-resolution algorithm is applied which will increase the quality of the image. By applying the single image super resolution algorithm the image is again converted into the high resolution image. The training samples are also taken in order to check whether the holes in the images is filled or not.This framework can be illustrated with the help of the diagram as follows:



III. EXAMPLAR-BASED INPAINTING

The examplar-based method follows two classical steps as follows

1. Filling Order computation
2. Texture synthesis

The filling order computation defines a measure of priority for each patch in order to distinguish the structures from the textures. The priority of a patch centered on *p* is just given by a data term.

Three different data terms have been tested:

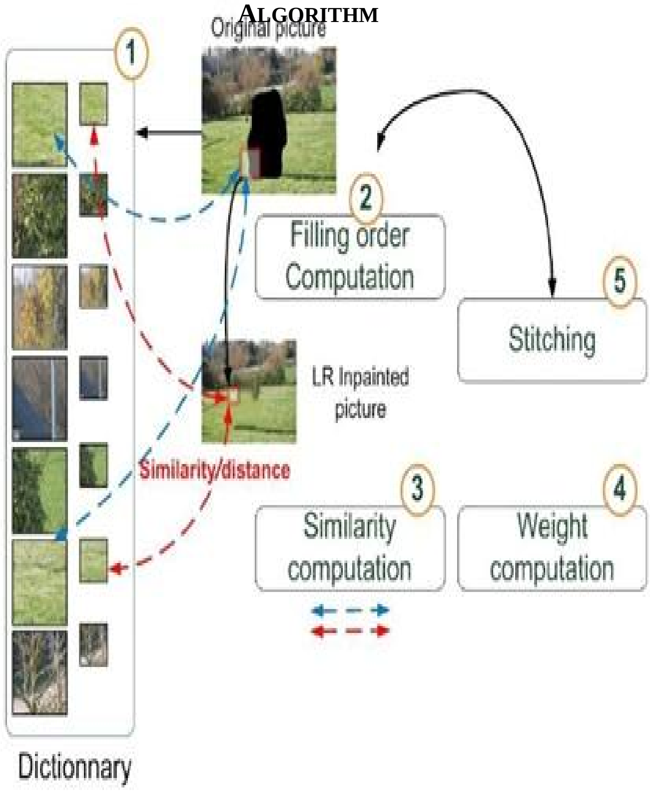
1. gradient-based priority
2. tensor-based
3. sparsity-based

In search window, a template matching is performed between the current patch $\square_p$ and neighboring patches $\square_{p,p_j}$ that belong to the known part of the image. By using a non-local means approach a similarly weight w_{p,p_j} is computed for each pair of patches. The sparsity term is defined as:

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

In texture synthesis, the filling process starts with the patch having the higher priority. Two sets of candidates are used to fill in the unknown part of current patch. A first set is composed of K most similar patches located in a local neighborhood centered on the current patch. They are combined by using non-local means approach. The weighting factor is defined as follows:

IV. FLOW CHART OF THE SUPER-RESOLUTION ALGORITHM



V. SUPER RESOLUTION ALGORITHM

After the process of inpainting a low resolution image, the single-image super-resolution algorithm is used to reconstruct the high resolution. The texture synthesis at the higher resolution is guided by the use of the low resolution inpainted areas.

The main steps involved are:

1. Dictionary building: It consists of the correspondence between the low and high resolution image patches. The 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 influence the overall speed/quality trade-off.
2. Filling order of HR image: It is computed by using the sparsity-based method. This improves the quality of the inpainted image compared to other techniques.
3. The case that deals with the LR patch corresponding to the HR patch having the highest priority, its K-NN in the inpainted image of LR are sought.
4. Weight are calculate by using the non-local methods. The distance is used to compute the weight and it is composed of two terms
   a) Patch and its LR neighbors
   b) Distance between the known parts to the HR
5. The Hr image is deduced by linear combination of HR patches with weights previously computed.
6. Stitching: The HR patch is finally placed in the missing area.
7.

VI. EXPERIMENTAL RESULTS

The experimental results provides the following details about the implementation and parameters:

1. Reproducible research
2. Parameters
3. Line front feathering

By using the executable software it is possible to reproduce the results.

The dictionary size is same for the two versions available. It can cotain 6000 patches evenly distributed over the image.

The line front method is used to hide the border between the known and the unknown visible areas. This is done by feathering the pixel value across the steam.

VI. CONCLUSION

We introduce a framework in which the cropped image is inpainted to low resolution image and the super-resolution algorithm is applies in order to convert it again into a high resolution image. The inpainting method will fill the holes that are present in the cropped region and the super-resolution algorithm will add quality to the image.

After the process of applying the algorithm, the stitching process is done to fill the cropped region with the SR image. After the stitching process the line front feathering is done in order to make the stitches perfect.

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