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A Review on Super Resolution Based In painting

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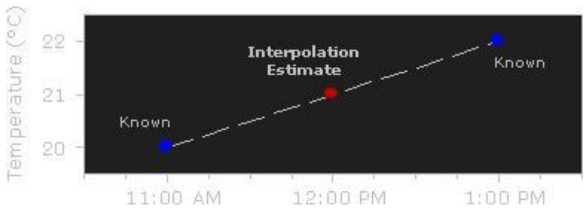
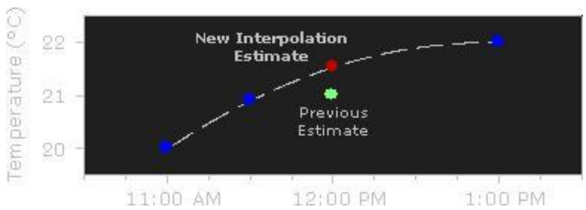
Abstract- In this Paper, We study about Image interpolation technique and its applications. It is a technique of filling the gaps in an image. There are two types of algorithms available in web market. We had made some improvements to Exemplar based inpainting technique so as to overcome drawbacks such as computational complexity, noise and image structure. The Existing method introduces blur while in case of filling large holes and the advantage of proposed one can fill it without causing blur. First, we input an image which to be restored for some detail then to select the required region and now a single super resolution image is formed by sampling then with a series of low resolution image, it fills the required hole. Experimental results demonstrate the effectiveness of the proposed method.

Keywords- Inpainting, Interpolation, Exemplar based, Super-resolution, image hole, gap, Low resolution, Sampling.

INTRODUCTION Image Inpainting refers to image interpolation used for restoring images. First introduced for filling the cracks and scratches in the valuable arts and to replace lost details but now the technique has extended to object removal, text removal and other modifications of images and also to videos. Since the wide applications of digital camera and the digitalization of old photos, inpainting has become an automatic process, which is operated on digital images by means of external software. It happens anytime as we resize or remap an image from one pixel grid to another. Image resizing is necessary when we need to increase or decrease the total number of pixels, whereas remapping can occur under a wider variety of scenarios like correcting for lens distortion, changing perspective and rotating an image. Interpolation
works by using known data to estimate values at unknown points. The important attribute of the Super Resolution algorithm is to modify the damaged region in an image in such a way that the inpainted region is undetectable to the ordinary observers who are not familiar with the original image. For instance, if we wanted to know the temperature at noon, but only measured it At 11am and 1pm, we could estimate its value by performing a linear interpolation.



If we had an additional measurement at 11:30am.



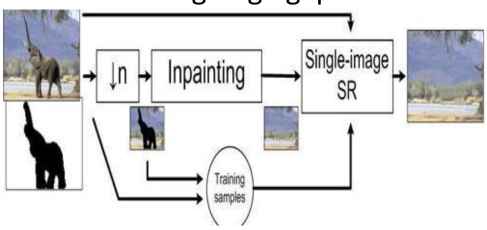
II. EXISTING WORK

Existing methods can be classified into two main categories. The first category concerns diffusion-based approaches which propagate linear structure by partial differential equations and variation

methods. In this approach missing region is filled by diffusing the image information from the known region into the missing region at the pixel level. This algorithm produces superb results on filling the non-textured or relatively smaller missing region. But 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 the image and copy the best matching texture patches from the known image neighborhood. They have proved to be very effective. 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. These methods have been inspired from texture synthesis techniques and are known to work well in cases of regular or repeatable textures.

III. PROPOSED SYSTEM

A low-resolution image is first built from the original picture. An inpainting algorithm is applied to fill-in the holes of the low-resolution picture. The Unknown pixels are calculated by using bilateral method. It takes known pixel values of its surrounding and then finding an average. By this way it calculates the unknown intensity. Now with those pixels, again it resizes to high resolution with same technique. The quality of the in-painted regions is improved by using a single-image SR method. The Resultant image will be built on same inputted resolution. This Model is more efficient than the existing algorithm and also less computational. Since it is subjective, differences can be visible or invisible in some cases. This is well suited for filling large gap.



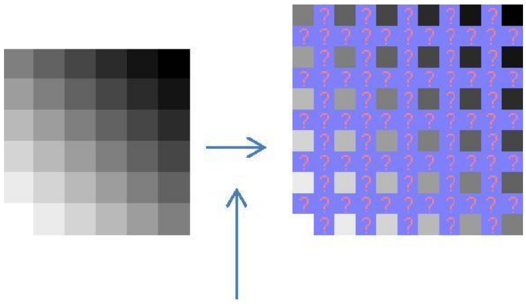
IV. RELATED CONCEPTS

Image InPainting-In painting is the process of reconstructing lost or deteriorated parts of images and videos.

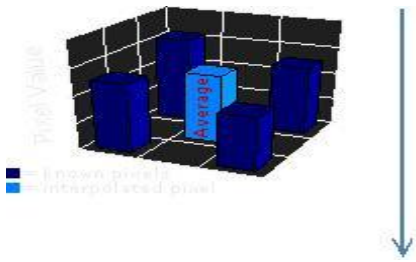
Image Restoration-Image restoration is the operation of taking a corrupted/noisy image and estimating the clean original image.

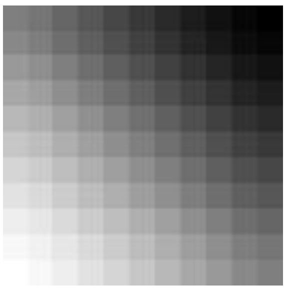
Super Resolution-Super resolution (SR) is a class of techniques that enhance the resolution of the image.

V. VISUAL REPRESENTATION



Input Image **Single LR Image**





Single HR Image

VI. Super Resolution Algorithm

A. Dictionary Building:

A series of low and high resolution image patches are stacked. A dimensional array has been used to store the patch Information. With unique constraint and priority, it predicts its validity. The Size influences the speed and accuracy of image. An array is used to store the spatial

coordinates of HR patches.

Consider it as input image

Inpainting

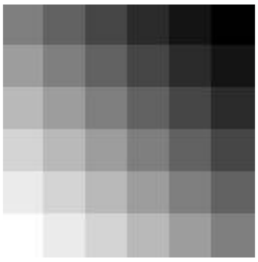


Image Restored

B. Patch Priority and filling order

Once dictionary of patches from both low and high resolution is formed, labeling the patch with priority initiated. The Computation takes with the highest patch priority.

There are three types of data terms available.
Gradient Based priority
Tensor Based priority
Sparsity Based priority

We prefer Sparsity based priority as it has proved visible difference than the other two. The matching is performed between the current patch and neighbor. It centers the similarities of current patch with the neighbor. The Sparsity term is defined as:

$D(p) = ||wp||_2 \times$ ——

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 $|| W_p ||_2$

Is high, it means larger Sparsity whereas a small value indicates that the current

Input patch can be efficiently predicted by many candidates.

C. Determining Wp(weight)

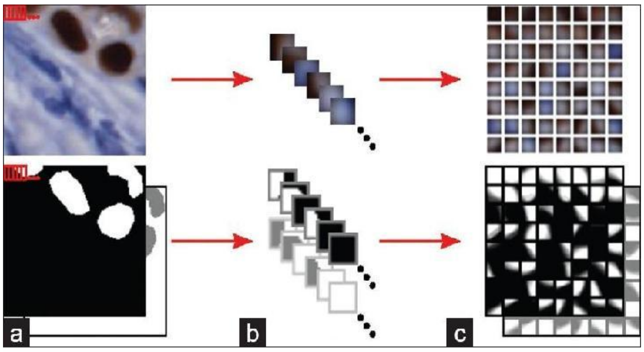
The Number of neighbors is adapted locally so that the similarity of chosen neighbors lies within a range

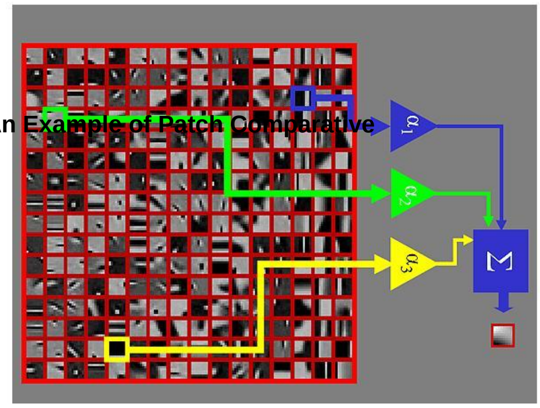
$(1 + \alpha) \times d_{min}$, where d_{min} is the distance between the current patch and its closest

neighbor, α is equal to 0.75. The similarity distance used to compute the weights is composed of two terms.

Distance between current and Neighbor patch of LR image.

Distance between current and Neighbor patch of HR image.
Now selected patch for HR image given by
$\psi^{HR} p = \Sigma_{pj \in D}{}^{HR} (w_p, p_j \times \psi_p, p_j)$



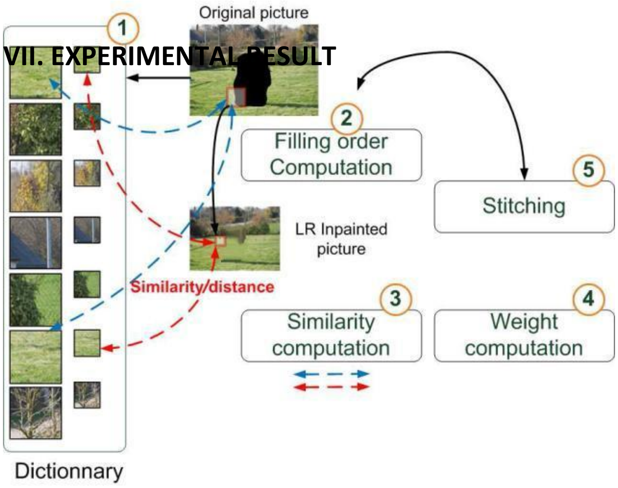


An Example of Patch Comparative

High Priority Patches

D. Stitching

Finally the HR patch is pasted into the missing areas. It may get overlap (seam cut) and can be rectified by minimum error boundary cut. By Euclidean distance, it rechecks the boundaries (left, right, top, bottom) and performs patching until all the boundaries are synthesized.



VII. EXPERIMENTAL RESULT

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

A. Parameters:

Two versions of the proposed method are evaluated. One uses a down sampling factor of 4 in both directions and the patch size is equal to 5 × 5 whereas this factor is set to 2 for the second version and the patch size is equal to7 × 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.

B. Front line feathering:

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 can be used to perform the filtering.

C. Comparison With State Of Art Methods: State-of-the-art inpainting methods

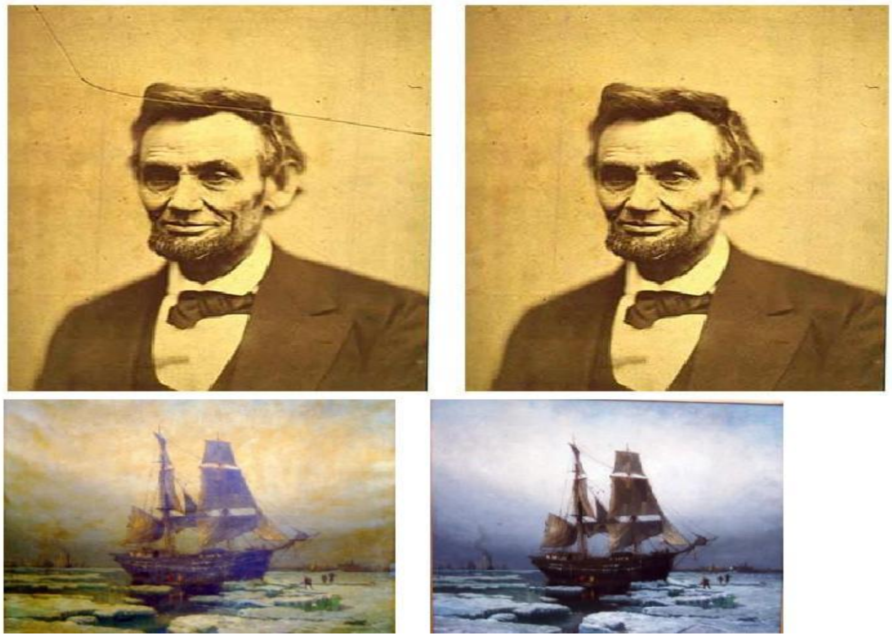
are used for comparison purposes. The first one is the well known method proposed by Criminisi *et al*. The second one is the Patch Match method which is a fast algorithm for computing dense approximate nearest neighbor correspondences between patches of two image regions. This algorithm is available in Adobe Photoshop CS5. The last one is Super Resolution method. For deterministic textures, results are very good. For stochastic ones, some artifacts are visible. However, increasing the patch size would cope with these artifacts.

VIII. CONCLUTION

The Algorithm attempts to replicate the basic techniques used by professional restorers. The basic idea is to smoothly propagate information from the surrounding areas. The user needs only to provide the region to be inpainted; the rest is automatically performed by the algorithm.

Its application extends from restoration of old paintings and damaged film, removal of superimposed text, and removal of objects.

The results can either be adopted as a final restoration or be used to provide an initial point for manual restoration, thereby reducing the total restoration time by orders of magnitude. Our future work will concentrate on further modifying the current algorithm to process complicated structure and texture in still photographs as well as dynamic videos.



Original Proposed

Original Criminisi **Patch Method** **Proposed** **Comparison With State Of Art Methods**

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