

Rendering Dis-Occlusion by Modified Exemplar Based Inpainting Technique

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Abstract: Inpainting is a technique of rendering an image in an undetectable form. Inpainting technique is applicable for restoration of scratched photograph, removal of undesirable objects, reconstruction of 3D surfaces etc. Here we are using a modified exemplar based inpainting [1] to remove occlusion from an image. Here we are using a modified data term from gradient based data term. Here in this paper we remove object(s) from digital photographs, and then fill the hole with information extracted from the surrounding area. The modifications we introduced are, changing the window size after each iteration and a modified data term is used.

Keywords: Confidence Term, Data Term, Priority Term, Source region, Target region.

I. INTRODUCTION

As the introduction of mobile cameras photography has a dominant role in our day to day life. Photographs remain as the memory of past. Sometimes we may lose our valuable old photographs due to scratches. Inpainting is a technique for removing the scratches from an image and also inpainting technique removes occlusion from an image. There were several existing applications available for image editing. Photoshop is one of the existing applications available for inpainting.

But the main disadvantage is that Photoshop is a manual method. Our method is an automatic method for inpainting.

Here we are manually selecting the object which we have to remove from an image. Placing a mask over the selected region, then filling process is done over the masked region. In this filling process we can use any of the inpainting techniques. We are using a modified exemplar based inpainting technique for filling the masked region from the surrounding area.

II. METHODOLOGY

The complete process of inpainting can be divided into three steps.

Object selection

Object selection can be manually done using the mouse. User can select the occlusion or the scratch which we have to remove and a mask is placed over the selected region. Then the selected region will be the target area. And the outside region of the selected part will be the source region.

Color Masking

Color masking is done to separate the source and the target region. It is done by separating the RGB components in an image.

Color masking is done by

Green : [0 255 0]
Red : [255 0 0]
Blue : [0 0 255]

Boundary Detection

Boundary detection is done by using Laplacian filter. Convolve the Fill region Matrix with Laplacian filter shown in the matrix below. Thus we can obtain the boundary of the selected region for the filling process.

1	1	1
1	-8	1
1	1	1

Fig. 1. Laplacian matrix

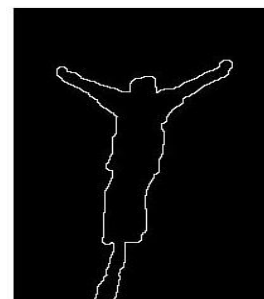


Fig. 2. Boundary of the target region

Filling Process

Filling process can be done by any of the inpainting techniques. There are several inpainting techniques which are listed below.

1. PDE based Inpainting
2. Variational Inpainting
3. Texture based synthesis
4. Hybrid Inpainting
5. Exemplar based Inpainting

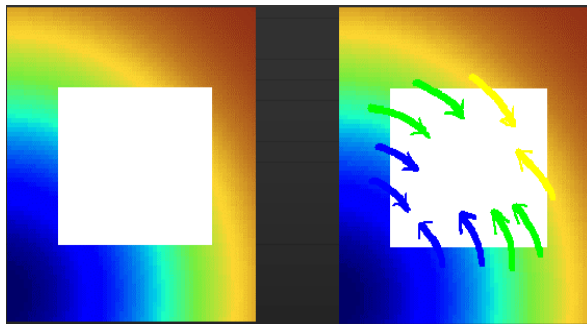


Fig. 3. Isophotes

In PDE based inpainting [1] partial differential equation is used, here simply diffusion is done. Here the source region is extended to the target region and the filling process is done. The isophote values are extended to the target region. Isophotes are lines of constant intensity in an image shown in Fig. 3.. In Variational Inpainting [4], inpainting is done based on total variation. Here the extension of source region is based on level lines. Texture based synthesis is done only for texture images. In Hybrid inpainting as the name indicates it uses two methods. Image will be separated as texture and structure and inpainting is done separately. After that it joins together. We can see from the procedure that it is too difficult method, but the output is too efficient. In Exemplar based inpainting technique [3] the image will be separated as the source region and the target region. The extension of source region to target region will be based on some terms known as the Confidence term and the Data term. There is a balancing between the confidence term and the data term. The data term tends to pull inwards and the confidence term will oppose it and extension will be allowed based on some criteria. In our method we made some modification for this data term and the confidence term.

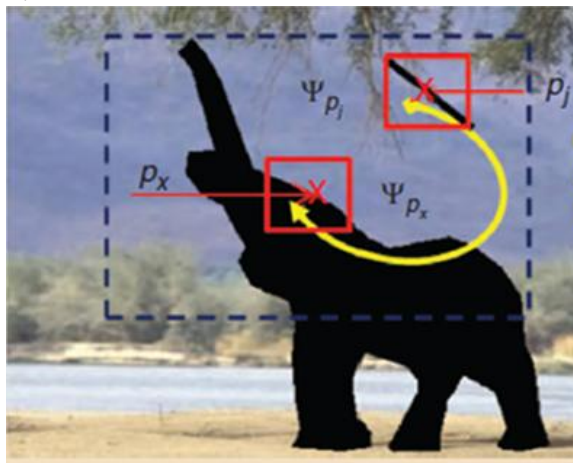


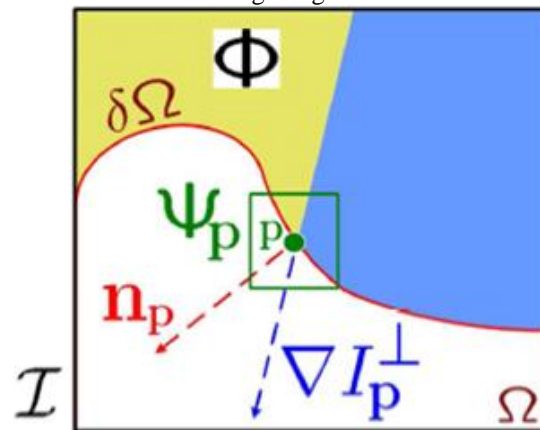
Fig. 4: Patch selection [1]

Two types of texture synthesis are there Patch based texture synthesis and Pixel based texture synthesis. We are selecting a patch centered at pixel p_x at the boundary of the target region. The specialty of this boundary patch is that it is half filled. Then we go for a search of best match for this patch from the surroundings. This best match is calculated using sum of square difference. We can use

NLM (Non Local Mean) or K means clustering for finding the best match. It is an algorithm in image processing. Unlike "local mean" filters, which take the mean value of a group of pixels surrounding a target pixel to smooth the image, non-local means filtering takes a mean of all pixels in the image, weighted by how similar these pixels are to the target pixel. This result in much greater post-filtering clarity, and less loss of detail in the image compared with local mean algorithms.

In fig. 1 we can see that we are selecting a best match patch centered at p_i . In case of patch based texture synthesis we are pasting the whole patch ψ_{p_i} into the patch ψ_{p_x} . In Pixel based texture synthesis we are only pasting the centre pixel p_j into the patch ψ_{p_x} . This will destroy the naturalness of the image. Hence we prefer patch based texture synthesis.

For selecting this pixel p_x at the boundary there are some criteria based on the priority term. Priority term P_p is calculated using the equation below. The selected area to be inpainted is shown in white color known as the target region represent as Ω . The surrounding region is represented as the source region ϕ . $\delta\Omega$ is the boundary between the source and target region.



$$P_p = C_p + D_p \tag{1}$$

Priority term is calculated as the sum of the two terms. C_p is the confidence Term and D_p is the Data term. This confidence term is calculated as the below equation.

$$C_p = \frac{\sum (\Psi_p \cap (I - \Omega)) C_q}{|N_p|} \tag{2}$$

Where N_p is the number of elements or pixels in the patch Ψ_p and $(I - \Omega)$ is the source region.

After each iteration we are updating confidence value.

$$C_q = C_p, \forall q \in N_p \cap \Omega$$

The Modified data term is defined as

$$D_p = |\Delta I_p \cdot n_p| + \alpha \tag{3}$$

Where ΔI_p is the max gradient vector and n_p is the normal to the contour $\delta\Omega$.

Flow chart of the method

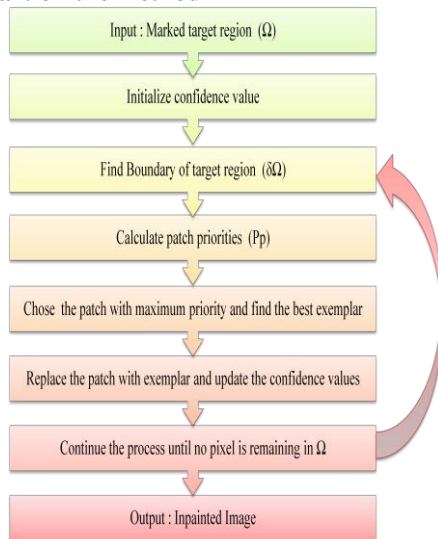
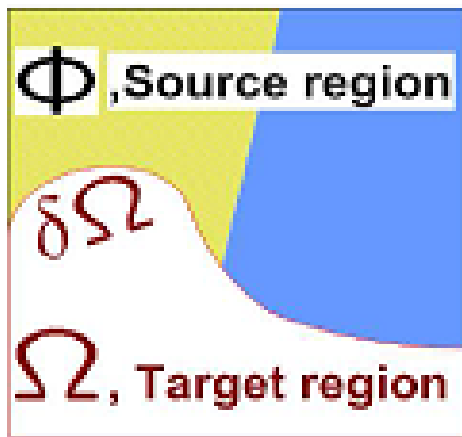


Fig. 5: Flow chart of the filling process

The Inpainting algorithm is shown in the flow chart. Until the whole target region filled the process will be continued.



Filling process algorithm is shown in the figure above. The original image here the selected area to be inpainted is shown in white color known as the target region represent as Ω . The surrounding region is represented as the source region ϕ . $\delta\Omega$ is the boundary between the source and target region. We are selecting a pixel p at the boundary of the image and a patch is selected with pixel p as the centre. The size of selected patch is 9×9 which is variable according to the image. We are selecting some of the neighboring patches and finding the best match using sum of square difference calculation. After finding the best match, we are pasting the best patch into our patch ψ_p

Search of Best matching Patches

Exemplar-based inpainting method search for K-nearest neighbors (KNNs) within the known part of the image. The solution to the NN search problem is to compute the distance from the search patch to all possible candidate patches, treating each patch as a point in a high-dimensional space. Faster and approximate NN search methods exist that organize the candidates in specific

space-partitioning data structures, such as the k - dimensional trees (kd-trees) or the vantage point trees (vp trees), according to their distribution in the search space. The best match patches are find which are having a minimum SSD value. The equation for finding the best match is shown below.

$$Coh(\psi_q) = \arg \min \{d_{SSD}(\psi_p; \psi_q)\} \tag{4}$$

Search window size

The size of window during the first iteration of window search is enough for the filling process. But after n iterations the size of search window is not enough, the availability of source region is less here. Hence this may cause to produce blur on output images. Hence we are introducing a modification to the window size. We are changing the window size after each iteration. The Improvement that applied for the search window is that ,after each iteration we are changing the size of the search window. The initial size of search window is taken as $[nn \times mm]$,where nn and mm are the size of the patch and here in default we use the size of patch as 9×9 .The maximum size applied for the search window is $(N-nn) \times (M-mm)$ where $[N M]$ is the size of the Original Image.

III. RESULT

The original image to be inpainted is shown below, The color image which have to inpaint is selected, The specialty of the image is that, images which have backgrounds are occluded by an object. The image garden is shown below, which is occluded by a man.



Fig. 6: (a) Original Image

Here in the image shown above we can see that a garden is occluded by a man. To remove the occlusion we are selecting the object using the mouse pointer. The object to be removed is selected using mouse and the selected image is shown in Figure 4.2 below. Mask is placed over the selected part of the image Fig 6(b) shows the masking.

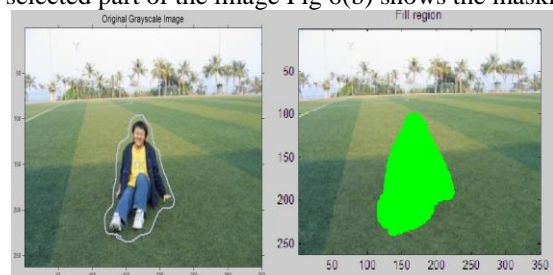


Fig. 6 : (b)Object selection and masking

The Inpainted output Image is shown in Figure 6(c), The background Occluded by a man is removed and the removed area is filled from its surroundings.

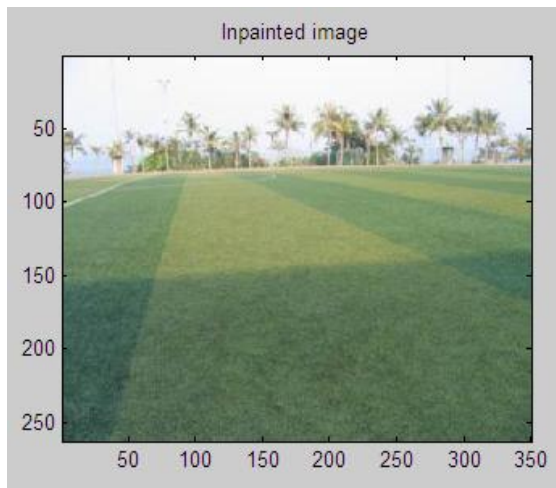


Fig. 6:(c) Inpainted Output

For an image Data term which represent the texture of an image and confidence term which represents structure of an image is shown in Figure 6(d)

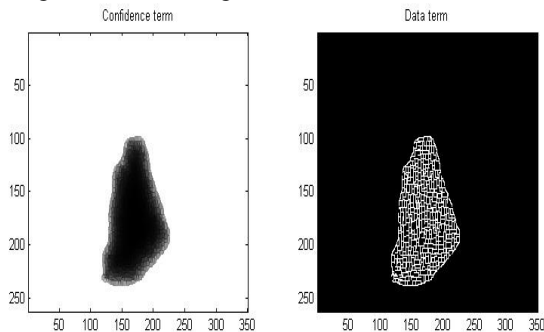


Fig.6 (d): Priority term (a) Confidence Term

(a) Data Term

The priority term is calculated using the data term and the confidence term. There is a balance between the confidence and data terms. The data term tends to push isophotes inward, while the confidence term tends to suppress this sort of incursion into the target region.

As presented in the results section, this balance is handled gracefully via the mechanism of a single priority computation for all patches on the contour.

Result Comparison

Comparison of our result with other classical methods for different images is shown below. The quality assessment of inpainted images is an open and difficult issue, as no quantitative metrics exists.

Fidelity metrics cannot be used given that, for most inpainting applications, the ground truth is in general unknown. One has to rely on a subjective assessment to evaluate whether the inpainted images are visually pleasing and physically plausible [1].

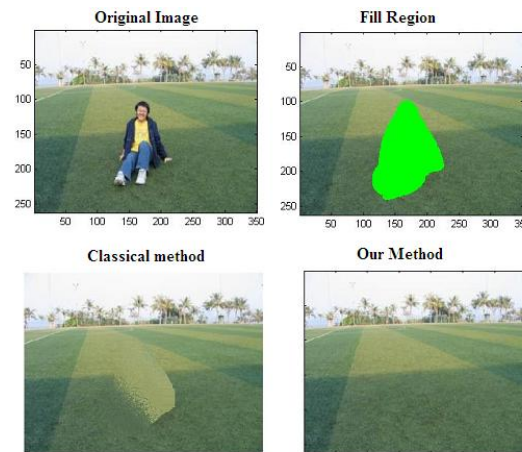


Fig. 7. (a) Comparison of image Garden with the classical method

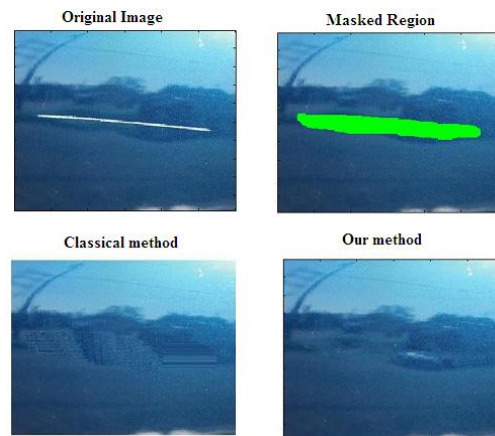


Fig. 7. (b) Comparison of Image Scratch with classical method

Since there is only subjective assessment to evaluate whether the inpainted images are visually pleasing and physically plausible, we compared our method with classical Inpainting Techniques. By analyzing the outputs it is clear that this method outperforms than the classical method. Fig. 7. (a),(b),(c),(d) shows comparison our method with the classical on different images.

In all the three cases our method gives better result. In case of other methods the pasted patches are visible and thus it is seen as a blur at the inpainted part. In our method the edges of pasted patches are not visible hence no blur at the inpainted region.

Therefore no need of any patch blending algorithm for artefact detection. The complexity of our method is also less as compared to other methods, since they are using another algorithm for the artefact detection on the inpainted image. Since there is no need of any enhancing method for the inpainted output, this will reduce the complexity of this method and it will reduce the time for inpainting.

As compared to other method our method gives better synthesized output.

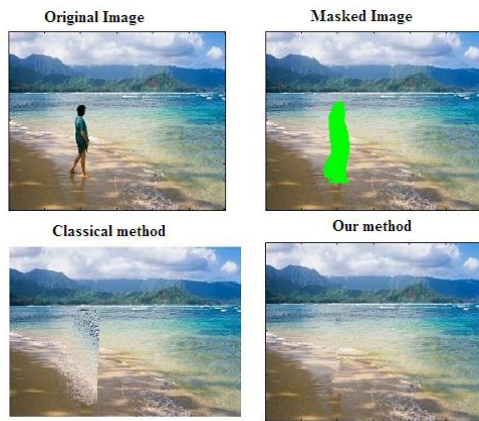


Fig. 7 . (c) Comparison of image of sea with the classical method

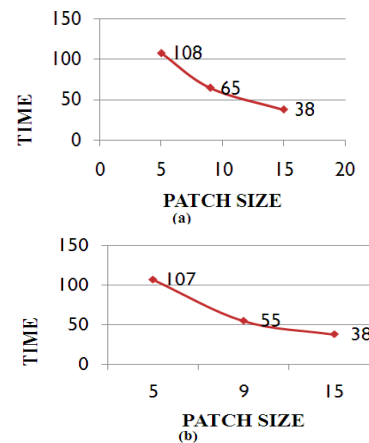


Fig. 8. Patch size Influence on Images (a) On image1 Garden (b) On image 2 Bungee

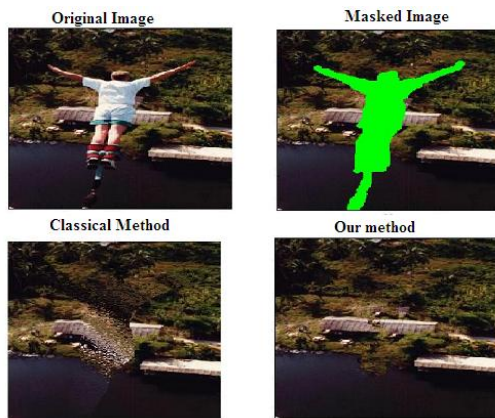


Fig. 7 (d) Comparison of image Bungee jumping with the classical method

Fig. 9. shows the results obtained for different patch size using the Proposed Method. The time required for Inpainting will depends on size of the hole we have to filled in. To obtain a faster output we can change the size of the patch. But in case of some images the increased patch size will destroy the output image. So by conducting tests on different images we find that 9x9 patch is a better size and the selection of patch size will depend on the Images.

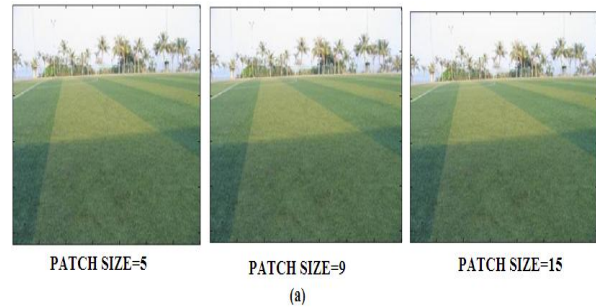
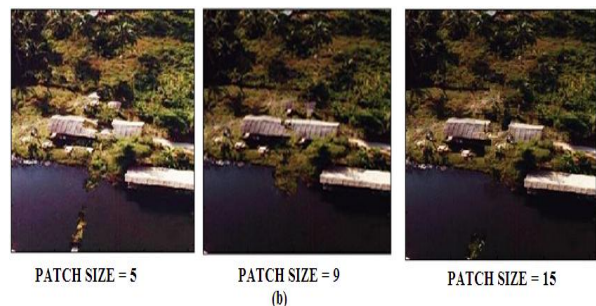


Fig. 9. : Patch size Influence (a)on image1 Garden



(b) on image2 Bungee

Patch Size Influence on Image

There is an inverse relation between patch size and time. As the Patch size increases the time for inpainting will be reduced. The graph below shows the relation between the patch size and time. Tests are conducted for three different patch sizes (5,9,15) on two images, on Image of Garden and On Image of Bungee jumping Fig illustrates how the choice of patch size affects the quality of the inpainted image. Graph shows the influence of patch size on the input image. Smaller patch sizes allow more matching possibilities without capturing the image structure, and this does not always permit to obtain a good reconstruction. Up to a certain limit, a bigger patch size can capture the texture characteristics better, however with less matching possibilities. From the experiments conclude that larger patch size permits to obtain satisfactory results in lesser time.

By Analyzing the result obtained shown in Fig. 8 we can see that in case of Image 1 Figure 8 (a) (Garden) there is no change in the output of image for different patch size ,so we can use larger patch size for such images(Images having lesser number of elements in the background)and time taken to inpaint can be reduced. But In case of Image 2(Bungee Jumping) shown in Figure 8 (b) we can see that it gives better result for 9x9 patch size. As the patch size increases thequality of inpainted output may be lost.

IV. CONCLUSION

Discussed about different inpainting techniques and our method is discussed in detail. Modification in data term can reduce the artefacts in an image, therefore no need of any spatial artefact blending algorithm. This will reduce the complexity of inpainting method.Here the priority term calculation is modified along with the modification in data term and confidence term. The future work in inpainting is video inpainting.

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