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Restoration of Image using SR Based Image Inpainting Techniques

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Abstract:**Image completion of large missing regions in a selected image is a challenging task. Old photographs have some part of the image distorted or some part of it is ruined by folds and creases. Hiding these flaws or covering such missing regions is a necessity sometimes and needs to be solved by using some advanced techniques. Inpainting is one such technique that helps to overcome these problems. Inpainting is a technique of modifying an image in an undetectable form. Using inpainting requires the user to select a part of the image to be removed and the algorithms used in it will restore the required part or patch. Image inpainting methods can be classified into two main categories viz. Diffusion based and Examplar based approaches. Diffusion based approach has varying methods and mathematical evaluations involved. Examplar based approach samples and copies best matching samples from the neighboring pixels of the image surrounding the selected patch. A recent approach in image inpainting is a combination of two methods namely examplar based approach and single image super resolution. The super resolving is done after the examplar based approach finishes its operations so that the patching, which is coarse, gets the finishing touch by super resolving it. If the area to be restored is large then the diffusion based approach introduces some blurring whereas examplar based approach can handle large areas effectively.**

Keywords: **Examplar based, Inpainting, Super resolution.**

I. INTRODUCTION

There are many methods by which a particular image can be repaired or inpainted. These methods include techniques to fill in the missing regions in that image. The current methods are primarily divided into two important classifications namely ‘Diffusion based’ and ‘Examplar based’. In diffusion-based method on partial differential equations [1],[10] and variational methods[9] are used. The disadvantage of diffusion-based methods is that it makes the image sort of blur when the hole to be filled in is large. The second method is the exemplar based method in which there is a dictionary for parts of image samples and the best matching samples or patches of the image neighboring are used[3],[6]-[8].These methods have been inspired from texture synthesis techniques [11] 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 [7].The examplar based methods have a good tuning with repeating patches or in other words when the missing region is large in size. The reporting authors in [6] have improved 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. These two methods (diffusion and examplar based) can be optimally used together as a combination. A new method has been introduced in which exemplar based method with a super-resolution technique can be used. It is a two phase algorithm. Firstly a rough version of the inputpicture is inpainted. Secondly an enhanced resolution picture from the rough inpainted image is obtained. Examplar based inpainting is a subject being researched since a long time but, still there exists a number of faults. The most important one is related to the parameter settings such as the filling order and the patch or sample size. This problem is being solved by considering multiple inpainted versions of the input image. Different adjustments have to be made to do so. The inpainted pictures are then appended which then gives the final inpainted image. The inpainting algorithm is mostly applied on a rough version of the input image and this is specifically very helpful 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. Then in the second phase the full resolution inpainted image is recovered by using a super resolution (SR) method likely to

[5]. SR methods refer to the process of creating one enhancedresolution image from one or multiple input low resolution images. The proposed SR-aided inpainting methodfalls within the context of single-image SR. The super resolution problem is not framed correctly since the multiple high-resolution images can produce the same low resolution image. To solve the problem some prior information is required. The prior information can be an energy (here frequency) determining unit defined on a class of images which is then used as a regularization as term together with interpolation techniques [12]. This prior information can also be used example images or corresponding LR-HR (Low Resolution – High Resolution) pairs of patches that are realized from the rough version of images or from the input low resolution image itself. This method togetherly is known as examplar based super resolution method. An examplar based super resolution method embedding *K* nearest neighbors found in an external patch database has also been described in [13]. Instead of constructing the LR-HR pairs of patches from a set of un-related training images, 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 builds upon the super resolution based inpainting method proposed in [5] which is based on examplar-based inpainting and single image examplar based super resolution. The main novelty of the proposed algorithm is the combination of multiple inpainted versions of the inputpicture. The rationale behind this approach is to cope with the sensitivity of examplar based algorithms to parameters such as the patch size and the filling order. Different combinations have been tested and compared. Besides this major point, different adjustments regarding examplar-based inpainting and SR methods are described such as the use of the coherence measure to constrain the candidate search. In summary, the proposed method improves on the state of the art examplar based inpainting methods by proposing a new framework involving a combination of multiple inpainting versions of the input picture followed by a single-image examplar-based SR method. Notice that the SR method is used only when the inpainting method is applied on a low resolution of the input picture.

II. LITERATURE REVIEW

The most fundamental inpainting approach is the diffusion based approach, in which the missing region is filled by diffusing the image information from the known region into the missing region at the pixel level. These algorithms are well founded on the theory of partial differential equation (PDE) and variational method. Bertalmio [1] filled in holes by continuously propagating the isophote (i.e., lines of equal gray values) into the missing region.

Chan and Shen [9]proposed a variational framework basedon total variation (TV) to recover the missing information.Then a curvature-driven diffusion equation was proposed torealize the connectivity principle which does not hold in theTV model. Recently, image statistics learned from the naturalimages are applied to the task of image inpainting. Thediffusion-based inpainting algorithms have achievedconvincingly excellent results for filling the non-textured orrelatively smaller missing region. However, they tend tointroduce smooth effect in the textured region or largermissing region.

The second category of approaches is the examplar-basedinpainting algorithm. This approach propagates the imageinformation from the known region into the missing region atthe patch level. This idea stems from the texture synthesistechnique proposed, in which the texture is synthesized bysampling the best match patch from the known region.However, natural images are composed of structures andtextures, in which the structures constitute the primalsketches of an image (e.g., the edges, corners, etc.) and thetextures are image regions with homogenous patterns orfeature statistics (including the flat patterns). Pure texturesynthesis technique cannot handle the missing region withcomposite textures and structures. Bertalmio proposed todecompose the image into structure and texture layers, theninpaint the structure layer using diffusion-based method andtexture layer using texture synthesis technique. It overcomesthe smooth effect of the diffusion-based inpaintingalgorithm; however, it is still hard to recover larger missingstructures. Criminisi designed an examplar-based inpaintingalgorithm by propagating the known patches (i.e.,examplars) into the missing patches gradually. To handle themissing region with composite textures and structures, patch priority is defined to encourage the filling-in of patches on the structure. Wu proposed a cross-isophotesexamplar-based inpainting algorithm, in which a cross isophotes patch priority term was designed based onthe analysis of anisotropic diffusion. Wong proposed a nonlocal means approach for the examplar-based inpaintingalgorithm. The image patch is inferred by the nonlocal meansof a set of candidate patches in the known region instead of asingle best match patch. More examplar-based inpaintingalgorithms were also proposed for image completion.Compared with the diffusion-based inpainting algorithm, theexamplar-based inpainting algorithms have performedplausible results for inpainting the large missing region.

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III. RELATED WORK

A. Patch Propagation

In our proposed algorithm, the examplar-based inpaintingalgorithm through patch propagation. The two basicprocedures of patch propagation are:

- Patch selection
- Patch inpainting.

In the patch selection, a patch on the missing regionboundary with the highest priority is selected for furtherinpainting. The priority is defined to encourage the filling-inof patches on structure such that the structures are morequickly filled than the textures, then missing region withcomposite structures and textures can be better inpainted.Traditionally, the patch priority is defined based on the innerproduct between isophote direction and the normal directionof the missing region boundary.

In the patch inpainting, the selected patch is inpainted bythe candidate patches (i.e., examplars) in the known region.The approach in Criminisi'sexamplar-based algorithm, P.Perez, and K. Toyama utilizes the best match candidate patchto inpaint the selected patch. The approach Wong'sexamplar-based algorithm uses a nonlocal means of thecandidate patches for robust patch inpainting.

B. Patch Sparsity

To better address the problems of patch selection and patchinpainting, two novel concepts of patch sparsity of naturalimage, are proposed and applied to the examplar-basedinpainting algorithm.

- Patch Structure Sparsity
- Patch Sparse Representation

C. Patch Structure Sparsity

We define a novel patch priority based on the sparseness ofthe patch's nonzero similarities to its neighboring patches.This sparseness is called structure sparsity. It is based on theobservation that a patch on the structure has sparser nonzerosimilarities with its neighboring patches compared with thepatch within a textured region. Compared with the prioritydefined on isophote, this definition can better distinguish thetexture and structure, and be more robust to the orientation ofthe boundary of missing region.

D. Patch Sparse Representation

To inpaint a selected patch on the boundary of missingregion, we use a sparse linear combination of examplars toinfer the patch in a framework of sparse representation. Thislinear combination of patches are regularized by thesparseness prior (regularization) on the combinationcoefficients. It means that only very few examplarscontributeto the linear combination of patches with nonzerocoefficients. This representation is called patch sparserepresentation. The patch sparse representation is alsoconstrained by the local patch consistency constraint. This model extends the patch diversity by linear combination and preserves texture without introducing smooth effect by sparseness assumption.In summary, the structure sparsity and patch sparserepresentation at the patch level constitute the patch sparsity.The patch structure sparsity is inspired by the recent progresson the research of sparseness prior of natural image. Theprevious sparseness prior generally models the sparseness ofimage's nonzero features, e.g., gradients or filter responses. This kind of sparseness prior has been successfully applied to the image denoising, super resolution, inpainting, deblurring and so on. The structure\ sparsity also models the sparsity of natural image. However, it models the sparseness of nonzero similarities of a patch with its neighboring patches instead ofhigh-frequency features.

IV. PROPOSED SYSTEM

In proposed system, the robust exemplar-based inpaintingand region segmentation map this two algorithm are used.The modules of proposed system are:

i. *Initialize the target region.*
This is generally performed separately from the inpaintingprocess and requires the use of an additional imageprocessing tool. This is performed by marking the targetregion in some special color. Without any loss of generality,let us consider that the color that the target region will bemarked in is green (i.e. R = 0, G = 255, B = 0).

ii. *Find the boundary of the target region.*
After selecting the target region the boundary of the patch isdetermined.

iii. *The source image is divided by using segmentation map.*In this module, the target region is separated as foregroundand background region. Moreover, source regions aredivided and represented as gray-scale values according totheir local texture similarities. This is done to recognize thepatch easily.

iv. *Find a patch from the image which best matches theselected patch.*
The proposed method fills efficiently the target regionwith patches in source regions. We can adaptively choose thepatch size between 4×4 and 17×17 using segmentinformation in the target patch. If the image is morecomplicated then patch size will be high else for easy imagethe patch size will be less. It is always necessary to selecta patch size.

v. *Update the image information* according to the patchfound in the previous step and the inpainting is performed.

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V.RESULTS

The CPU time required for inpainting depends on the size of damaged portion. In all the color examples here presented, the inpainting process was completed in less than 1 minute. All the examples use images available from public databases over the Internet. In this section we tested various images.

1. Vertical Crop:

In this test the damages portion is very large along with y-axis as compare to x-axis. After using the inpainting algorithm we found out that the recovered image contains more adjacent pixels of y-axis than the x-axis.

2. Horizontal Crop:

In this test the damages portion is very large along with x-axis as compare to y-axis. After using the inpainting algorithm we found out that the recovered image contains more adjacent pixels of y-axis than the x-axis.

3. Large Missing region:

In this test the missing region is very large, and after applying the inpainting algorithm the missing portion is almost recover.

4. Small Missing region:

In this test the missing region is small, and after applying the inpainting algorithm the missing portion is completely recover with undetectable way.

Picture	Resolution	Missing Area	Inpainting	SR	Total
Bear	241 x 391 px	35 %	5.6 sec	8.2 sec	13.8 sec
Letter	500 x 280 px	5 %	2.4 sec	4.2 sec	6.6 sec
Batman logo	421 x 354 px	10 %	3.7 sec	5.3 sec	9.0 sec
Champion cup	371 x 385 px	15 %	3.7 sec	5.5 sec	9.2 sec

Table I .RUNNING TIME OF FUNCTIONS

VI. DISCUSSION

The entries in Table I show that the time required forfunctioning Inpainting module and super resolution module. There is one more column of missing area shows that how much portion of the image is missing. As the large area missing more time is required to recover the image.

Below there are some result images shat shows that how precisely the inpainting is done. There are 2 factors we want to discuss in here. The inpainting function is works in similar way always. In some case the recovery of the image is as expected but in some case there might be unexpected result.

Here in below image 1(a) there is a poster of the movie called *Hobbit*. So we crop the lower portion of the letter 'H' and then applied inpainting function. Here I want to tell you that the inpainting function is works in similar way as a said earlier but which way? The answer is the inpainting function starts filling the missing region from left to right and right to left simultaneously. Means it fills in horizontal way and not vertical way every time. That's why the letter 'H' is not recover fully. Because it wants to fill vertically to recover the letter but that's not happens.

In case of 2(a) there is name 'UEFA' and we just want to remove it . So we crop the portion around 'UEFA' you can see that in 2(b). Here the inpainting function works as we expected, the function recovers all portion i.e. background color.

We tried the function in all images in a data set and found lots of time function returns with expected result.

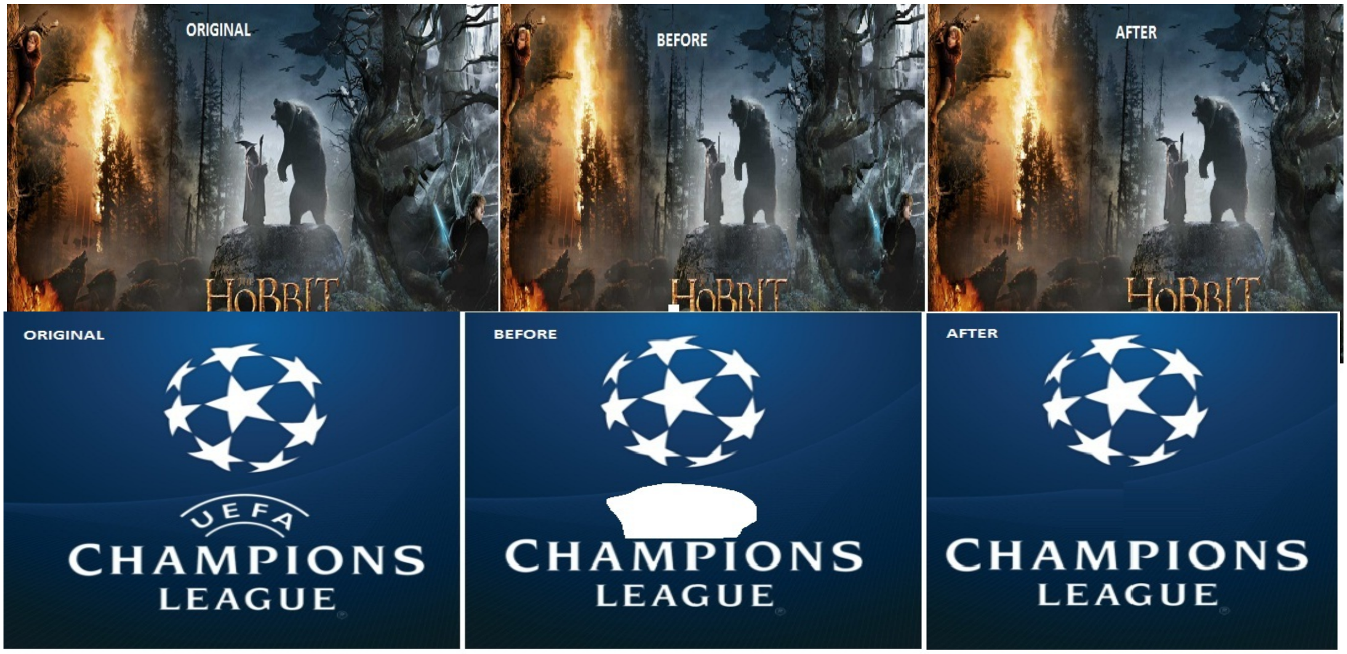
VII. FUTURE RESEARCH DIRECTIONS

Degradation Models

Accurate degradation/observation models promise improved SR reconstructions. Several SR application areasmay benefit from improved degradation models. For improved reconstruction of compressed video, degradation models for loss compression schemes are most promising one to use [23].

Motion Estimation

SR enhancement of random scenes containing global, multiple independent and individual motion,



2(a) 2(b) 2(c)

occlusions,transparency etc. is a main focus of SR research. Obtaining this is critically dependent on robust, model based, sub-pixel accuracy motion estimation and segmentation techniques is a crucial research problem [24]. Motion istypically estimated from the observed under-sampled data.

Restoration Algorithms

MAP and POCS based algorithms are very successful. Hybrid MAP/POCS restoration techniques will combine the mathematical stiffness and uniqueness of solution of MAP estimation with the convenient a priori constraints of POCS [13], [24]. Simultaneous motion estimation and restoration gains improved reconstructionssince motion estimation and reconstruction are correlated. Separate motion estimation and restoration, as iscommonly done, is sub-optimal as a result of this interdependence. Simultaneous multi-frame SR restoration isexpected to achieve higher performance since additional patio-temporal constraints on the SR imageensemblemay be included. In SR reconstruction this technique has limited application.

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