

Investigation of Exemplar based Techniques for Image Inpainting

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Abstract— Image inpainting is a technique for editing and estimating damaged pixels or missing part of a deformed image. This is realized by procuring nearby pixel information of the missing part or using information from external data. Various algorithms exist for restoring missing part of an image. These methods adopt either diffusion-based approach or patch-based approaches for the restoration process. Diffusion based approach use surrounding pixels information and Partial Differential Equations (PDE) to fill damaged or the missing part. This method is best suited for recovering missing image parts that are significantly small. However, in case the missing part is large then the same may be prone to visual impairments such as blurring in the restored part of an image. This is especially the case when the restored part is highly textured. Additionally, these approaches have a disadvantage of increased time complexity making it unsuitable for large area image filling. In this article we focus on the second approach viz, patch-based or exemplar-based method which is known to perform well for larger restoration areas. Experimentations are carried out to investigate the performance of this approach for different images along with parameters such as sizes of restoration patches and priority method. Quantitative results indicate that with proper choice of patches and related parameters, it is possible to obtain acceptable restoration performance even for large sized restoration area.

Index Terms— Image inpainting, Image restoration, Diffusion based method, Exemplar-based method, Peak Signal to Noise Ratio and Structural Similarity Index..

I. INTRODUCTION

Image inpainting is a technique used for restoring the damaged or missing part of an image using surrounding pixel information or from an external data. Image inpainting [1] can be used in many applications such as recovering damaged old paintings, removing noise & unwanted objects from photographs, etc. Old and historical images are normally damaged due to factors such as environmental conditions, water damage, compression, transmission and bad storage methods like folding of the image. They also get degraded due to long storage with some bearing of logos or stamps.

The basic purpose of image inpainting is to fill the damaged part from an image in such a way that the completed image region is undetectable for a normal observer. In the era of computer and digital world, various digital techniques exist for automatic image restoration. Current image completion methods perform well for small parts of an image and for plain areas like sky, grass or uniform textures, etc.

However, as the area to be recovered becomes non-uniform, image complexity increases resulting in blurring or visual artefacts in the images. Additionally, for large regions and complex boundary structure of images, performance [2] is not satisfactory as it produces blurring at edges of the image.

Generally, any image inpainting methodology faces challenges [1] in the form of domain complexity, image complexity and pattern complexity. For different image areas, the missing inpainting domains can vary arbitrarily depending on particular applications. As an example, for cat animal inpainting, inpainting domains consist of various types of cats. Similarly, for old art inpainting, the missing domains are usually cracks on ancient paintings, that may have occurred randomly due to bad weather conditions or natural aging of pigments. On the other hand, for super resolution or zooming, missing information is scattered across the entire image domains, and the inpainting regions look more like porous media, i.e., scattered blank holes surrounded by available image features.

In general, image inpainting can be accomplished either in spatial, frequency or scale-space domains. For complex images, at coarse scales, images can be well approximated using multi-resolution wavelet analysis. But in small scales, images carry fully localized details which are spatially organized into coherent structures. For human and computer vision, singular features of images, such as edge jumps, corners, T-junctions, and features of fractal dimensions convey crucial visual information. An ideal inpainting scheme is expected to respect these geometric or inhomogeneous features. Conversely, a realistic inpainting scheme cannot be merely built upon the fine properties of images as functions. It must also respect visually meaningful patterns viz. mirror symmetries.

Conventional techniques for image inpainting can be categorized as diffusion-based approach or the patch-based approach (exemplar-based). Diffusion based approaches use surrounding pixels information to fill the damaged or missing part of the image with the help of a Partial Differential Equation (PDE). This method is appropriate for recovering small missing part from the image. If the missing part in the image is large then it is prone to the blurring in the textured part. Patch based approach may be useful in such cases. Current advancements in image inpainting focus on usage of machine learning techniques for restoring missing / distorted parts of the image. This approach is very useful specifically when the pixel values [3-7] are missing. Although these methods are known to give satisfactory results, the computational complexity of these methods is significantly large. In this paper, we focus on patch based or exemplar-based techniques for image inpainting applications. Experimentations are carried out to investigate the performance of this approach for parameters such as sizes of restoration patches and priority method. For performance measurements quantitative parameters such as Peak Signal to Noise Ratio and Structural Similarity Index is used.

The organization of the paper is as follows. Section II presents a literature survey of different methods used for image inpainting. Section III and IV discuss the exemplar-based method for image inpainting along with its procedure. Section V deals with experimentations done and results obtained. Detailed analysis of results is also done in this section. This is followed by conclusions in Section VI.

II. LITERATURE SURVEY

Various techniques exist for image inpainting applications. Broadly image inpainting methods can be divided into two categories. The first category includes traditional patch based [8-10] and diffusion-based methods [11]. The second category is based on recent deep neural networks [11-13]. In recent times, diffusion-based and patch-based inpainting methods are combined to obtain promising results. In this approach, image is first decomposed into two parts. One part captures the high frequency component of the image, and the other captures the low frequency component of the image. Then the low frequency image is inpainted with a diffusion-based method and the high frequency image with a patch-based method. Subsequently, the inpainted images are combined together to obtain the final inpainted image. However, the performance improvement provided by such methods is trivial compared to patch-based inpainting.

Sergio R. M. Penedo et al. [14] proposed a wavelet-based approach for image completion. A method is proposed based on wavelet coefficient regularity property. The algorithm works in wavelet transform domain that detects and fixes damaged area of image from a designed decay function for wavelet coefficient. This method gives better results in terms of peak signal-to-noise ratio (PSNR) and other subjective terms if used along with cross-correction through wavelets.

Recently, facial image inpainting is considered as one of the challenging research areas in digital image inpainting. Various features of the images are used to process the image. Low level image features refer to the characteristics of an image like colour, pixel intensity etc. while semantic image features refer to the features commonly used by human to describe images (objects, actions). Jinsheng Wei et al. [15] mentioned that the traditional patch based and diffusion-based methods are not optimal for facial image inpainting as it requires

semantic features. Nevertheless, with the help of deep generative model-based methods user can generate these semantic features due to which it is possible to generate the damaged portion data from the image. However, this method may generate blurry or distorted image.

Moreover, computational complexity of these methods is high making practical implementation difficult for large sized images.

A proper investigation of current inpainting techniques indicate that there is a scope for variations in exemplar-based methods in order to yield better results.

The variations may be in the form of algorithm parameters, patch size and selection, along with usage of frequency or scale at multi-resolutions. In this paper investigation is done with respect to impact of parameters such as patch size and priority method on the quality of inpainted image.

III. EXEMPLAR BASED IMAGE INPAINTING DETAILS

It is a technique used to fill in missing or damaged regions in an image by using information from similar regions, called exemplars, within the same image or from other images. The goal is to generate a visually plausible completion of the missing area. The basic steps of exemplar-based image inpainting are listed as follows

- **Input Image and Mask:** The process begins with an input image that contains a damaged or missing region. Additionally, a binary mask is provided, which indicates the location of damaged or missing pixels. The masked area represents the region to be inpainted.
- **Exemplar Selection:** Exemplar selection is a crucial step where the algorithm finds suitable regions to use as a reference for the inpainting process.
The search for exemplars can be limited to the same image (intra-image) or may also include patches from other images (inter-image).
The choice of exemplars can impact the quality and realism of the inpainting result.
- **Similarity Measurement:** For each pixel or patch in the masked region, the algorithm calculates the similarity between the patch to be inpainted and the candidate exemplar patches. Various metrics can be used for measuring similarity, such as pixel-wise distance, texture similarity, or feature-based comparisons.
- **Patch Priority:** The similarity measurements are used to determine the priority of filling each pixel in the masked region. Pixels with high similarity to exemplars are given priority for inpainting, while pixels with lower similarity are filled later.

IV. EXEMPLAR BASED IMAGE INPAINTING PROCESS

The exemplar-based image inpainting process can be given in the form of the following algorithm.

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Input an image ( $I$ ) of size  $m \times n$ 
Identify target regions from the  $I$  which are to be inpainted. This can be done by specifying an ellipse or rectangle surrounding the
region. Let the number of target regions be  $t$ 
Generate a binary mask ( $M$ ) of size  $m \times n$  with target region having nonzero pixels values
Locate the source region. The complete image, excluding target regions, comprises the source region

While  $t > 0$ 
    For every patch of size  $p \times r$  centered on a boundary pixel of the target region, calculate the patch priority ( $V$ ) by using either
    the gradient or tensor method.
    Find the patch having the maximum priority (Target patch)
    For the determined target patch, search for the best-matching patch in the source region by using the sum of square difference
    method
    Copy image data from the best-matching patch in the source region to the target patch.
    Update the parameters viz.  $I$ ,  $M$  and  $V$ . Decrease the value of  $t$  by one.

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Do

A modified version of the standard image inpainting process is the coherence transport based inpainting method. In this method, a specific inpainting radius is chosen and the modified (inpainting) value for a pixel in the target region is computed using the weighted average of known pixel values contained by its inpainting radius.

During weighing, the coherence direction is estimated by using a structure tensor.

Subsequently, known pixels along the coherence direction are assigned higher weight value than the incoherent neighbouring pixels.

Once the inpainting process is complete, post-processing techniques may be applied to further enhance the visual quality of the inpainted region. This could involve smoothing, colour correction, or texture refinement.

V. RESULTS AND DISCUSSION

For experimentations we have considered “lighthouse.png” image available as a test image in MATLAB. The image is a colour image of size 640 rows by 480 columns. MATLAB 2024 software is used for implementation of the algorithms and obtaining the results.

We have considered three different sized patches viz. 5×5 , 7×7 and 9×9 . For insightful analysis we have considered three different regions incorporating the uniform part as well as the edges. The same is indicated in Fig. 1.



Figure 1: Image inpainting results for different sized patches and regions using tensor filling

TABLE I. PERFORMANCE COMPARISON FOR TENSOR FILLING USING DIFFERENT SIZED PATCHES AND REGIONS

Size of Patch	Region 1		Region 2		Region 3	
	Position [138 297 49 48]		Position [242 352 46 43]		Position [173 367 44 43]	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
5 x 5	26.32	0.8912	26.31	0.8910	26.20	0.8918
7 x 7	26.39	0.8915	26.34	0.8925	25.99	0.8912
9 x 9	26.44	0.8917	26.34	0.8934	26.41	0.8931

Position: first two coordinates indicate the coordinates of top left corner of rectangular patch. Remaining two values indicate width and height

The Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM) values are indicated in Table I. It can be seen that in general, a larger sized patch is better for image inpainting.

This may due to a larger region being considered for the estimation of the distorted part.

A performance degradation is observed for region 3 for patch sizes 5×5 and 7×7 . The distortion is primarily at the edges where the estimation of the patch is difficult due to sharp changes in the target region characteristics.



Figure 2: Image inpainting results for different sized patches and regions using gradient filling

TABLE II. PERFORMANCE COMPARISON FOR GRADIENT FILLING USING DIFFERENT SIZED PATCHES AND REGIONS

Size of Patch	Region 1		Region 2		Region 3	
	Position [138 297 49 48]		Position [242 352 46 43]		Position [173 367 44 43]	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
5 x 5	26.19	0.8908	26.32	0.8910	26.37	0.8921
7 x 7	26.40	0.8915	26.34	0.8922	26.26	0.8925
9 x 9	26.44	0.8917	26.32	0.8927	26.37	0.8929

Position: first two coordinates indicate the top left corner of rectangular patch. Remaining two values indicate width and height

Similar results are depicted in Fig. 2 and Table II for inpainting using gradient method. It can be seen that the performance is similar to tensor method. However, the results are better for tensor method especially in the regions where there is an abrupt change in the target area of the image.

We now present results for coherent transport-based method for image inpainting applications. We consider the “circlesBrightDark.png” image from MATLAB which is overwritten (fused) with “text.png” image. The original image and the image to be inpainted are shown in Fig. 3. The parameters considered for analysis are the radius of inpainting and the smoothing factor. The performance is measured in terms of PSNR and SSIM.

$$PSNR \text{ is calculated as } PSNR = 10 \cdot \log_{10} \frac{L^2}{MSE} \quad (1)$$

where L is the highest possible pixel value and MSE is the Mean Squared Error given by

$$MSE = \frac{\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} (I(m,n) - \hat{I}(m,n))^2}{M \cdot N} \quad (2)$$

M & N are the number of rows and columns in the image I and $\tilde{I}$ is the restored image. The PSNR plots are indicated in Fig. 4 and few sample output images are shown in Fig. 5.

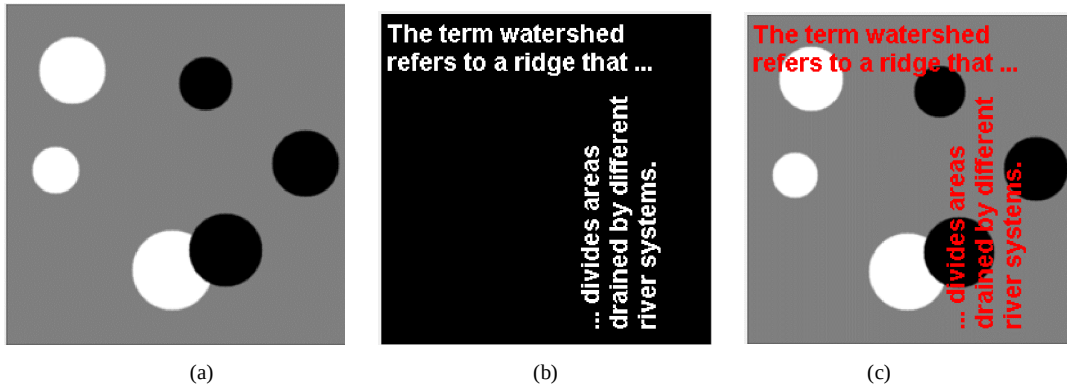


Figure 3: (a) Original image, (b) Image used for overwriting (fusion) (c) Image used for inpainting

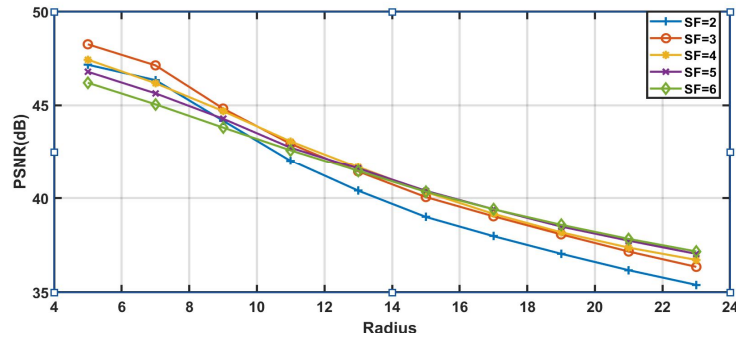


Figure 4: Plot of PSNR versus inpainting radius for coherent transport-based method considering varying radius values and smoothing factors (SF)

From Fig. 4, it can be seen that the performance deteriorates with increase in the radius of inpainting. This is due to the fact that for a smaller radius, the local characteristics can be utilized more efficiently for pixel value estimation. For a larger the same becomes more difficult due to variation in the image characteristics.

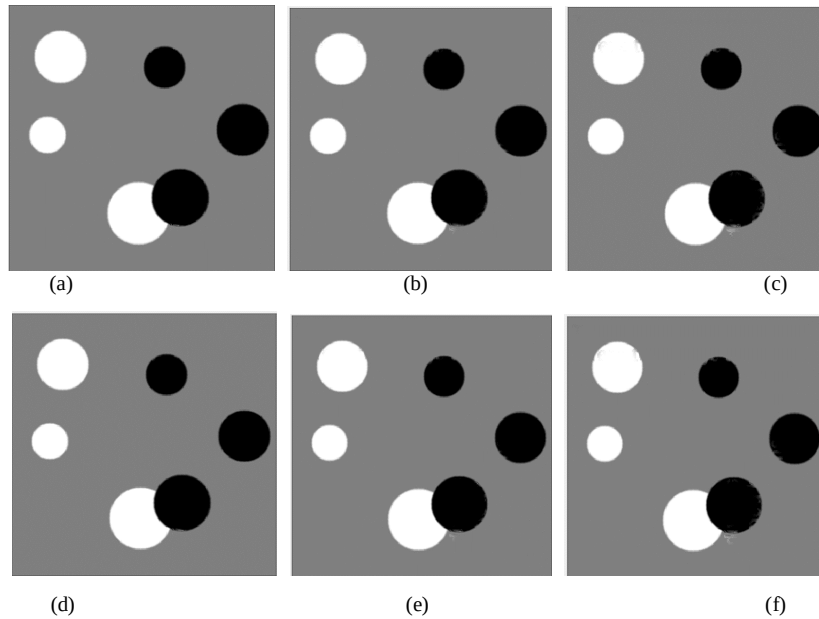


Figure 5: Sample outputs obtained for coherent transport-based method considering varying radius values and smoothing factors. 1st row: smoothing factor = 3, 2nd row: smoothing factor = 5, 1st column: radius = 5, 2nd column: radius = 11, 3rd column: radius = 17

For better insight into perceptual quality of restored image, SSIM index is calculated. SSIM is a perception-based model that considers structural changes in the image information along with important perceptual phenomena, luminance masking and contrast masking parameters. The SSIM values are tabulated in Table III.

TABLE III. SSIM VALUES FOR COHERENT TRANSPORT-BASED METHOD CONSIDERING DIFFERENT RADIUS VALUES AND SMOOTHING FACTORS (SF)

Row: SF / Col: Inpainting Radius	5	7	9	11	13	15	17	19	21	23
2	0.9991	0.9988	0.9978	0.9965	0.9941	0.9897	0.9846	0.9786	0.9728	0.9670
3	0.9994	0.9991	0.9983	0.9971	0.9955	0.9935	0.9914	0.9883	0.9838	0.9780
4	0.9992	0.9989	0.9983	0.9972	0.9956	0.9935	0.9914	0.9889	0.9861	0.9830
5	0.9991	0.9988	0.9981	0.9969	0.9955	0.9935	0.9914	0.9889	0.9864	0.9837
6	0.9991	0.9986	0.9980	0.9969	0.9955	0.9933	0.9912	0.9887	0.9862	0.9835

Observations from SSIM values are in accordance with that of PSNR plots. However, a notable observation with coherent transport-based method is that the SSIM values are better as compared to gradient filling method. This in turn reflects in the perceived quality of the restored image. Moreover, using transport-based method, the SSIM values are more than 0.9 in most of the cases which implies acceptable quality restoration for practical images

VI. CONCLUSIONS

This article investigates image inpainting process using the exemplar-based technique. Approaches considered are tensor filling, gradient filling and coherent transport-based method. Performance evaluation is done in terms of quantitative measures as well as perceptual visual quality.

The tensor and gradient filling method gives better results for low patch sizes and for those regions which have uniform intensity. The coherent transport-based method is better for low inpainting radius values.

The ideal values of smoothing factor are 3 or 4.

However, for larger radius values, the performance is similar irrespective of the smoothing factor. Usually, coherent transport-based method performs better than the gradient method.

However, performance of both the methods, is slightly degraded for regions with varying intensities. Further investigation may be carried out in this direction.

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