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DIFFUSION-BASED INPAINTING METHODS COMPARISON WITH DAMAGE AREA REDUCTION TECHNIQUES

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Abstract. *Ancient murals beautifully reflect the social and religious characteristics of several cultural groups in a particular historical era. Unfortunately, the irreplaceable historical murals have been damaged by both natural and human-made deterioration. Image inpainting can restore the visual appeal of a mural. Image inpainting involves repairing any damaged or missing regions. In this paper, in order to address the issue of color bias, the gray scale image undergoes an inpainting process, resulting in a lack of noticeable color differences. For the mask generation, mask is generated automatically by using thresholding. That is why it prevents over-identifying damage or missing regions by user interaction. Experiments are conducted on mural images of Po-Win-Daung, Myanmar. To assess the inpainted results without the presence of a ground truth image, the paper puts forward the idea of using the damage area reduction technique for evaluation purposes. Comparisons are carried out on directional median diffusion and coherent transport methods.*

Keywords: Ancient murals, Directional median diffusion, Coherent transport, Image inpainting, Mask generation, Sketch generation, Damage area reduction

1. **Introduction.** It is crucial for mural inpainting to meet the important requirement of restoring damaged murals to their original appearance as closely as possible. The two primary elements of an image are structure and texture [1]. Consequently, they both play a significant part in image inpainting. Inpainting is the process that tries to fill values in the missing regions by using valid pixels from the image. It becomes essential to identify the target area in the image because the localization of the damage area has no relevance with the inpainting procedure. The success of the inpainting technique is greatly influenced by the precision and quality of the masks created. The issue with mask generation is that no single method can automatically detect all varieties of deterioration because murals are complex in terms of both structure and color, and several types of degradation might appear in a single image.

The inpainting techniques can be generally divided into traditional-based and learning-based methods. Traditional approaches include those that are based on geometry and patches [2]. Geometry-based methods work by diffusing the components of the image from the missing region's boundary towards its interior, and they fill in the missing area. Patch-based methods fill the target regions patch by patch by searching for patches that match well throughout the whole image and duplicating them to the missing areas [3].

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Deep learning-based approaches have become common in research because they yield such excellent inpainting outcomes.

Different types of inpainting approaches were discussed so this section presents the literature review of the different methods proposed by the authors. Li et al. [4] proposed a deep learning based inpainting method with line drawing guided progressive for mural damages. In the paper, for the contributions, they introduced line drawing as an assistance and the histogram loss as a constraint for the problem of large-area mural damage inpainting. And for the problem of color bias, they proposed a novel strategy with two steps: structure reconstruction network (SRN) and color correction network (CCN). For the experiments, they constructed 1714 mural images which were collected from Dunhuang Mogao Grottoes and the corresponding line drawings. The proposed framework not only restores the structure of the image but also keeps the color consistent. The proposed method was evaluated against the current state-of-the-art methods and it produced excellent results with the highest SSIM, PSNR, LPIPS and the lowest MSE. Xu and Huang [5] proposed a depth map restoration algorithm based on improved super-resolution and fast marching method by using weigh function. The paper proposed a depth map restoration algorithm based on improved super-resolution and FMM by using weight function in order to overcome the problem of low resolution and missing depth information in depth maps obtained by low-resolution depth cameras. Finally, the effectiveness of this study for depth information restoration during image enhancement is shown by an experiment which down-samples a depth map of 300,000 pixels taken by a binocular depth camera, then doubles the resolution and repairs the depth information at the same time. Abdulla and Ahmed [6] proposed an improved image quality algorithm for exemplar-based image inpainting which finds the best-matching patch. It consists of two phases. The first phase is for searching the most similar patches in the whole image by using Euclidean distance. The second phase is to measure the distance of the selected patches and the the missing region. The method works well for filling-in different regions such as shapes, edges, textures and different backgrounds. With SSIM and PSNR measures, the experimental results demonstrated the great performance over the state-of-the-art approaches.

The major contributions of the paper are listed as follows.

- Performance evaluation methods like SME and PSNR cannot be applied for inpainted result images that do not have their original ground truth image. To the problem of lacking ground truth data in ancient murals, we introduce damage area reduction concept which can access the accuracy of the method.
- An automatic mask generation by using simple thresholding method was applied for mural damage localization, on which different diffusion-based inpainting methods were performed.

2. **Problem Statement and Preliminaries.** In brief, current techniques for restoring murals through inpainting still have numerous challenges. A lot of work has been left for enhancement in this field, especially when dealing with extensively damaged areas that contain complex textures. And it still has limitations and difficulties in achieving visually plausible outcomes. In ancient cases, it is impossible to get the ground truth image that the model needs for training. Ancient murals often exhibit unique artistic styles and techniques that reflect the period and culture in which they were created. These facts make it difficult to use the learning-based methods. Additionally, to train for higher performance, at least 1000 training data points are needed. The study paper is, therefore, focused on utilizing the structural-based methods. The aim is to ensure that the restored images closely resemble the original murals in terms of consistency.

The general flow of the system is organized into three main process groups: sketch production, mask generation and inpainting process. The ancient mural's brightness needs to be adjusted, and noise like shadows needs to be removed; thus, image enhancement methods are processed before the sketch generation step. Although noise may still persist, we employ median filtering as a preprocessing technique to significantly reduce noise levels in the mural image. By applying this technique, we not only achieve noise reduction and image smoothing but also ensure the preservation of the image's structural edges. Since the proposed strategy is based on the drawing strategy, the sketch image is generated. Because the absence of color information in sketches eliminates potential color mismatches or inconsistencies during inpainting process. After that, inpainting on sketch image is carried out with diffusion-based approach. Color image inpainting will be the future work of the research process. The procedure of inpainting depends heavily on the accurate identification of the damaged areas. Hence, the mask generation stage plays an important role. For the inpainting step, diffusion-based methods like coherent transport and directional median diffusion methods are used.

2.1. **Sketch production.** Sketches provide a simplified representation of the image, emphasizing the underlying structure and important features while removing unnecessary details. Therefore, sketching plays a vital role in the process and it makes informed decisions before diving into the final inpainting process. In the system, gaining a grayscale image with enhanced image attributes, such as edges and intensities, is the aim of sketch creation. The general steps in the sketch generation process are as follows:

- Conversion of the RGB color space to the HSV color space, followed by the enhancement of the color values by adding weight values to the H and S channels;
- Using unsharp masking to sharpen edges;
- Color inversion process;
- Generating an enhanced grayscale image as the final sketch.

2.2. **Mask generation.** Mask generation refers to the process of creating a binary mask that indicates which parts of an image need to be filled or inpainted. The goal of the mask generation is to accurately detect the damaged regions of the image [7]. The mask generation process can be performed manually or automatically. This study computes the automatic mask generation by identifying the lacunae regions in the murals. The input image's spatial values are properly analyzed to detect degradation of the lacuna type automatically. The key operation in the mask generation step is thresholding. Based on the experiments, single threshold value is not enough for all images. Threshold value is needed to adjust based on the images because of the different nature of murals such as color, and structure. For the mask generation step, automatic mask generation for all images is still a challenging problem because of their uniqueness in color, structures and so on.

2.3. **Coherent transport vs directional median diffusion.** In digital image processing, diffusion involves the propagation of image information from neighboring pixels to the damaged or missing pixels. The process is based on the assumption that the missing pixels would have similar characteristics to their neighboring pixels [8].

Inpainting process initiates from the boundary of the target region and uses pixel values from the surrounding region of the image to fill the missing information. By using the Euclidean distance to the target region's boundary, it is possible to determine the order in which the pixels in the target region should be inpainted [9]. It selects the most important coherent structures and propagates their information to the missing regions using a diffusion process. The weighted average of all known pixels within the inpainting radius is used to estimate each pixel's value from its coherent neighboring pixels. The weights are based on the coherence measure and the distance between the neighbors and missing pixels. In order to fill in the missing areas while maintaining the structural information of the image, structure tensors are utilized to estimate the coherence direction. These enhanced gradient attributes enable a more accurate representation of the local gradient properties. The equation of the structure tensor matrix is described in Equation (1).

$$S = \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \tag{1}$$

where I_x and I_y indicate the pixel's change in image brightness in both the x and y directions. Finally, the estimated values are used to fill in the missing pixels. In summary, the method is faster than traditional techniques and can handle larger missing regions. It is a powerful image restoration technique based on coherent structure propagation [10]. It can be used to repair or restore images with missing or corrupted regions and is faster and more efficient than traditional techniques.

The direction median diffusion method is one of the inpainting methods used to fill the target domain. The target regions must first be determined before directional median filtering is applied. The process is simply accomplished by taking the median in each direction. The damaged pixel (center) is then replaced with the median of these medians [11]. The process of directional median diffusion in image inpainting starts by identifying the areas in the image that are missing or damaged. The region is inpainted by median filtering using the following equation.

$$I(i,j) = \text{median}(I(i,j)) \text{ for } \forall(i,j) \in \Omega \tag{2}$$

The median filter is an effective tool for estimating the missing pixel values. It calculates the median value of pixels and replaces the missing pixel value with this median value so it is useful in situations where there is strong directional information in the image.

2.4. **Damage area reduction method.** Since it is impossible to get the ground truth image for ancient murals to test the accuracy, the damage area reduction method is proposed.

Due to the uniqueness and lack of an objective image of historical murals to compare the output inpainted image, the damage area ratio computation has been implemented to evaluate the system's performance.

$$\text{Damage Area Ratio} = (\text{Mask Area})/(\text{Total Number of Pixels}) * 100\% \tag{3}$$

where Mask Area means the total missing regions to be inpainted.

The accuracy is tested based on the concept of how much percentage of the missing regions, the inpainting method can fill. It is the comparison result between the damage area ratio of before and after inpainting. The damage area ratio is computed prior to the inpainting process. Then, the experiments are carried out sequentially from top to bottom of the framework. After the inpainted image has been produced, the system will loop back to the mask generation step and the damage area ratio is calculated again. As the final, the ratios of before and after inpainting are compared and analyzed.

3. **Main Results.** The Po-Win-Daung murals have been employed as the dataset for this research. It is a location where Myanmar's artistic culture and historic landscape are preserved. Ancient relics, wall paintings, sculptures, and wooden gates with ancient sculptures decorated on them may all be found inside the Po-Win-Daung temple. In the mountains and caves of Po-Win-Daung, monkeys are naturally habitable and they are protected and preserved. The majority of the murals appear to date from the 14th to the 18th century, while it is difficult to accurately date them (Nyaungyang and early Konbaung dynasties) [12]. Matlab is used to develop the inpainting framework. For the experiment, 40 photos from Po-Win-Daung which is located in Monywa, Myanmar, were used. Figure 1 shows the deteriorated murals from Po-Win-Daung and the damaged regions are illustrated with rectangles. For the inpainting method comparison, directional median diffusion and coherent transport method are performed and analyzed.

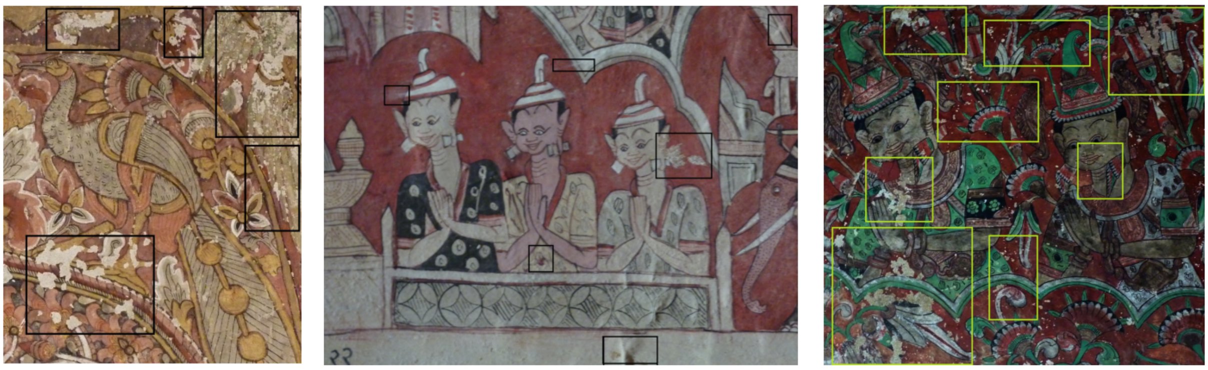
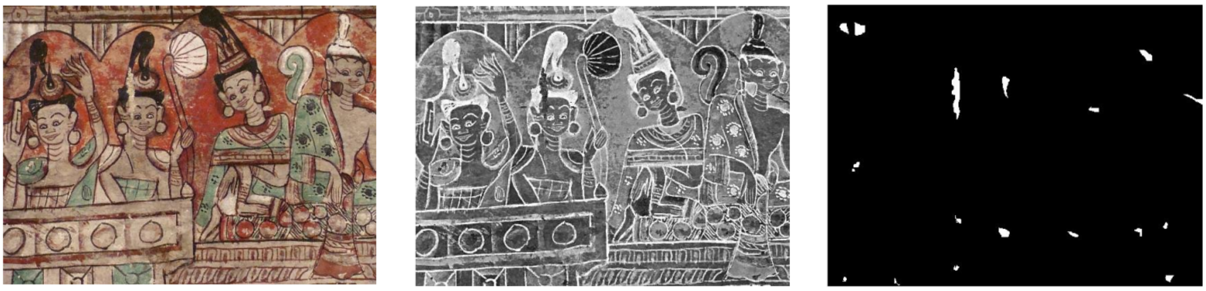


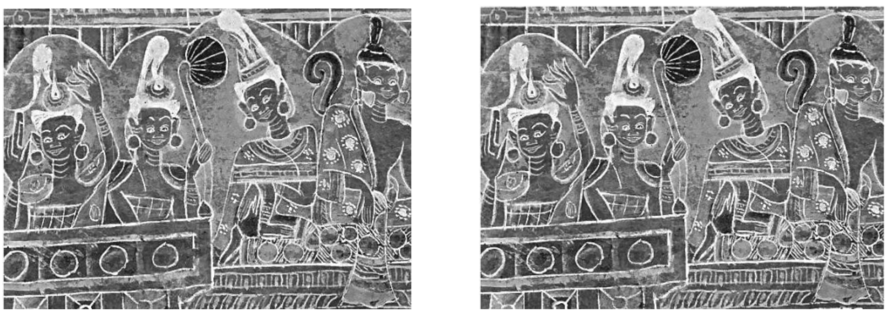
FIGURE 1. Deteriorated murals from Po-Win-Daung, Myanmar

One of the murals utilized in the experiment can be seen in Figure 2(a). As shown in Figure 2(b), a sketch picture is created from the input image. Prior to the filling procedure, the system must specify the target locations that will be inpainted. Mask creation uses spatial values and the thresholding method and the result image is illustrated in Figure 2(c). Inpainting results with coherent transport and directional median diffusion methods are illustrated in Figures 3(a) and 3(b), respectively. There is no significant difference in visual appearance of the inpainting images. Therefore, these two methods are compared based on the time and percentage.



(a) (b) (c)

FIGURE 2. (a) Degraded image, (b) sketch image, and (c) mask image



(a) (b)

FIGURE 3. (a) Coherent transport result, and (b) directional median diffusion result

The advantages and disadvantages of the methods are described based on the computational time and damage ratio calculation. The following table shows the comparison results of the two methods in terms of inpainting time and damage area filling percentage.

Table 1. Comparison results between diffusion-based methods

Mask/damage ratio of the whole image	Coherent transport		Directional median diffusion	
	Inpainting time (Elapsed time in seconds)	Damage area reduction	Inpainting time (Elapsed time in seconds)	Damage area reduction
10%	3.38	96%	4.56	93%
20%	5.57	91%	7.32	89%
30%	13.45	87%	15.94	84%
40%	28.32	78%	45.60	75%
50%	32.34	67%	56.89	63%

The mask ratio indicates that the total damage or missing area to be filled is about 10% of the whole image. For the damage area that is less than 10% of the whole image, the coherent transport method can fill up to 96% of the mask region while the directional diffusion method can fill around 93% of the missing region. For the mask ratio greater than 40%, the percentages of the methods are slightly decreased. Half of the image values are missing and there is less data for inpainting. For comparing the inpainting time of the two methods, there is no significant difference in less than 30% mask ratio. For the greater damage area ratio, it shows more delay time in the directional median diffusion method. It takes a lot of time compared to the coherence transport method. In median diffusion, due to the step-by-step calculation, filling one pixel takes time. As a result, for the large area missing regions, the method can be computationally intensive and may require high-performance computing resources to achieve real-time performance. In contrast, the coherence transport method is undeniably faster compared to the directional median diffusion method although it is also a pixel-based method. Hence, coherent transport method stands as a groundbreaking advancement in the section of speed and efficiency. Moreover, the inpainted images generated by our proposed system were visually sharper and more accurate. Overall, the experimental findings show that our proposed approach is a promising and practical strategy for image inpainting, with notable advancements over the state-of-the-art techniques at the time.

4. **Conclusions.** The damaged section of the original mural has been repaired and the style of the mural has been restored to match the original. The original tone is maintained, and the overall harmony and consistency as well as the clarity and integrity of the part are well preserved. According to the experiments, the coherence transport method proves to be more effective than the directional median diffusion method in terms of time and damage ratio rate. The color bias problem is resolved by performing an inpainting process on the gray scale image, resulting in a lack of discernible color variations. As the future work, color image inpainting will be processed and texture consistency preservation will be the contribution of the next research work. If the mural is destroyed to around half of the entire image, it is still challenging to manually fill in the gaps or even to visualize with the naked eye; thus, this method cannot do the fantastic job. The lack of comprehensive references, such as original sketches or detailed documentation, can make inpainting challenging. With these suggested approaches, it is inconvenient if there might not be enough available information to accurately reconstruct the missing parts.

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