

Performance Analysis of Different Applications of Image Inpainting Based on Exemplar Technique

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Abstract— In this age of rapidly developing image processing, inpainting has been a popular and practical art. Researchers have paid considerable attention to image inpainting throughout the years due to its enormous significance and effectiveness in a wide range of image processing applications, including the removal of scratches, the elimination of objects, and the modification of faces. It is one of the most challenging issues in image processing, demanding a comprehensive understanding of the image's texture and structure. The quality of inpainted image is a crucial factor which determines how close the inpainted image is to the original image. Many improvements have been implemented in the exemplar-based approach to increase the quality of inpainted regions containing structure and texture information. There are numerous ways to assess the quality of an inpainted image. In this study, the applications of exemplar based inpainting are evaluated using standard analytical measures including Sum of Absolute Difference (SAD), Peak Signal-to-Noise Ratio (PSNR), Correlation Coefficient, and Structural Similarity Index Measure (SSIM).

Keywords— Exemplar based inpainting, Peak Signal-to-Noise Ratio (PSNR), correlation coefficient, Structural Similarity Index Measure (SSIM), and Mean Square Error (MSE).

I. INTRODUCTION

Autonomous or semi-autonomous image restoration methods are being used more and more for image inpainting. Inpainting can be used for a lot of different things besides restoration, such as removing objects, covering up loss after a picture has been

sent, rendering images, etc. Image inpainting has been done in many different ways over the past ten years. The goal of all techniques for inpainting is to change visual information in a way that a viewer wouldn't notice and would think nothing has changed.

There has been significant development in the methods used for inpainting during the past three generations. The first generation of methods that are based on partial derivative equations was suggested by Bertalmio et al. [1] in the year 2000. (PDE). The primary idea was to send geometric and photometric information that had an effect on the boundaries of a missing region inwards. This was done in order to fill in the missing area. The solution that they have proposed is able to simultaneously fill a number of occluded zones, however it is unable to fill in large gaps. In addition, anisotropic diffusion has a blurring effect on the region that was repaired, which might lead to the loss of information regarding the region's original texture. Oliveira et al. [2] introduced an approach that makes use of isotropic diffusion and gets around the slowdown in speed that the method proposed in Bertalmio[1] exhibits. It also makes things look blurry because the same steps are done over and over again. Telea [3] offered a way for recovering a pixel's value depending on the pixel's restored locality. This method was published in the journal Computer Graphics Forum. The mathematical model for inpainting that Chan and Shen [4] created was called the "Total Variation (TV) approach," but it was not able to conform to the connection principle [5-6] that is connected with the human visual system. They were able to fix the problem in [6] by making changes to the diffusion term. The fact that none of the methods used in the first generation were capable of recovering texture information was one of the many drawbacks associated with those methods. As a result, methods of the second generation recover the original content and texture with greater determination.

"Texture Synthesis" refers to the process of creating an unending texture from a restricted source texture. It's possible that these methods are based on individual pixels or patches. Efros and Leung [7] suggested an approach in which each pixel is treated as an independent entity. A pixel's identity can be deduced by analyzing its neighbors and its surroundings. Image Quilting is a block-based approach that was developed by Efros and Freeman [8] as a method for the production of textures. Blocks were changed out utilizing the currently available texture, and minimal border cut [8]. Unfortunately, it was ineffective when applied to surfaces that had a high level of organization. Drori et al. [9] suggested a multi-resolution technique that replaces each fragment with its best source-based match. It blurs sharp edges and cannot handle perpendicular intersections.

The third generation of techniques combines the process of restoring structure with that of restoring texture. [10] We have developed and implemented a weighted similarity function that is based on non-local means. This technique resulted in photographs with a great overall visual quality and no discernible blur anymore. Inpainting is a technique that involves using statistical regularization and the similarity between

several picture regions in order to extract the significant linear features of a region that has been designated as a target [11]. After that, the Markov Random Field model is applied in order to re-create the sections that are absent (MRF). Ding et al. used patch-based nonlocal texture similarity and local smoothness intensity to solve the image inpainting problem [12]. In addition to this, a non-local Gaussian-weighted texture similarity metric was utilized so that appropriate patches could be produced for each and every target patch. Patch-based inpainting was developed to improve the performance of separated priority algorithms [13]. These algorithms may be misled in their patch search. Gray entropy serves as a regulator for the process of looking for a patch. [14] Describes a mechanism for patch-based filling that is based on the direction of the picture structure.

The article is divided into five sections: The second section focuses on the exemplar-based inpainting technique. The third section describes evaluation metrics to test the quality of an image. In section IV, the evaluation of various performance metrics is presented for different applications. In section V, a conclusion and prospective extension of the work are provided.

II. EXEMPLAR TECHNIQUE

Exemplar-based algorithms are among the most widely used image inpainting techniques. They are utilized to achieve better results compared to classical methods. The inpainting procedure fills the missing patch in an image with neighboring pixels from a similar patch. Since inpainting begins at the edge of the region in an image and spreads inward, the selection of suitable regions on the image becomes a crucial factor. The process of inpainting is iterative, and any errors that occur in the early stages will propagate throughout the rest of the process. Thus, it becomes essential to select the optimal starting position on the region. Compared to earlier stated procedures, this method is capable of filling in comparatively larger voids. Priority Allocation and patch selection form the foundation of Exemplar-based approaches. Best matching patch in source region is copied into target region is shown in fig.1 and fig.2.



fig.1 Input image with target region

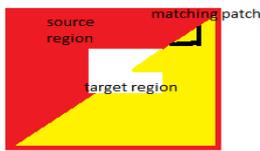


fig.2 Best matching patch in source region is copied into target region

To summarize, exemplar-based strategies are an iterative strategy that works as follows (fig.3):

1. Target region initialization: Paints the target region with an initial color to identify the missing hole from the rest of the image.
2. Priorities computations: At the start of each iteration, computes a priority function for priority assignment for all missing patches.
3. Choose the most suitable candidate patch: To fill the vacant area, the patch with the most identical matching patch forms an actual image.
4. After each cycle, update the missing region until it is completely filled

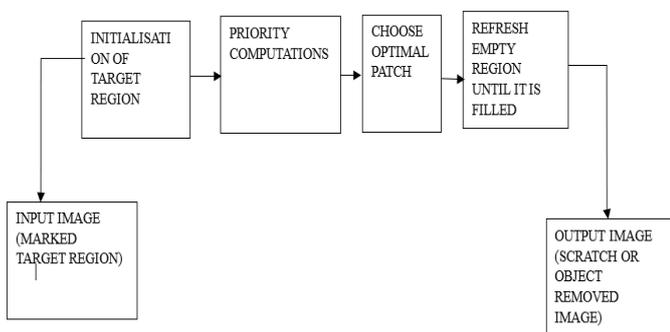


fig.3 Block diagram of Exemplar based inpainting technique

III. EVALUATION METRICS

Image quality is one of the most important criteria used in object recognition. Evaluation of the output image quality with respect to the original image is necessary for authenticity. In actuality, however, it might be quite challenging to detect the exact original image. Image quality is typically evaluated using comprehensive reference metrics, such as MSE (Mean Square Error) and PSNR (Peak Signal to Noise Ratio). In contrast to MSE and PSNR, SSIM have been developed in recent years with the intention of comparing the structural similarity measure between restored and original objects on the basis of perception.

Peak Signal to Noise Ratio (PSNR): The ratio of the maximum possible power of a signal to the power of corrupting noise that influences the fidelity of its representation is referred to as the

peak signal-to-noise ratio (PSNR). This is a word that comes from the field of engineering. PSNR is typically stated as a logarithmic quantity utilizing the decibel scale. This is typically done since the dynamic range of many signals can be quite broad. PSNR is a standard metric that is used to measure the quality of reconstruction for images and videos that have been compressed using a lossy method.

$$PSNR = 10 \log_{10} \left(\frac{R^2}{MSE} \right) \quad (1)$$

R represents the amount of variation that may be found in the supplied picture data type. Using these formulae performance can be measured, if the PSNR value is high then the errors in that is very less and vice versa.

Mean Square Error (MSE): The mean squared error is a measure of how significantly the original and compressed versions of an image compare to one another. When the value of MSE is reduced, the amount of error also decreases.

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M * N} \quad (2)$$

Where m represents the total number of rows and n represents columns. I_1 is the gray value of the corresponding pixel in the original picture and I_2 is the gray value of the current pixel in the inpainting image.

Correlation Coefficient (CC): The value of the correlation coefficient is given as a number that might range from -1.0 to 1.0. If the correlation coefficient between two images is 1.0, it indicates that the pixel values in both photographs are identical to one another. A correlation coefficient of -1.0 indicates that there is no significant relationship between the two images pixel values in any way.

Sum of Absolute Difference (SAD): The sum of absolute differences, also known as SAD, is a metric that is used in digital image processing to evaluate the degree of similarity between individual image blocks. To measure it, take the absolute difference between each pixel in the original block and the pixel that corresponds to it in the block that is being used for comparison.

$$SAD = \text{sum}(\text{abs}(I_1 - I_2)) \quad (3)$$

Where I_1 and I_2 are output image and reference image respectively.

Structural Similarity (SSIM): SSIM measures the perceptual difference between two images that are comparable. It cannot determine which of the two is superior. In contrast to PSNR (Peak Signal-to-Noise Ratio), SSIM is based on visible picture structures.

$$SSIM(x, y) = \frac{(2 \cdot \mu_x \mu_y + c_1) \cdot (2 \cdot \sigma_{xy} + c_2)}{(c_1^2 + \mu_x^2 + \mu_y^2) \cdot (c_2^2 + \sigma_x^2 + \sigma_y^2)} \quad (4)$$

where μ_x and μ_y are the local means, σ_x and σ_y are the standard deviations and σ_{xy} is the cross-covariance for images x and y sequentially.

IV. EXPERIMENTAL RESULTS

Object removal is a technique that will be used on many photos. Each image has a unique texture and size. The objects to be extracted from these photographs will possess various types of characteristics. Many factors were considered when designing this approach. The object eliminated from each image has a unique existence in the image, such as a huge, small region, an object from two neighboring backdrops, or a pattern, as seen in figures 6 and 7. A numerical study was performed to demonstrate the validity and precision of the exemplar based system. The accuracy check for pixel replacement is performed using the ratio of confidence terms and data terms of the pixel selected for replacement to the confidence terms and data terms of the pixel being replaced. The output of scratch removal application is shown in fig.6 and fig.7. Table 1 displays the results of the quantitative analysis of exemplar based inpainting applications that has been computed.

Table1: A Quantitative report of different exemplar-based image inpainting applications

Application/Parameter	Peak Signal to Noise Ratio (PSNR)	Sum of Absolute Difference (SAD)	Structural Similarity (SSIM)	Correlation Coefficient (CC)	Mean Square Error (MSE)
Scratch removal	27.11	454852	0.936	0.268	126.3
Object removal	28.39	840442	0.99	0.43	94.1

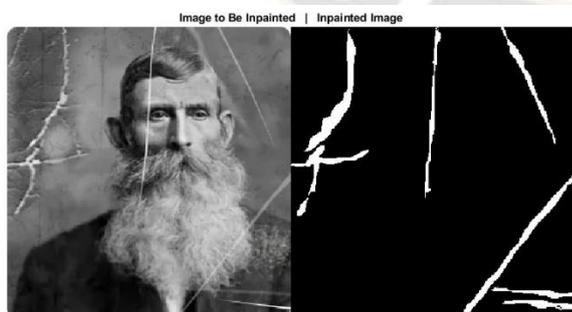


fig.4 Scratch removal application (Damaged image on left side and masked image on right side).

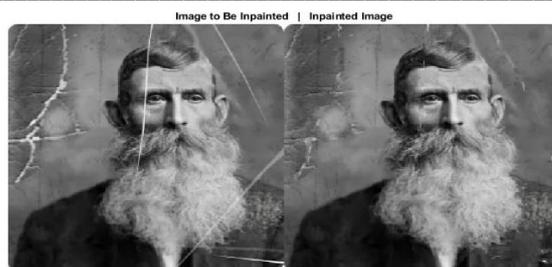


fig.5 Scratch removal application output (Damaged image on left side and in painted image on right)

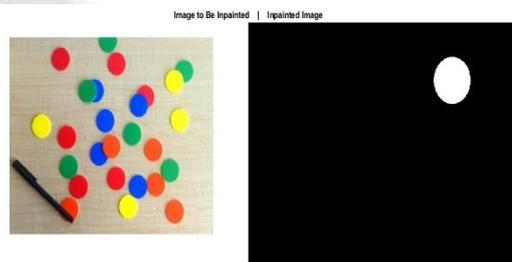


fig.6 Object Removal application (input image on left side and masked image on right side)

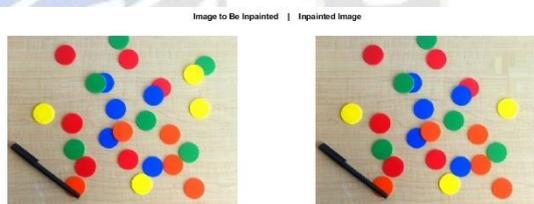


fig.7 Object Removal application output (input image on left side and in painted image on right)

V. CONCLUSION AND FUTURE SCOPE

Image processing plays a crucial part in the cultural society to restore and enhance the existing images. Image manipulation has become a requirement of the time. Manipulation of images has become quite important, beginning with the addition of filters and extending to the removal of objects from photos in order to understand what may exist behind the object. Image inpainting is a form of object removal in which the object is eliminated based on its structural characteristics. Exemplar-based approaches for picture inpainting have successfully inpaint images. The selection of a starting position also affects the precision of inpainting. From the experimental and quantitative analysis of the exemplar based inpainting applications it has observed that the metrics calculated have shown good performance.

There are a vast variety of algorithms that are capable of creating better outcomes, but they are typically confined to photographs with specific characteristics. Overall, the developed inpainting approaches have limits that require further investigation. It is intended that the results obtained would offer a strong basis for any subsequent study that might be conducted to enhance the methodologies presented.

- [14] Y. Chen *et al.*, “Research on image inpainting algorithm of improved total variation minimization method,” *Journal of Ambient Intelligence and Humanized Computing*, 2021.

REFERENCES

- [1] M. Bertalmio, G. Sapiro, V. Caselles, and C. Ballester, “Image inpainting,” in *Proceedings of the 27th annual conference on Computer graphics and interactive techniques, SIGGRAPH '00*, New York, NY, USA: ACM Press/Addison-Wesley Publishing Co, 2000, pp. 417–424.
- [2] M. Manuel, B. Oliveira, R. Bowen, and Y.-S. Mckenna, “Fast Digital Image Inpainting,” in *Proceedings of the International Conference on Visualization, Imaging and Image Processing*, 2001.
- [3] A. Telea, “An image inpainting technique based on the fast marching method,” *Journal of Graphics Tools*, vol. 9, pp. 23–34, 2004.
- [4] T. F. Chan and J. H. Shen, “Mathematical models for local non-texture inpainting,” *SIAM Journal of Applied Mathematics*, vol. 62, pp. 1019–1043, 2002.
- [5] R. Leonid, I. Osher Stanle, and F. Emad, “Nonlinear total variation based noise removal algorithms,” *Physica D: Nonlinear Phenomena*, vol. 60, pp. 259–268, 1992.
- [6] T. F. Chan and J. H. Shen, “Non-texture inpainting by curvature-driven diffusions (CDD),” *Journal of Visual Communication and Image Representation*, vol. 12, pp. 436–449, 2001.
- [7] A. A. Efros and T. K. Leung, “Texture Synthesis by Non parametric Sampling,” *The Proceedings of the Seventh IEEE International Conference on Computer Vision*, vol. 2, pp. 1033–1038, 1999.
- [8] A. A. Efros and W. T. Freeman, “Image Quilting for Texture Synthesis and Transfer,” in *Proceedings of SIGGRAPH '01*, Los Angeles, California, 2001, pp. 341–346.
- [9] “Fragment-Based Image Completion,” *Proceedings of ACM SIGGRAPH 2003*, vol. 22, pp. 303–312, 2003.
- [10] A. Wong and J. Orchard, “A Nonlocal-means Approach to Exemplar-based Inpainting,” in *Proceeding of 15th IEEE International Conference on Image Processing*, 2008.
- [11] F. A. Guilin, K. J. Reda, T.-C. Shih, A. Wang, and B. Tao, *Image Inpainting for Irregular Holes Using Partial Convolutions*, 2018.
- [12] D. Ding, S. Ram, and J. J. Rodríguez, “Image inpainting using nonlocal texture matching and nonlinear filtering,” in *IEEE Transactions on Image Processing*, 2018.
- [13] J. Zeng, X. Fu, L. Leng, and C. Wang, “Image inpainting algorithm based on saliency map and gray entropy,” *Arabian Journal for Science and Engineering*, 2019.