

DIGITAL IMAGE RESTORATION USING SURF ALGORITHM

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Abstract. In contemporary times, the preservation of scientific and creative endeavours often relies on the utilization of film and image archives, hence emphasizing the significance of image processing as a critical undertaking. Image inpainting refers to the process of digitally altering an image in a manner that renders the adjustments imperceptible to a viewer lacking knowledge of the original image. Image inpainting is a technique mostly employed to restore damaged regions within an image by utilizing information obtained from matching characteristics in relevant images. This process involves filling in the damaged areas and removing undesired objects. The SURF (Speeded Up Robust Feature) algorithm under consideration is partitioned into three primary phases. Firstly, the essential characteristics of the impaired image and the pertinent image are identified. In the second stage, the relationship between the damaged image and the relevant image is determined in terms of translation, scaling, and rotation. Ultimately, the destroyed area is reconstructed through the application of the inverse transformation. The quality assessment of inpainted images can be evaluated using metrics such as Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Mean Squared Error (MSE). The experimental findings provide evidence that the suggested inpainting technique is effective in terms of both speed and quality.

Keywords: SURF, inpainting, image restoration, image features

CYFROWA REKONSTRUKCJA OBRAZÓW Z WYKORZYSTANIEM ALGORYTMU SURF

Streszczenie. We współczesnych czasach utrwalanie dorobku naukowego i twórczego często opiera się na wykorzystaniu archiwów filmowych i obrazowych, co podkreśla znaczenie przetwarzania obrazu jako przedsięwzięcia krytycznego. Inpainting odnosi się do procesu cyfrowej zmiany obrazu w sposób, który sprawia, że korekty są niezauważalne dla widza nie znającego oryginalnego obrazu. Inpainting to technika stosowana najczęściej w celu przywracania uszkodzonych obszarów obrazu poprzez wykorzystanie informacji uzyskanych na podstawie dopasowania cech odpowiednich obrazów. Proces ten polega na wypełnieniu uszkodzonych obszarów i usunięciu niepożądanych obiektów. Rozważany algorytm SURF (Speeded Up Robust Feature) dzieli się na trzy główne fazy. Po pierwsze, identyfikowane są podstawowe cechy obrazu zaburzonego i obrazu istotnego. W drugim etapie określa się relację pomiędzy obrazem uszkodzonym a obrazem odpowiednim pod względem translacji, skalowania i rotacji. Ostatecznie zniszczony obszar rekonstruuje się poprzez zastosowanie transformacji odwrotnej. Ocena jakości renowacji obrazów można ocenić za pomocą wskaźników, takich jak wskaźnik podobieństwa strukturalnego (SSIM), szczytowy stosunek sygnału do szumu (PSNR) i błąd średniokwadratowy (MSE). Wyniki eksperymentów dostarczają dowodów na to, że sugerowana technika renowacji jest skuteczna zarówno pod względem szybkości, jak i jakości.

Słowa kluczowe: SURF, inpainting, renowacja obrazu, cechy obrazu

Introduction

All visual stimuli perceived by the human visual system are stored within the human brain, which can be considered the most extensive storage system in existence. Individuals often make efforts to retain a multitude of information, although there are inevitably certain aspects that elude their memory. As individuals age, there is a gradual deterioration of cognitive function, resulting in the loss of important information from our memory storage system. Every year, a substantial number of images, ranging in the thousands or hundreds, are preserved. Despite the considerable time elapsed since their capture, there is a strong need to access and reminisce upon these cherished instances. Without the presence of a photograph or a well-crafted artistic representation, the true visage of Einstein shall forever remain elusive to humanity. Although historical information is predominantly conveyed through written texts and spoken accounts, the artistic creations produced by artists across different periods of history provide a vivid and tangible representation that enlivens our imaginative faculties. By examining such works, it is possible to gain insight into the lifestyles and environments of various time periods.

The rise in usage of image processing software, such as Photoshop, has presented a growing challenge in distinguishing between an unaltered image and its manipulated counterpart. The presence of numerous manipulated photos that lack discernible evidence has led to a significant need for automated forgery detection systems. These systems are created to assess the reliability and authenticity of a given image [4]. Blind forgeries, unlike digital signatures and watermarks, do not necessitate any prior knowledge of the image. In contrast, the method exclusively relies on the image itself for the purpose of identifying any indications of manipulation [9]. To date, a considerable body of research has been conducted on blind image forensics, encompassing a range of picture tampering techniques such as copy-move forgery, image retouching, image splicing, and even picture steganalysis. The concept of picture inpainting was

initially introduced as a means of restoring images and correcting damages. However, picture inpainting can also be employed for the purpose of object removal, wherein the available information in the surrounding areas is utilized to fill the voids created by the process. Image inpainting is a technique that effectively removes objects from an image while maintaining the integrity of the texture and structure. This process ensures that no discernible signs of tampering are left behind. Among all the inpainting techniques, Exemplar based technique is widely used because of its enhanced quality.

The exemplar-based inpainting approach entails iteratively synthesizing the unknown region, referred to as the target region, by employing the most similar patch identified in the source region. Based on the prescribed filling sequence, the approach employs gradient information from adjacent regions to populate structures within the areas that are absent. This methodology demonstrates high efficiency in the reconstruction of extensive target regions. Typically, exemplar-based inpainting methods utilize a pre-determined patch size and do an exhaustive search throughout the whole source region. Nevertheless, the utilization of a patch with a fixed size may present certain disadvantages, as exemplar-based techniques rely on the assumption that textured patterns inside the source region may be discerned adequately with an acceptable patch size. If the patch size is not suitable for adequately covering the designated area of a target region, the accurate assignment of structure and texture information becomes compromised. For instance, in the event that the dimensions of each individual patch are very huge, there is a possibility of erroneous reconstruction of the structure. Conversely, in cases where the patch size is insufficiently large, the process of synthesizing a sizable region with comparable texture patterns becomes too time-consuming [13].

This paper introduces a new methodology for image inpainting that utilizes the Speeded Up Robust Features algorithm and affine transformation to efficiently address computational expenses. It is postulated that the pertinent image depicting the identical situation is already accessible and the data derived



from such image is employed for the rectification. The SURF algorithm demonstrates efficient and precise identification of salient features within both impaired and pertinent images. The establishment of an affine transformation in a repaired image and its corresponding relevant image necessitates the consideration of these important factors. The aforementioned relation serves as a reciprocal transformation for the purpose of retrieving the absent region.

1. Literature review

In the study conducted by Jia et al., the image segmentation process involved the division of an image into many parts, utilizing color and texture information as the basis for this segmentation [8]. Subsequently, each region was subjected to an inpainting procedure on an individual basis. Bertalmio et al., proposed a novel hybrid approach that integrates the diffusion-based scheme with texture creation techniques [2, 3, 7]. The technique demonstrates effective performance in the retrieval of both geometric structures and tiny texture patches.

Criminisi et al., proposed a method that effectively and straightforwardly promotes the completion of missing regions by prioritizing the boundary area where nearby isophotes exhibit high strength [6]. Cheng et al., extended the priority function to enhance the overall performance and reliability of the algorithmic family [5]. Wong et al., proposed a similarity function that use many source patches for the reconstruction of the target patch, as opposed to relying on a single source patch [11]. The method Wu et al., proposes uses local textured information and cross-isophotes diffusion data to calculate the variable size of exemplars in a cross-isophotes exemplar-based model [12]. Inpainting will be used to repair the damaged areas. This technique connects contours by applying curve filling and makes use of the structure information. The majority of contemporary exemplar-based algorithms tend to employ a greedy method, resulting in the inherent drawbacks associated with such algorithms. Specifically, the order in which the exemplars are filled, or their priority, becomes a crucial factor in these algorithms. The effectiveness of exemplar-based inpainting is contingent upon the simplicity of the structure and texture within the missing region. If the number of samples in the image is insufficient, it becomes unfeasible to synthesize the intended image.

The optimization of Markov random fields entails the application of the Scale-Invariant Feature Transform technique to identify interest spots. Furthermore, the direct linear transform approach is utilized to obtain the affine transformation. However, the application of the Scale-Invariant Feature Transform Technique and the integration of multiple sequential stages in the algorithm result in a reduction in overall system efficiency and an escalation in complexity. The absence of a discussion of the performance assessment metric employed for analysing the quality of findings is noted in the report. According to the findings presented, it has been observed that the performance of the SIFT algorithm is comparatively slower when compared to the SURF algorithm. This can be attributed to the fact that SIFT utilizes feature descriptors with larger dimensionality. The performance of SURF is comparable to that of SIFT [1].

2. Proposed method

This study endeavours to address the issue of inpainting by utilizing a pertinent image. When creating the proposed inpainting model, two fundamental assumptions are taken into consideration: The image that is utilized as a reference image is the snapshot obtained at the same place, with potential transformations such as translation, rotation and scaling. Therefore, the system is referred to as the Inpainting Model Based on Affine Transformed Relevant Image. Additionally, it is important to note that the photographs were captured using the same camera and under consistent lighting conditions.

The design flow of proposed method is elucidated in figure 1. The corresponding key points in the impaired and pertinent image are acquired utilizing the SURF algorithm. The affine transformations, including scaling, translation, and rotation are applied to the two input images in order to establish a relationship between them. The aforementioned relationship is employed in an inverse manner to determine the extent of the area in the corresponding image that is utilized to fill the region that is absent in the impaired image.

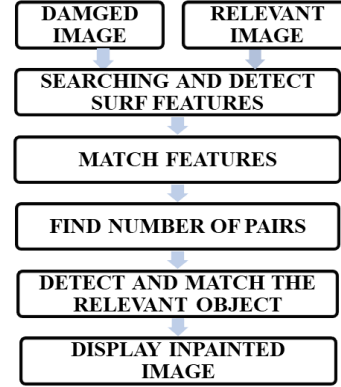


Fig. 1. Flow chart of SURF technique-based image inpainting

The process of designing the transformation function for Inpainting Model Based on Affine Transformed Relevant Image involves the identification and calculation of the scaling, translation and rotation parameters. The scaling transformation refers to the alteration of the camera's zoom level, either by magnifying or reducing the visual field. Rotation, on the other hand, involves the camera's movement in a clockwise or counter clockwise direction. Lastly, translation pertains to the horizontal or vertical displacement of the camera, either to the left or right, or upward or below.

$$\frac{d_1}{d_1'} = \frac{d_2}{d_2'} = r \quad (1)$$

where d_1 represents the distance between $A(x_1, y_1)$ and $B(x_2, y_2)$, d_1' represents the distance between $A'(x_1', y_1')$ and $B'(x_2', y_2')$, d_2 represents the distance between $A'(x_1', y_1')$ and $C'(x_3', y_3')$ and d_2' represents the distance between $A(x_1, y_1)$ and $C(x_3, y_3)$.

$$\theta = \tan^{-1} \left[\frac{x_2' - x_1' - a(y_2' - y_1')}{x_2 - x_1} \right] \quad (2)$$

$$a = \frac{x_2x_3' - x_2x_1' - x_1x_3' - x_2x_3 - x_1x_2' - x_3x_1'}{x_2y_3 - x_2y_1 - x_1y_3 - x_3y_1 - x_1y_2 - x_3y_1} \quad (3)$$

$$h = x_1 \cos \theta - y_1 \sin \theta - x_1' \quad (4)$$

$$K = y_1 \cos \theta + x_1 \sin \theta - y_1' \quad (5)$$

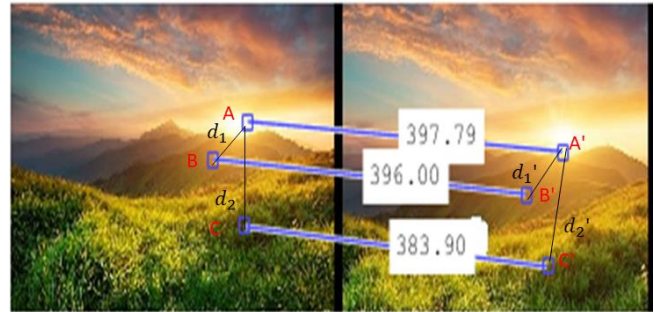


Fig. 2. Detection of key points with SURF algorithm

In figure 2, three-line segments are drawn to detect features and denoted as AA' , BB' , CC' respectively. As an example, we will choose a set of matched key points $A(x_1, y_1)$ and $A'(x_1', y_1')$. Subsequently, the distances between these locations can be calculated and other corresponding important points, namely $B(x_2, y_2)$ and $B'(x_2', y_2')$, $C(x_3, y_3)$ and $C'(x_3', y_3')$. The distances are represented as d_1 and d_1' , d_2 and d_2' respectively. The rotation transformation function is subsequently utilized to compute

the angle of rotation. The symbol θ will be used to denote the angle of rotation between the restored image and the reference image. The variable h represents the translation along the x-axis, whereas the variable k represents the translation along the y-axis. When the value of r is less than 1, it signifies a magnification effect or zoom-in. In the event that the value of r exceeds 1, an observable zoom-out effect occurs. In all other cases, the zoom factor remains constant. Once the zoom factor has been ascertained, it becomes apparent that the appropriate course of action is to adjust the dimensions of the pertinent image by this factor.

The SURF algorithm can be broken down into the following sequential steps:

- identify the corresponding key points in the repaired image and the relevant image with the SURF algorithm, as mentioned in figure 1,
- determine the zoom factor, denoted as r , between the repaired and relevant image using equation (1),
- the rescale procedure should be executed on the pertinent image. The rescaling operation is performed using a scaling factor denoted as r ,
- utilize the SURF algorithm to identify the corresponding key points between a rescaled relevant image and a repaired image.
- in order to determine the transformation parameters, namely θ , h , and k , the matched key points obtained in step 4 should be utilized in conjunction with the transformation functions in equations (2), (4), & (5),
- the subsequent stage involves the implementation of the inverse transformation. For every pixel within the designated region that requires restoration in the damaged image, perform the following task,
 - 1) determine the associated x and y coordinates in the relevant image by employing the inverse transformation function in equation (2),
 - 2) replace the damaged image pixel with the intensity values found at the new coordinates in the corresponding image obtained in the previous step.

The transformation parameters, denoted as r , h , and k , are determined based on the matched feature points and the utilization of transformation functions in equations (2), (3), (4) & (5). The specific values of these parameters are as follows: 1.008 for r , 0° for θ , 357 for h , and 20 for k . The resizing factor, represented as r , is applied to the respective image. The identification of the missing region inside the resized pertinent image can be accomplished by utilizing the inverse transformation function's parameters, namely θ , k , and h . The process involves identifying the corresponding region in the damaged image and transferring the intensity values from the appropriately scaled relevant image to fill in the missing information.

3. Results and discussion

The outcomes derived from our implementation exhibit promise. Assessing the quality of repair poses a multifaceted challenge. The currently employed metrics, such as Mean Squared Error (MSE) and Peak Signal-to Noise Ratio (PSNR) are straightforward to implement. The computation of the PSNR index involves the utilization of both the original and restored image. By measuring the peak signal strength to the noise strength, in decibels, the PSNR can be utilized as a measure of image quality. The ratio indicated above is commonly used as a criterion for evaluating the quality of an image in relation to its compressed version. A greater PSNR indicates a superior level of quality in the compressed or reconstructed image. The concept of MSE pertains to the average of the squared differences between calculated values and real values.

In the aforementioned cases, distinct values such as the PSNR, MSE were computed. The exemplar-based method and SURF algorithm are two prominent techniques utilized in the field of image inpainting. The values of Signal-to-Noise Ratio and mean square error are 62.8 dB and 0.03 respectively. In this proposed inpainting method, signal ratio is enhanced by 2.5 times. Figure 6 display the input image with visible scratches, followed by the image following the process of exemplar based inpainting.



Fig. 3. Relevant Image



Fig. 4. Damaged Image



Fig. 5. Output of Proposed method (SURF algorithm)

Table 1. Performance Analysis of different Image inpainting Techniques

	PSNR (dB)	MSE
Exemplar method	27	126
SURF extraction method	62,8	0,03



Fig. 6. Exemplar based image inpainting [13]

The objective of the studies is to validate the efficacy of the suggested method and to conduct a comparative analysis with the existing exemplar-based method [10]. The implementation was conducted using MATLAB on a central processing unit (CPU) with an Intel i3 core operating at a clock speed of 2.10 GHz and equipped with 7 GB of random-access memory (RAM). To evaluate the efficacy of the suggested method, the PSNR, MSE is employed as the metrics for performance assessment. The findings of our study indicate that our system yields superior outcomes. The preservation of visual quality is ensured.

4. Conclusion

The method of repairing damaged photos using SURF feature extraction has demonstrated success in the restoration of images that have incurred damage or have been removed. The aforementioned findings demonstrate that the utilization of this approach is a proficient means of image restoration, as it minimizes the loss of the original image's quality to a significant extent. The present study has showcased the efficacy of the Speed Up Robust Features method in the restoration of impaired photos, hence establishing its viability as a dependable tool for digital image repair. The experimental results have shown that our methodology is capable of achieving outcomes that are equivalent to other methodologies that are now considered to be at the forefront of the field [10].

References

- [1] Bay H., Tuytelaars T., Van Gool L.: Surf: Speeded up robust features. 9th European Conference on Computer Vision—ECCV 2006, Austria, 2006.
- [2] Bertalmio M. et al.: Image inpainting. Proceedings of the 27th annual conference on Computer graphics and interactive techniques, 2000.
- [3] Bertalmio M. et al.: Simultaneous structure and texture image inpainting. IEEE transactions on image processing 12(8), 2003, 882–889.
- [4] Birajdar G. K., Vijay H. M.: Digital image forgery detection using passive techniques: A survey. Digital investigation 10(3), 2013, 226–245.
- [5] Cheng W. H. et al.: Robust algorithm for exemplar-based image inpainting. Proceedings of International Conference on Computer Graphics, Imaging and Visualization, 2005.
- [6] Criminisi A., Pérez P., Toyama K.: Region filling and object removal by exemplar-based image inpainting. IEEE Transactions on image processing 13(9), 2004, 1200–1212.
- [7] Drori I., Cohen-Or D., Yeshurun H.: Fragment-based image completion. ACM SIGGRAPH 2003 Papers, 2003, 303–312.
- [8] Jia J., Tang C. K.: Image repairing: Robust image synthesis by adaptive and tensor voting. IEEE Computer Society Conference on Computer Vision and Pattern Recognition 1, 2003.
- [9] Kakar P.: Passive approaches for digital image forgery detection. Thesis, 2015.
- [10] Prasanthi T. S. et al.: Performance analysis of different applications of image inpainting based on exemplar technique. International Journal on Recent and Innovation Trends in Computing and Communication 11(4), 2023, 113–117.
- [11] Wong A., Orchard J.: A nonlocal-means approach to exemplar-based inpainting. 15th IEEE International Conference on Image Processing, 2008.
- [12] Wu J., Ruan Q.: Object removal by cross isophotes exemplar-based inpainting. 18th International Conference on Pattern Recognition (ICPR'06) 3, 2006.
- [13] Yogesh Laxman Tonape V.: Faster and Efficient Method for Robust Exemplar Based Inpainting Using Block Processing. International Journal of Computer Science and Information Technologies 6(3), 2015.

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