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Image Inpainting using Efficient Patch Selection Technique

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Abstract: **Image inpainting is a well growing research area in the field of image processing. It is used to reconstruct the spoiled images due to aging. It can also reproduce the images by removing any unwanted objects in the image. Exemplar inpainting methods gain the most attention for object removal applications. The major difficulty observed in these methods includes mismatching of patches while selecting the exemplar patches, which leads to fill by miscellaneous objects in the target region. In this paper, the new patch selection is employed to overcome the above stated issue. The combination of Sum of Squared Difference (SSD) and Logarithmic Similarity (LS) is proposed in this paper. The results generated from the proposed work are compared to the available method in the literature qualitatively. It shows that proposed work outperformed the state-of-art works.**

Index Terms: **Mismatch, Exemplar, SSD, Logarithmic Similarity, qualitative**

I. Introduction

Image inpainting refers to the procedure of restoring a damaged image or eliminating an object within an image [3], [4]. The underlying principle of image inpainting involves the utilization of the surrounding information within a certain region to complete or restore the missing portions of an image. Image inpainting techniques have a wide range of applications, including the automatic removal of text and objects in images or films for special effects [5]. These techniques can also be used to delete blurs caused by dust in an image, correct red eye, create inventive effects by removing objects [6], [7], remove logos from videos [8], restore old images or films [9], and correct missing or distorted information in medical images [10]. Typically, image inpainting approaches can be classified into five primary categories, namely: (1) inpainting based on partial differential equations, (2) inpainting based on texture synthesis, (3) exemplar-based inpainting, (4) semi-automatic and fast inpainting, and (5) hybrid inpainting [11], [12]. Each category possesses distinct benefits and constraints, and each category restores the impaired areas based on specific expectations for the restored visual material. This study primarily centers on the third category, specifically exemplar-based image inpainting.

Exemplar-based image inpainting is widely recognized as a crucial category of inpainting techniques, having demonstrated superior efficacy compared to other forms of inpainting methods [13]. Exemplar-based image inpainting primarily comprises two fundamental stages. The initial stage involves prioritizing the assignment. During this stage, a single patch from the outer edge of the region that is lacking must be chosen based on a priority function. This patch is then filled in as the first step. The second stage entails conducting a search for the most suitable patch by employing one of the available search algorithms. Within the realm of this particular field of study, scholars' endeavor to enhance either one or both of these processes in order to achieve superior outcomes in relation to the caliber of the rebuilt image. This study aims to enhance the search method by leveraging the spatial proximity between the patch to be inpainted and the other most suitable matching patches.

The main contributions of the proposed work are as follows:

- Exemplar based image inpainting technique is proposed using efficient patch matching.
- A new patch selection method is proposed to avoid the mismatching patches problem.
- This patch selection method is implemented using cumulative distance of SSD and LS.
- The experimentation is performed on Berkely Segmentation Dataset.
- The qualitative results are compared with the state-of-art methods of inpainting in literature.

The subsequent sections of the paper are structured in the following manner: Section II of the document encompasses the presentation of the related works of the image inpainting. The proposed inpainting methodology is described in detail in section III. In section IV, the experimental results are discussed. The conclusions are presented in Section V.

II. Related Work

The previous section discusses many classifications of image inpainting. The focus of this study is on exemplar-based image inpainting. As a result, this part will provide a review of significant methodologies that are relevant to exemplar-based image inpainting.

Criminisi et al. [13] introduced a technique that effectively addressed the processing of images containing comprehensive structural and texture information, while also effectively filling in wide areas of unknown regions. The present approach involves filling the patches located at the periphery of the unknown region by prioritizing the patches

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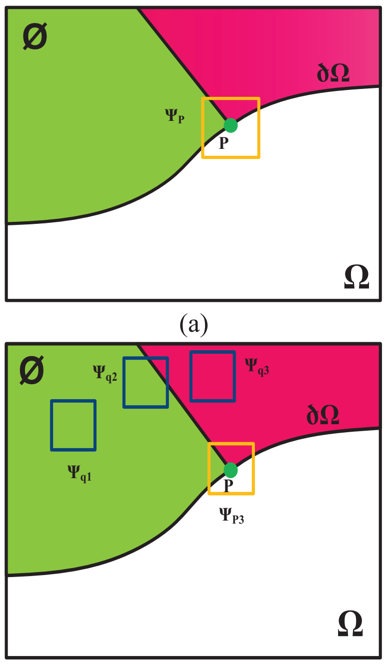
with the highest similarity to an exemplar patch from the source region. Liang et al. [14] introduce a proficient technique for detecting forgeries in object removal with the use of exemplar-based inpainting. This approach incorporates three key components: center pixel mapping (CPM), greatest zero-connectivity component labeling (GZCL), and fragment splicing detection (FSD). The CPM algorithm enhances the efficiency of identifying suspicious blocks by effectively comparing blocks with comparable hash values and subsequently identifying pairs that exhibit suspicious characteristics. In order to enhance the accuracy of detection, the technique of GZCL is employed to identify the manipulated pixels inside the suspected block pairings. The use of FSD serves the purpose of differentiating and precisely identifying manipulated areas from their corresponding regions with the highest degree of similarity. Tiang et al. [15] introduced a novel approach to image inpainting that utilizes exemplars, aiming to preserve geometric structures and effectively reproduce textures, resulting in aesthetically pleasing results. In order to enhance the efficiency of the filling order, a novel adaptive two-stage structure-tensor based priority function is introduced. Zhang et al. [16] introduced a highly effective technique for image inpainting, utilizing surface fitting as the underlying prior knowledge and incorporating angle-aware patch matching. In order to enhance the accuracy of patch matching, we propose the utilization of a Jaccard similarity coefficient. In order to alleviate the burden of the task, we employ a dynamic approach to determine the sizes of both target patches and source patches. Instead of exclusively choosing a single source patch, our approach involves a global search for numerous source patches using an angle-aware rotation strategy. This strategy is employed to ensure the preservation of both structural and textural consistency. In their study, Janardhana Rao et al. [17-19] proposed an enhanced method for calculating priorities, which encompasses the regularization factors and adaptive coefficients. The exemplary patch is chosen through the use of SSE and SAD metrics. Yao [20] implemented a priority calculation that took into account how similar the target patch was to its neighbors. They also made a change, switching addition for multiplication. To further improve the restoration's efficiency, also created a novel similarity calculating function. In their study, Zhang et al. [21] utilized a similarity metric that combined the mean squared difference and the square of mean differences in order to identify the example patch. In their study, Wang et al. [22] proposed the incorporation of a space-varying updating function to enhance the confidence term. The estimation of the priority function was achieved by using a matching confidence term. The target patch was populated through the utilization of structural consistent patch matching. In their study, Wang et al. [23] put out a novel approach for calculating priorities in exemplar-based inpainting. This method incorporates a regularization component to mitigate the dropping effect. The source region was subjected to a patch search using a combination of SSD and Normalized Cross-Correlation (NCC). Ahmed and Abdulla [24] introduced a novel approach for identifying the optimal similar patch inside the source region. Their method involves the integration of Euclidean distance and positional or locational distance measures between the patches. The aforementioned procedure is iteratively executed until the process of inpainting is successfully accomplished inside the designated target area. Further the exemplar-based methods are employed for implementing video inpainting techniques for object removal applications [25-28] along with spatio-temporal coherence.

III. Proposed Work

A. Annotations of the work

The annotations corresponding to the different components involved in the application of exemplar-based image inpainting are displayed in Figure 1. The symbol Ø represents the source region that is employed to populate the target region, Ω which is created subsequent to the removal of undesired objects. The boundary of the target region ($\partial\Omega$) refers to the region's outermost edge. A patch on the border of the target region is a small section located on this edge. The number of patches will be considered on the boundary with pixels on the boundary as center. Out of these patches, priority of the patch to fill initially is decided based on sophisticated methods. This prioritized patch is filled with patches taken on the source region($\Psi_{q1}\Psi_{q1}$, $\Psi_{q2}\Psi_{q2}$, $\Psi_{q3}\Psi_{q3}$) considering the similarity checking between these patches. The patch with high similarity is used for filling the high priority patch on the boundary. Later the boundary is updated, and the process will continue till it completes the target region.



(a)

(b)

Figure 1. Diagram of Annotations.

From the above literature survey, the patch similarity verification methods produce matching error. While comparing the similarity between existing pixels of highly prioritized patch and the pixels in the source region patch there is a high difference of similarity value. Which leads to generating miscellaneous objects in the place of holes in the target region, which means that the inpainting process has not taken place properly. In order to avoid the matching error occurring in the available methods, the new patch similarity computation method is proposed in this paper. In the exemplar based inpainting technique, highest priority patch computation and exemplar patch selection without matching error is the vital part. The proposed work for the two vital parts is described in this section.

B. Patch Priority Computation

The decision of the filling order in image inpainting is predicated upon the assignment of priority values to the different patches extracted from the boundary of the target region. The methodology utilized in this study entails employing to calculate the priority of patches. The selection of this specific method is based on its capability to assign elevated priority values to patches that are situated along prominent edges, hence maintaining structural coherence.

$$Prty = R_C(p) * D_p \tag{1}$$

where, $R_C(p)$ represents the confidence term with regularization factor (β) and D_p represents the data term.

$$R_C(p) = (1-\beta)C_p + \beta \tag{2}$$

where, C_p denotes the confidence term. It is given by,

$$C_p = \frac{\sum_{t\epsilon(\Psi_p \cap \Phi)} C(t)}{|\Psi_p|} \tag{3}$$

where, tt indicates the coordinates of the pixels of Ψ_p and Ø. $|\Psi_p|$ was the number of pixels in the target patch.
The data term D_p is taken as,

$$D_p = \frac{|\nabla I_p^{\perp} \cdot n_P|}{255} \tag{4}$$

where, $\nabla I_p^{\perp}$ indicates the isophote vector and n_p was the unit vector orthogonal to boundary of target region at pixel p.

C. Patch Matching Methodology

This study presents a novel matching rule for evaluating the similarity between the highest priority patch and the exemplar patch. The given information is provided as,

$$\Psi_{q'} = \arg \min_{\Psi_{qi}\epsilon\emptyset} [SSD(\Psi_p, \Psi_q) + LS(\Psi_p, \Psi_q)] \tag{5}$$

where, $SSD(\Psi_p, \Psi_{q1})$, is the Sum of Squared Difference (SSD) and $LS(\Psi_p, \Psi_{q1})$ is the Logarithmic Similarity (LS) Index.
The patches that exhibit the lowest distance value while employing the combination SSD and LS method are recognized as the most optimal matching patches.

The SSD distance between the patches is computed as,

$$SSD(\Psi_p, \Psi_q) = \sum (\Psi_p - \Psi_q)^2 \tag{6}$$

The SSD is the efficient distance matching method for images, which produces values ranging from 0 to 100. The value 0 indicates the highest correlation and 100 means the lowest matching between the patches.
The logarithmic similarity between the patches is generated with equation,

$$LS(\Psi_p, \Psi_q) = \log\{\Psi_p - \Psi_q\} \tag{7}$$

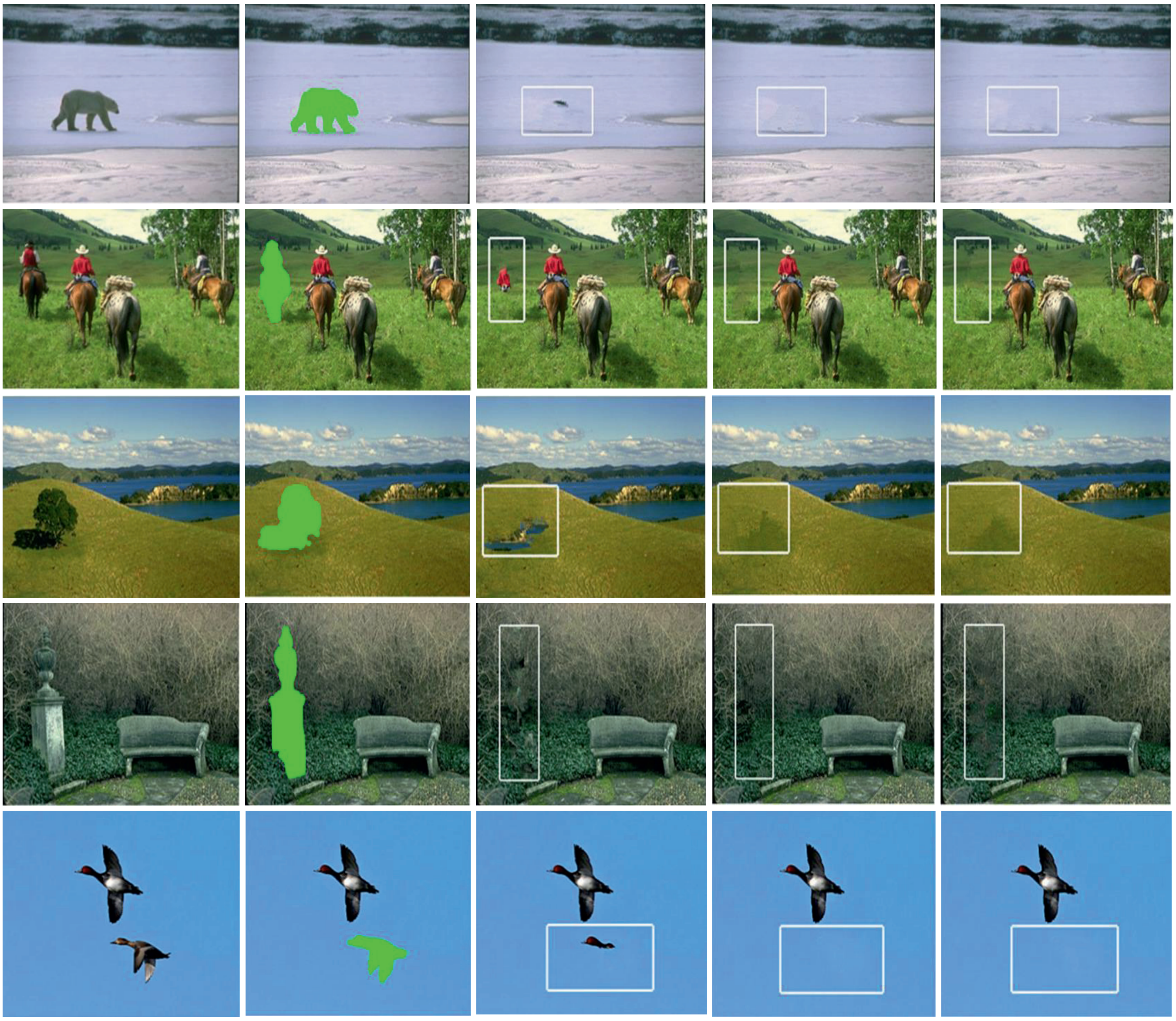
The logarithmic similarity between the two images yields a numerical number within the range of 0 to 100. A number 0 denotes a complete absence of similarity between the image in question, while a value of 100 signifies a 100% similarity.

IV. Results and Discussion

The proposed methodology is executed using the MATLAB software on a machine equipped with a 2.7GHz processor and 12GB of RAM. The evaluation of the suggested methodology is conducted through experiments on the Berkeley Segmentation Dataset [30]. The findings are subjected to qualitative analysis by comparison with existing works of high scholarly significance in literature. The visual quality of the proposed methodology of inpainting is compared to the available methods of inpainting in state-of-art works, it is described in figure 2. In figure 2, column (a) is input image with object, column (b) depicts the mask of the object to remove, column (c) shows the results obtained from the Criminisi et al. [13], column (d) given the results produced by Zhang et al. [21], and column (e) represents the results of inpainting from proposed method. The restored image by removing the unwanted object after filling is indicated in the white color box in figure 2. It is clearly showing that methods in the literature had some blur or not filled properly, our proposed method generated the results exceptionally good compared to other works.

V. Conclusions

The exemplar-based image inpainting techniques play a vital role in large object removal applications. The priority of the patches is estimated with an efficient available method in the literature to overcome the dropping effect and completely focused on similar patch selection from source region. This is implemented by employing cumulative distance of SSD and LS. The experimentation is performed on Berkely Segmentation Dataset, the qualitative results are superior compared to existing methods of inpainting in the literature.



(a) (b) (c) (d) (e)

Figure 2. Comparison of the proposed method with available works in the literature

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