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Letters

Robust object removal with an exemplar-based image inpainting approach

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ABSTRACT

Object removal can be accomplished by an image inpainting process which obtains a visually plausible image interpolation of an occluded or damaged region. There are two key components in an exemplar-based image inpainting approach: computing filling priority of patches in the missing region and searching for the best matching patch. In this paper, we present a robust exemplar-based method. In the improved model, a regularized factor is introduced to adjust the patch priority function. A modified sum of squared differences (SSD) and normalized cross correlation (NCC) are combined to search for the best matching patch. We evaluate the proposed method by applying it to real-life photos and testing the removal of large objects. The results demonstrate the effectiveness of the approach.

1. Introduction

Object removal is the recovery of missing parts of an image in a given region so that the restored image looks natural. Image inpainting is a typical method to accomplish this object removal task. The term inpainting was first emerged in the art realm with the meaning of repairing the ancient paintings [1]. It has become a standard tool in digital photography for image restoring. Intensive research is under way to generalize the image inpainting to a key tool for video and 3D movie post-production [2,17,18]. Besides its applications on images and videos, the inpainting problem involves the analysis of structural and texture patterns, which makes an impact in other image processing fields from the theoretical view.

The basic notations of image inpainting are shown in Fig. 1. Here I is the original image, Λ denotes the undestroyed or fixed region, and Ω is the region to be inpainted. The goal of image inpainting is to repair the missing region Ω with the undamaged region Λ and restore the original image I. As one of the representative researches on image inpainting, exemplar-based method [3] tries to find a correspondence map that assigns regions in Ω corresponding regions in Λ. Then, some well-founded heuristics follow this basic idea to accomplish the inpainting task. The key aspects are to determine the filling priority and to search for the best matching candidates. However, the priority model proposed in [3] is problematic because of the large dropping confidence value when the filling proceeds. Also, the method in [3] does not consider the condition that numerically close candidates are found in the stage of the best matching searching.

In this paper, we propose an improved exemplar-based inpainting aiming at solving the problems mentioned above. We first introduce a regularized factor in the priority model. We then combine the strength of a modified sum of squared differences (SSD) and the normalized cross correlation (NCC) to search for the best matching patch. This would enhance the robustness of the inpainting model, especially for the large removal regions. The rest of the paper is organized as follows. Section 2 introduces the related work. In Section 3, we describe the current exemplar-based image inpainting algorithm. Based on this, we point out the weakness in original exemplar-based inpainting algorithm and introduce our improved method in Section 4. Experiments are introduced in Section 5, followed with a conclusion in Section 6.

2. Related work

As a type of image restoration problem, image inpainting involves a number of theories and approaches in image completion [10], texture synthesis [7,9], image replacement [8], image

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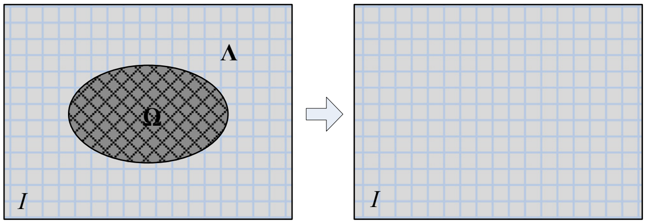

Fig. 1. A schematic illustration of image inpainting which is to repair the missing region **Ω** with the undamaged region **Λ**.

interpolation [15], image deblurring [16], image search [19], etc. The research on image inpainting technology mainly includes three directions. The first direction is inpainting based on the variational partial difference equations (PDEs) for repairing some small image scratches. The second direction is inpainting based on the texture synthesis technology for filling some large image regions, and the third one is the combination of the methods.

For the first direction, researchers pay attention to the structure inpainting in images. Inspired by the partial difference equations of physical heat flow, Bertalmio et al. [4] propose a novel image inpainting algorithm that replicates the basic techniques used by professional restorators. This algorithm restores small regions in image by propagating information from the surrounding areas in the isophotes direction. Later, Chan and Shen [5] develop general mathematical models for inpainting involving the recovery of edges, and the total variation (TV) model is built for local non-texture image inpaintings. Although the TV inpainting model can keep the image edges and compute efficiency, it destroys the connection principle in human disocclusion process. Thus, Chan and Shen [6] present the curvature-driven diffusions (CDD) inpainting model that modifies the conductivity coefficient with the curvature of the isophotes.

For the second direction, texture synthesis technique is the main research foundation. Based on Heeger and Bergen's work [7], Igehy and Pereira [8] present an image replacement technique by integrating composition into the texture synthesis algorithm. Then, Harrison [9] synthesizes an image by using a given input image as the texture mask. This method could replace an object in image even if the background is non-homogeneous. Drori et al. [10] propose a fragment-based image completion algorithm that iteratively approximates the unknown region and fills in the image by adaptive fragments. The input image is completed by a composition of fragments under the combinations of spatial transformations. Under constraint inpainting conditions, these two class algorithms could do an impressive work for repairing structure or texture regions in image.

In recent years, researchers try to explore new image inpainting techniques that could repair structure and texture regions simultaneously [11]. At the beginning, Bertalmio et al. [12] proposed an algorithm for the filling of texture and structure in the regions of missing image information. The basic idea is to first decompose the image into the sum of two functions with different basic characteristics and then reconstruct each one of these functions separately with structure and texture fill-in algorithms. The shortage is the blur effect at the edge of the inpainted region. Combined the advantages of structure and texture inpaintings, Criminisi and Toyama [3] first present an exemplar-based inpainting algorithm for removing large region objects. This approach computes the fill order of patches in missing region by using the confidence value and image isophotes of pixels on the boundary of missing region, then finds the best match patch in the remaining regions to fill in the missing regions. For exemplar-based inpainting, Xu and Sun [13] use the sparsity of natural image patches to lead patch propagation that the two concepts of sparsity at the patch level are proposed for modeling the patch priority and patch representation.

3. Exemplar-based inpainting

According to Criminisi's model [3], an image is divided into two parts: Λ represents the undestroyed image region which called source region, and Ω represents the damaged image region called the target region (see Fig. 1). The boundary of Ω is denoted by $\delta\Omega$. The original exemplar-based inpainting algorithm contains three main steps as follows.

3.1. Compute the filling priority

This step determines the filling order of patches in target region. After computing the filling priority of all the pixels along the boundary of target region, the pixel p with the highest priority is used as the center pixel to choose the target patch Ψ_p to be inpainted. The filling priority equation can be described as follows:

$$P(p) = C(p)D(p) \tag{1}$$

where $C(p)$ denotes the confidence term and $D(p)$ denotes the data term. More specifically, $C(p)$ and $D(p)$ are computed by the following:

$$C(p) = \frac{\sum_{q \in \Psi_p \cap \Lambda} C(q)}{|\Psi_p|}, \quad 0 \le C(p) \le 1 \tag{2}$$

$$D(p) = \frac{|\nabla I_p^{\perp} \cdot n_p|}{\alpha}, \quad 0 \le D(p) \le 1 \tag{3}$$

Given a pixel p on the boundary of target region, its confidence $C(p)$ equals to the ratio between the confidence sum of pixels in $\Psi_p \cap \Lambda$ and the total number of pixels in Ψ_p. Considering the structure feature around p, $D(p)$ equals to the product of the unit normal vector n_p of p and the isophotes vector $\nabla I_p^{\perp}$, and α is the normalization factor.

3.2. Search for the best matching patch

In this step, the algorithm searches for the best matching patch $\Psi_{\hat{q}}$ for the target patch Ψ_p in source region. The SSD distance $d(\Psi_p, \Psi_q)$ is introduced to compute the similarity between each patch Ψ_q in source region and the target patch Ψ_p:

$$\Psi_{\hat{q}} = \arg\min_{\Psi_q \in \Lambda} d(\Psi_p, \Psi_q) \tag{4}$$

$$d_{SSD}(\Psi_p, \Psi_q) = \sum[(R_{\Psi_p} - R_{\Psi_q})^2 + (G_{\Psi_p} - G_{\Psi_q})^2 + (B_{\Psi_p} - B_{\Psi_q})^2] \tag{5}$$

In Eq. (5), R, G and B denote the values of intensity of each color channel.

3.3. Copy the best matching patch information and refresh the boundary of target region

In this step, the algorithm fills the region corresponding to $\Psi_p \cap \Omega$ by replicating the corresponding region in the best matching patch $\Psi_{\hat{q}}$ to the target patch Ψ_p. Besides, the boundary of the target region $\delta\Omega$ has to be renewed.

The above steps are implemented iteratively until the removal region is fully inpainted.