

Implementation of Exemplar based Image in Painting Using Object Removal

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Abstract

Exemplar-based image inpainting is a method for filling in missing or damaged regions of an image by searching for similar patches in the surrounding area and copying them into the damaged region. This paper presents a algorithm for removing objects from digital photographs and replacing them with visually plausible backgrounds. The algorithm effectively hallucinates new colour values for the target region in a way that looks reasonable to the human eye. note that exemplar-based texture synthesis contains the essential process required to replicate both texture and structure; the success of structure propagation, however, is highly dependent on the order in which the filling proceeds. The algorithm presented here combines the strengths of both approaches. As with inpainting, we pay special attention to linear structures. But, linear structures abutting the target region only influence the fill order of what is at core an exemplar-based texture synthesis algorithm. The result is an algorithm that has the efficiency and qualitative performance of exemplar-based texture synthesis, but which also respects the image constraints imposed by surrounding linear structures.

I. Introduction

Object removal from images is an image manipulation technique that has a long history. The purpose of removing objects varies from remove undesired object to improve the quality of the image, to “airbrushing” out political enemies from portraits of important events. Modern photographic manipulations, such as red eye removal from pictures, also utilized this technique. The process of removing objects from images starts with mask out the undesired object, making the area where the object previously occupies a gap. Then the gap will be filled using graphical techniques such as inpainting. Among the graphical techniques that are used to fill the gap after object removal, two most commonly used are: image inpainting and texture synthesis. Fixing images using inpainting has a long history. Most notably, during the Renaissance, many medieval artworks had been brought “up to date”. Missing or damaged parts in the paintings were reconstructed in a way that not detectable from human eyes. Structures and textures around the gap were carefully extended into the missing area. The results would look natural enough that observers

without prior knowledge of the original image will not notice the gaps. Bertalmio, etc.[2]'s algorithm imitates the traditional inpainting processes, such as determine the area to be corrected, exam the boundary of the region to be filled, and continuing lines of similar color. A series of differential equations are used to imitate these processes. The most important equation is to calculate the isophote (direction and intensity) of a pixel. Each pixel is modified by adding its current intensity to and updated intensity times a delta factor. The updated intensity consists of a change of smoothness estimation projected along the direction of shortest change. Smoothness is approximated by a discrete Laplacian. The direction of shortest change is defined as the vector perpendicular to the gradient, and the dot product of this vector with the vector consisting of the x and y changes in the Laplacian, is multiplied by a slope-limited norm of the gradient of numerical stability. Texture synthesis grows a new image outward from an initial seed. Efros and Leung [3] proposed a texture synthesis approach by non-parametric sampling. A Markov random field model is assumed. Before a pixel is synthesized, its neighbors are sampled. Then the whole image is queried to find out a pixel (source pixel) with similar neighbors. At this point, the source pixel is copied to the pixel to be synthesized. The biggest draw back of this algorithm is that generating every single new pixel needs to sample the whole picture, and thus not very efficient. Efros later went on to address this issue by modifying the algorithm to perform the sampling, search and synthesis in a patch. Each patch has an overlap with the next one, and they are quilted together. [4] This new algorithm improved performance greatly. Both image inpainting and texture synthesis have their strengths and weaknesses. Image inpainting extends linear structure into the gap by utilizing the isophote information of the boundary pixels. The linear structures will be naturally extended into the gap. However, since the extension actually using the diffusion techniques, artifacts such as blur could be introduced. On the other hand, texture synthesis copies the pixels from existing parts of the image, thus avoids the blur. The shortcoming of texture synthesis is that it focuses on the whole image space, without giving higher priority to the linear structures around the boundary of the gap. As a result, the linear structures will not be naturally extended into the gap. The result would likely have distorted lines, and noticeable differences between the gap and its surrounding area would be expected. One interesting observation is that even though image inpainting and texture synthesis seem to differ radically, yet they might actually complement each other. If we could combine the advantages of both approaches, we would get a clear gap filling that is the natural extension from the surrounding area. Criminisi, etc. proposed a new algorithm that does exactly this. [1]

Criminisi, etc. use the sampling concept from Efros' approach. The improvement over Efros' is that the new approach takes isophote into consideration, and gave higher priority to those "interesting points" on the boundary of the gap. Those interesting points are parts of linear structures, and thus should be extended into the gap in order to obtain a naturally look. To identify those interesting points, Criminisi gives a priority value to all the pixels on the boundary of the gap. The "interesting points" will get higher priorities according to the algorithm, and thus the linear structures would be extended first. For each pixel on the boundary, a patch is constructed with that pixel at the center. The patch's priority is the product of two elements: a confidence term $C(p)$, and a data term $D(p)$. $C(p)$ describes how many pixels are there in the patch. It is obvious that with more pixels in the patch, we would have a better confidence that a success target patch would be selected. $D(p)$

describes how strong the isophote is hitting the boundary. This term boosts the priority of a patch that an isophote “flows” into. $D(p)$ is especially important, since it encourages linear structures to be synthesized first, and thus propagated securely into the target region.

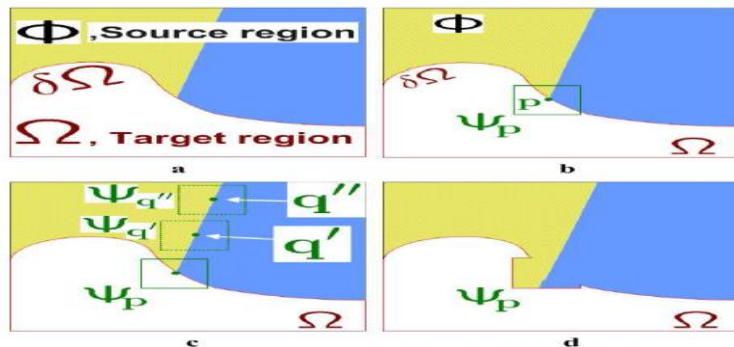


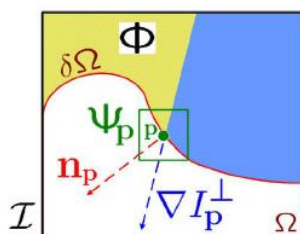
Figure 1. Structure propagation by exemplar-based texture synthesis.

The user will be asked to select a target region, Ω , manually. (a) The contour of the target region is denoted as $\delta\Omega$. (b) For every point p on the contour $\delta\Omega$, a patch Ψ_p is constructed, with p in the center of the patch. a priority is calculated based on how much reliable information around the pixel, as well as the isophote at this point. (c) The patch with the highest priority, would be the target to fill. A global search is performed on the whole image to find a patch, Ψ_q that has most similarities with Ψ_p . (d) The last step would be copy the pixels from Ψ_q to fill Ψ_p . With a new contour, the next round of finding the patch with the highest continues, until all the gaps are filled.

II. Implementation

The algorithm iterates the following three steps until all pixels have been filled:

- 1) Computing patch priorities
- 2) Propagating texture and structure information
- 3) Updating confidence values



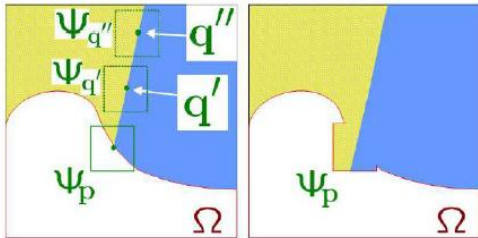
$$P(p) = C(p)D(p) \quad \text{where} \quad C(p) = \frac{\sum_{q \in \Psi_p \cap (\mathcal{I} - \Omega)} C(q)}{|\Psi_p|}$$

$$D(p) = \frac{|\nabla I_p^\perp \cdot \mathbf{n}_p|}{\alpha} \quad \mathbf{n}_p \text{ is unit vector orthogonal to the front } \delta\Omega$$

∇I_p^\perp is the isophote(direction and intensity)

Once all priorities on the fill front have been computed, the patch Ψ_p with highest priority is

found. $\Psi_q = \arg \min_{\Psi_q \in \Phi} d(\Psi_p, \Psi_q)$



This suffices to achieve the propagation of both structure and texture information from the source Φ to the target region Ω one patch at a time.

After the patch Ψ_p has been filled with new pixel values, the confidence $C(p)$ is updated in the area delimited by Ψ_p as follows:

$$C(p) = C(p) \quad \forall p \in \Psi_p \cap \Omega$$

As filling proceeds, confidence values decay, indicating that we are less sure of the colour values of pixels near the centre of the target region.

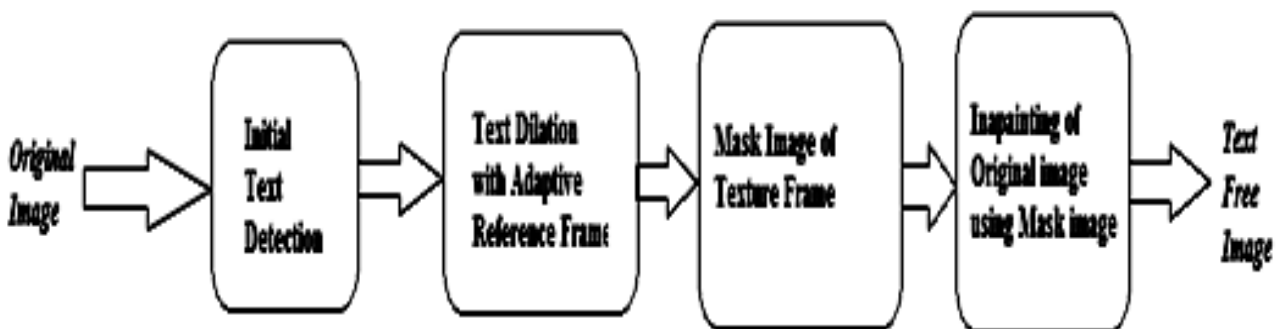


Figure2: Proposed methodology

Steps of achievement:-

- Using given input image first initial text detection is done.
- Secondly using text dilation with adaptive reference frame is generated.
- Using text dilation reference frame generate Mask image with Texture Frame of given image.
- Finally using image inpainting technology, inpaint the original image with reference to mask image.

III. Simulation Results

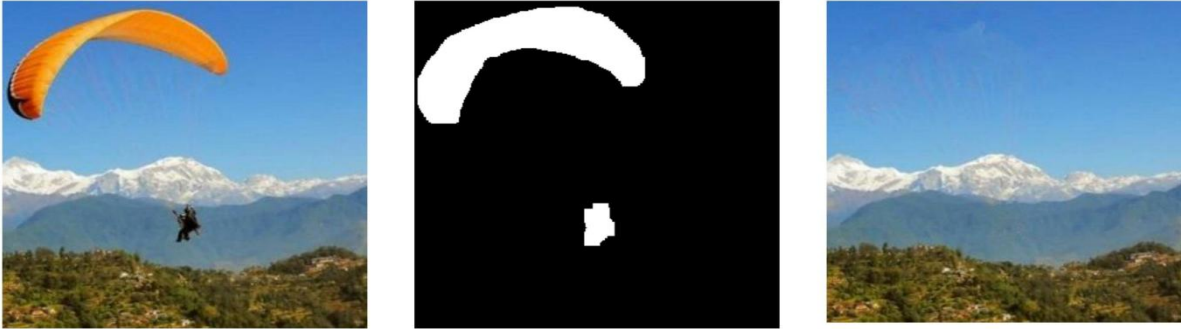


Figure 3: Simulation Results of parachute.



Figure 3: Simulation Results of fields.



Figure 4: Simulation Results of Bungee Jump.

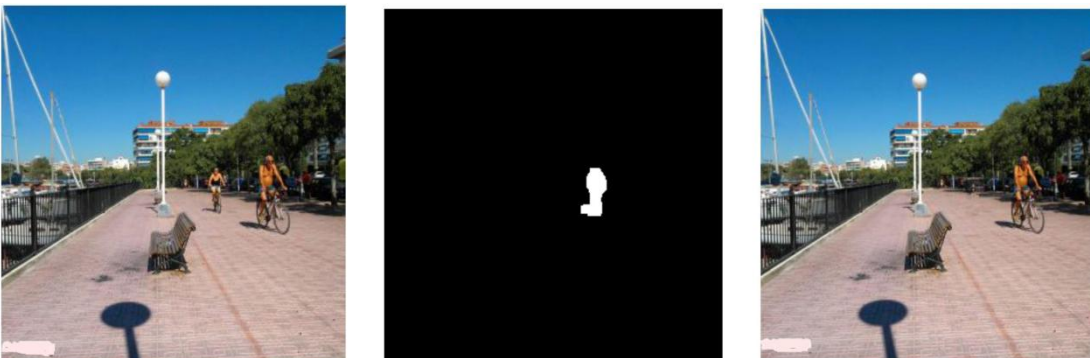


Figure 5: Simulation Results of Bicycling.



Figure 6: Simulation Results of Home flower pot.

IV. Conclusion

This paper has presented a novel algorithm for removing large objects from digital photographs. The result is an image in which the selected object has been replaced by a visually plausible. The “knitting” effect along the boundary between the two textures is correctly reproduced also by our technique background that mimics the appearance of the source region. Our approach employs an exemplar-based texture synthesis technique modulated by a unified scheme for determining the fill order of the target region. Pixels maintain a confidence value, which together with image isophotes, influence their fill priority. The technique is capable of propagating both linear structure and two-dimensional texture into the target region with a single, simple algorithm. Our method performs at least as well as previous techniques designed for the restoration of small scratches, and, in instances in which larger objects are removed, it dramatically outperforms earlier work in terms of both perceptual quality and computational efficiency. Moreover, robustness towards changes in shape and topology of the target region has been demonstrated.

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