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Image Restoration and Inpainting Using Belief Propagation with Dynamic Pruning Optimized Exemplar Algorithm

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Abstract

One of the most important premises of research in image processing happens to be Image inpainting which is a technique to fill missing region or reconstruct damaged area in an image. Through image inpainting one can also remove an undesirable object from an image in visually plausible way. For filling the part of image, it uses information from the neighboring area. In this paper, we present an Exemplar based method for filling in the missing information in an image, and its subsequent optimization through belief propagation which takes structure synthesis and texture synthesis together for achieving its goal. The algorithm is based on priority patch based filling procedure.

Keywords: Image inpainting, Exemplar based inpainting, Dynamic Pruning, Image Processing.

1. Introduction

There always exist situations in real life when one needs to repair damaged portions of an old archived image or remove unwanted elements from an image. The damages in image may be due to various reasons like scratches, overlaid text or graphics, scaled image etc. Nowadays, powerful photo-editing tools are available for retouching, drawing, and removal of objects like Adobe Photoshop. But, to fill the missing information or reconstruct damaged area in an image is still a difficult and computationally expensive task.

Hence there is always a need for having better algorithm that can do image inpainting with greater accuracy and less computation time. The ultimate goal of

Image inpainting happens to be modification and filling the missing area in an image in an undetectable way to an observer not familiar with the original image [1].

Image inpainting is different from other general image enhancement algorithms in the sense that image enhancement assumes that pixel in the damaged portion of image, contain both the information about real data and the noise, while in image inpainting, the pixel values are all assumed to be missing in the filling domain.

The concept of image inpainting was first introduced by Bertamio et al. [1][2]. The method was inspired by the real inpainting process of artists. The image smoothness information interpolated by the image Laplacian is propagated along the isophotes directions, which are estimated by the gradient of image rotated by 90 degrees. The work in [3] introduced another method using the framework of the Navier-Strokes equation and gave good result. The approach uses ideas from fluid dynamics to propagate isophote lines from the exterior into the region to be inpainted. Chan and Shen [4] introduced the space of Bounded Variation images to an inpainting system, which recovers missing information with total variation.

The major problem with the above methods is that they are unable to reconstruct texture regions. These methods have several disadvantages. The main disadvantage is that these approaches may lead to blurred filling in texture missing regions and large missing regions. Consequently, inpainting approaches based on texture synthesis are proposed to avoid this kind of problem.

The work in [5] decomposes the original image into two components, one of which is processed by inpainting and other by texture synthesis. The output image is sum of two processed components. This approach still remains limited to the removal of small gaps; however, as the diffusion continues to blur the field region

Exemplar Based method proposed by Criminisi et al. [6] used a best exemplar patch to propagate target patch including missing pixels. This technique uses an approach which combine structure propagation with texture synthesis and hence produced very good results. Wong and Orchard [7] combined plural non-local exemplar patches to propagate.

In this paper we present exemplar based approach which has been optimized by belief propagation with dynamic pruning.

2. Algorithm Description

Exemplar based approaches perform well for two dimensional texture as well as with liner image structure. First, given an input image, the user selects the object to be removed. This step requires user interaction because object to be removed depends on the subjective choice of the user. The part of the image from where the object is to be removed is known as target region or inpainting domain **Ω**. The sources region is entire image minus the target region.

Once all the parameters of the inpainting are specified, the region- filling proceeds automatically. During the algorithm, patches along the fill-front are assigned a temporary priority value, which determines order in which they are filled. Then the algorithm iterates following three steps until all pixels have been filled.

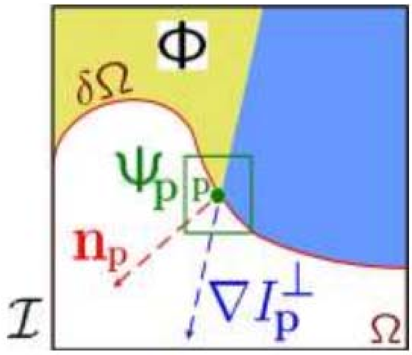


Fig. 1: Notation diagram.

Above Fig. shown the missing regions i.e. target region or inpainting region is denoted by Ω and its boundary δΩ also specify and the source region is denoted by Φ. Ψp is the best edge patch find from boundary of target region. Approach is divided in three parts.

2.1 Find Best Edge Patch

In the first step, a best edge patch Ψp is picked out using priority [6]. This algorithm uses best- first filling strategy that entirely depends on the priority values which are assigned to each patch on the fill-front. The priority computation is biased toward those patches which (1) are on the continuation of strong edges and (2) are surrounded by high-confidence pixels.

Given a patch Ψp centred at the point P for some P∈δΩ is shown in Fig. 1 Priority P (p) is defined as the product of two terms

$$P(p) = C(p)\,D(p)$$

Here, C (p) is the confidence term and D (p) is the data term. They are defined as follows.

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

$$D(p) = \frac{|\nabla I_p^{\perp} . n_p|}{\alpha}$$

Where $|\Psi p|$ is the area of Ψp, α is a normalization factor (e.g.,α=255 for a typical grey-level image), np is a unit vector orthogonal to the fill-front $\delta\Omega$ in the point P, and ⊥denotes the orthogonal operator. The priority is computed for every border patch, with distinct patches for each pixel on the boundary of the target region. During initialization, the function C (p) is set to C (p) = 0, $\forall p \in \Omega$ and C (p) = 1, $\forall p \in \mathcal{I} - \Omega$.

The confidence term C (p) may be thought of as a measure of the amount of reliable information surrounding the pixel P. The idea is to fill first those patches which have more of their pixels already filled. This automatically incorporates preference toward certain shapes of the fill-front. For example, patches that include corners and thin tendrils of the target region will tend to be filled first, as they are surrounded by more pixels from the original image.

The data term boost the priority of the patch in which a liner structure flows into. This term is very important because it allows broken lines to correct.

2.2. Find Best Match Patch

Once priority is finding for all patches on boundary then take patch Ψp which has highest priority. The most similar patch Ψq is the one which has the minimum difference in the pixel value with patch Ψp.

Difference between any two pixels p and q given by using sum of squared difference (SSD) method. It define as

$$SSD(\Psi_p, \Psi_q) = \sum_{i=1}^{M} \mu_i (\Psi_p(i) - \Psi_q(i))^2$$

Where, Ψp(i) and Ψq(i) are the i-th pixel value in respective patches. M is the size of the patch. µi is pixel mask function. An exemplar patch Ψq is a patch with the lowest SSD value. Which is define as

$$\Psi_q = \min_{\Psi_Q \in \Phi} SSD(\Psi_p, \Psi_q)$$

Above equation give the patch which is most similar to the patch Ψp in the image which has minimum SSD value. Here SSD method takes color value of two pixels for difference.

2.3 Copying Best Match Patch and Updating Confidence Values using BP with Dynamic Pruning

Once the patch Ψ_p is filled with new pixel value Ψ_q, confidence value in the area is updated as follows.

C (q) = C (p) for all q belonging to $\Psi_p \cap \Omega$.

This simple update rule allows us to measure the relative confidence of patch on the fill front. After completion of these three steps then update boundary with updated target region and repeat these three steps until all the pixels in the target region is not filled. Furthermore, once all of these regions are filled up using the above steps, the BP network is used for optimization of the filled values such that the texture of the image is accurately preserved.

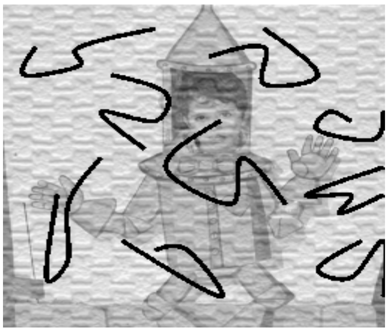
3. Algorithm Implementation and Simulation Results

In order to test the proposed algorithm we implemented it using MATLAB and ran tests on several images. The first result is shown in the Fig. below:

Fig. 1 shows the image with missing region while Fig. 2 shows the inpainted image.

Fig. 1 **Fig. 2**

The total computation time for the above result was 32 seconds. Another test was conducted on image as shown in Fig. 3 and its equivalent inpainted image is shown in Fig. 4.



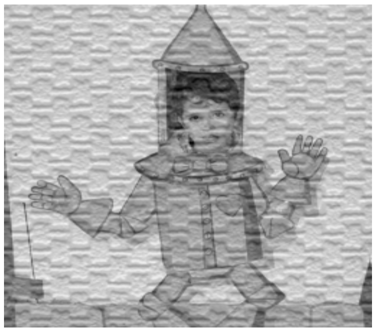


Fig. 3 **Fig. 4**

The total time taken for this computation was 59.2 seconds. As can be seen, the method proposed by us not only gives robust results but also computes it in significantly less time.

4. Conclusion

Image inpainting is a technique to fill missing region or reconstruct damaged areas from an image. In this paper, we proposed and implemented an exemplar based and BP optimized approach for image inpainting. This technique considers structure propagation and texture synthesis together which reduced blur and improved accuracy in inpainted image.

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