

Combined Structure and Texture Image Inpainting Algorithm for Natural Scene Image Completion

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Abstract

Image inpainting or image completion refers to the task of filling in the missing or damaged regions of an image in a visually plausible way. Many works on this subject have been proposed these recent years. We present a hybrid method for completion of images of natural scenery, where the removal of a foreground object creates a hole in the image. The basic idea is to decompose the original image into a structure and a texture image. Reconstruction of each image is performed separately. The missing information in the structure component is reconstructed using a structure inpainting algorithm, while the texture component is repaired by an improved exemplar based texture synthesis technique. Taking advantage of both the structure inpainting methods and texture synthesis techniques, we designed an effective image reconstruction method. A comparison with some existing methods on different natural images shows the merits of our proposed approach in providing high quality inpainted images.

Keywords: Image inpainting, Decomposition method, Structure inpainting, Exemplar based, Texture synthesis

1. Introduction

Digital Image inpainting is the process of filling-in missing or damaged image information. Its applications include removing scratches in old photos, removing text or logos, repairing damaged areas in unreliably transmitted images, image zooming, completing the holes after removing undesired objects from an image, or even creating artistic effects. Since the missing or damaged areas cannot be simply classified objectively; the user needs to identify them. These specified regions are called inpainting domain.

The removal of portions of an image is an important tool in photo-editing and film post-production, such as image restoration (e.g. scratch removal) and special effects (e.g. removal of objects). Image completion is an area related to texture synthesis. Inpainting techniques were naturally extended from paintings to images and films (Bertalmio et al 2000). Image inpainting and image completion differ in the area that is to be filled or completed. In image completion regions are large and consist of textures, large scale structures and smooth areas. The region to be removed is specified by the user. It is, generally, some foreground element that needs to be taken off the scene. After removing the foreground the area is to be filled so that the image looks naturally complete (Drori et al 2003).

Texture synthesis can also be used to complete regions where the texture is stationary or structured. Reconstructing methods can be used to fill in large scale missing regions by interpolation. Inpainting is suitable for relatively small, smooth and non-textured regions. Our approach focuses on image based completion; with no knowledge of the underlying scene (Drori et al 2003). The image is completed by searching for appropriate textures all over the image, such that on completion it preserves the natural appearance of the image.

For structure images and texture images, there are algorithms of two classes to tackle the inpainting problems: Partial Differential Equation (PDE) or Calculus of Variation (CoV) based inpainting algorithms for structure images (Bertalmio et al 2000, Chan et al 2001 and Chan 2002) and texture synthesis based algorithms for texture images (Efros and T. Leung 1999, Criminisi et al 2004, Wong and Orchard 2008, G. T. N. Komodakis 2007). The former class of algorithms completes the images by diffusing known surrounding information into the inpainting area, while the latter find texture block from known region best matched block formed by the neighborhood of a selected pixel on the boundary of inpainting domain, and then substitute the counterpart in the matched block for the unknown part of the pixel-neighborhood block. There are a few works of hybrid inpainting algorithms based on image decomposition (Bertalmio et al 2003, Harald (2004), Rane et al 2003).

2. Background and Review of Inpainting

For the inpainting problem it is essential to proceed to the discrimination between the structure and the texture of an image. As structure we can define the main parts - objects of an image, whose surface is homogeneous without having any details. As texture we can define the details on the surface of the objects which make the images more realistic.

2.1. Structure Inpainting

The term inpainting was first used by (Bertalmio et al 2000). The idea is to propagate the isophotes that arrive at the boundary of the inpainting region, smoothly inside the region while preserving the arrival angle. In the same context of mimicking a natural process, Bertalmio et al. suggested another similar model, where the evolution of the isophotes is based on the Navier Stokes equations that govern the evolution of fluid dynamics (Bertalmio et al 2001). Apart from physical processes, images can also be modeled as elements of certain function spaces. An early related work under the word"disocclusion" rather than inpainting was done by Masnou and Morel (1998). Chan and Shen (2001) derived an inpainting model by considering the image as an element of the space of Bounded Variation (BV) images, endowed with the Total Variation (TV) norm. The solution of the inpainting problem comes from the minimization of an appropriate functional. This TV inpainting model was extended by Chan and Shen (2001)to take into consideration curvature and the so called connectivity principle according to which the human eye tends to reconstruct the broken edges. Along similar lines, Mumford and Shah (1989) proposed another inpainting model, which takes explicit care of the edges on the functional to be minimized. Its extension to account for curvature was proposed by Esedoglu and Shen (2002) using the Euler's elastica.

2.2. Texture Inpainting

The problem of texture inpainting is highly connected with the problem of texture synthesis. A very simple and highly effective algorithm was presented by Efros and Leung(1999). In this algorithm the image is modeled as a Markov Random Field and texture is synthesized in a pixel by pixel way, by picking existing pixels with similar neighborhoods in a randomized fashion. This algorithm performs very well but it is very slow since the filling-in is being done pixel by pixel. An algorithm specific for texture inpainting was presented by Criminisi et al (2004). The algorithm uses the same texture synthesis techniques as the Efros-Leung algorithm. The only difference is that the pixels that are placed along the edges of the image are filled in with high priority. This slight difference is adequate to give better results for image inpainting as is presented in the results by Criminisi et al (2004).

2.3. Simultaneous Structure and Texture Inpainting

Since, in most images both structure and texture are present, a natural thing is to combine structure and texture inpainting techniques to obtain more effective techniques, regarding image inpainting. This was done by Brennan (2007). The algorithm is very simple. First the image is decomposed into its structure and texture components, and then inpainting techniques are performed for both structure and for texture. Brennan (2007) also proposed a model for simultaneous structure and texture image inpainting. Zhang Hong-bin, Wang Jia-wen (2007) proposed an approach for image inpainting by integrating both structure and texture features. For structure texture decomposition many variation methods can be used, like Meyer (2002) which was first used for image denoising, or Aujol et al (2005),] which discriminates between texture and noise.

3. The Proposed Method

There are a few works of hybrid inpainting algorithms based on image decomposition (Bertalmio et al 2003, Harald 2004 and Rane et al 2003). Inspired by Rane et al (2003), which categorized the lost transmission blocks and filled in separately, we present a novel hybrid inpainting algorithm, which first separates the damaged region into structure region and texture region. In this paper we use the combination of structure inpainting and texture synthesis schemes to provide a robust algorithm.

3.1 Image Decomposition

Knowing that texture synthesis algorithms exist to accurately fill in regions of missing texture, and image inpainting algorithms exist to fill in regions of missing image structure, a method is desired of decomposing a given image into two sub-images. One sub-image will be a structure image which will be a cartoon-like version of the input image where large-scale edges are preserved but interior regions are smoothed. The other sub-image will be a texture image which will contain all of the texture information of an image, including noise. These sub-images can then be reconstructed using image inpainting and texture synthesis techniques.

Various models can be used to decompose images. In this paper, a model in Bertalmio (2006) to Meyer's model (2005) is applied to the image *u*.

The basic model used in the paper is: f = u + v where f is the input image, u is the structural image, and v is the texture image. In this model, having the structure and texture images allows one to exactly reconstruct the original image. The end goal of the deconstruction method is to have a very smooth image u which preserves all the dominant edges in an image but is smooth on interior regions, and an image v which contains all the texture in an image as well as the noise. These images will then be fed into an inpainting algorithm and a texture synthesis algorithm respectively. The output of those algorithms can be recombined to obtain the final image.

3.2 Structural Part Inpainting

We apply the algorithm from *Zhon*gyu Xu et al (2008) for structure inpainting. This algorithm revealed the concepts in manual inpainting, thus got good inpainting results, especially for images with high contrast edges. The inpainting problem is viewed as a particular case of image interpolation in which we intend to propagate level lines. Expressing this in terms of local neighborhoods and using a Taylor expansion we derive a third-order PDE that performs inpainting. This PDE is optimal in the sense that it is the most accurate third-order PDE which can ensure continuation of level lines. The continuation is strong, allowing the restoration of thin structures occluded by a wide gap. The result is also contrast invariant.

3.3 Damaged Area Classification

The aim of this part is to reduce the pixels to be synthesized and reduce the region to search for similar texture blocks. We use algorithm developed by *Zhon*gyu Xu et al (2008) for texture segmentation, and there are few restrictions on which algorithm to adopt. Let us have a brief illustration.

A pixel **(*i, j*)** is called row maximum if ***u*(*i, j*-1)<*u*(*i, j*)>*u*(*i, j*+1),** and also there exists concepts of row minimum, column maximum and column minimum, which are called row extremua and column extremua. A pixel is called a local extremum if it is a row extremum and also a column extremum. Define the coarseness of a pixel as the percentage of local extremua in the neighborhood. A pixel with proper coarseness is classified into texture region, while high coarseness corresponds to noise and low coarseness to flat area.

3.4 Improved Exemplar Based Texture Synthesis

The exemplar-based inpainting algorithm consists mainly of three iterative steps, until all pixels in the inpainted region are filled. The region to be filled, i.e., the target region is indicated by Ω, and its contour is denoted ∂Ω. The contour evolves inward as the algorithm progresses, and so we also refer to it as the "fill front." The source region which remains fixed throughout the algorithm, provides samples used in the filling process. In order to find the most similar patch in the source region to the target patch, we search the whole source image to find the best fit. The similarity is measured by computing the sum of squared distance in color between each corresponding pixel in the two patches.

We adopt the notations similar to that used in inpainting literature. The region to be filled, i.e., the inpainting domain, is indicated by Ω, and its boundary is denoted δΩ. The *source* region, Φ, which remains fixed throughout the algorithm, provides samples used in the filling process. The similarity measure based only on color is insufficient to propagate accurate linear structures into the target region, and leads to garbage growing. So, we add to this distance function a new term G representing image gradient as an additional similarity metric.

$$G=G(\Psi_p)-G(\Psi_q)$$

Where G is the gradient value for each pixel in the two considering patches. Hence, the similarity function now depends on the difference between the patches according to two criteria, the difference in color and in gradient values. The details of the algorithm implementation is as follows,

3.4.1 Computing Patch Priorities

Given a patch Ψ_p centered at the point p for some $p \varepsilon \partial\Omega$, its priority P (p) is defined as the product of two terms $P(p)=C(p)D(p)$. C(p) is the confidence term and D (p) is the data term, and they are defined as follows: $C(p)=\frac{\sum_{q \varepsilon \Psi_p \cap \bar{\Omega}} C(q)}{|\Psi_P|}$ and $D(p)=\frac{|\nabla I_p^{\perp} . n_p|}{\alpha}$ Where $|\Psi_p|$ is the area of Ψ_p, α is a normalization factor (e.g., $\alpha = 255$ for a typical grey-level image), and n_p is a unit vector orthogonal to the front $\delta\Omega$ in the point p. The priority is computed for every border patch, with distinct patches for each pixel on the boundary of the target region. The patch with the highest priority is the target to fill.

3.4.2. Propagating Structure and Texture Information

Search the source region to find the patch which is most similar to $\Psi_{p^\wedge}$. Formally, $\Psi_{q^\wedge} = \arg\min_{\Psi_q \varepsilon \Omega} d(\Psi_{p^\wedge}, \Psi_q)$. The distance $d(\Psi_a, \Psi_b)$ between two generic patches Ψ_a and Ψ_b is simply defined as the sum of squared differences (SSD) of the already filled pixels in the two patches. $d = \sum_{i=1}^{i=A} (I_{ai} - I_{bi})^2 + (G_{ai} - G_{bi})^2$ Where, G presents the image gradient vector, I is the RGB color vector, D is the distance (the larger d is, the less similar they are), and A is the known pixels number in $\Psi_{p^\wedge}$. Having found the source exemplar $\Psi_{q^\wedge}$ the value of each pixel to be filled is copied from its corresponding position.

3.4.3. Updating Confidence Values

The confidence C (p) is updated in the area delimited by $\Psi_{p^\wedge}$, as follows:

$c(q) = c(p^\wedge) \forall q \varepsilon \Psi_{p^\wedge} \cap \Omega$ As filling proceeds, confidence values decay, indicating that we are less sure of the color values of pixels near the center of the target region. In texture synthesis the problem is that given a small patch containing texture we wish to fill a much larger region with a texture that is visually similar to the texture patch. From a probabilistic viewpoint the problem is that given a region that has some stationary distribution we wish to synthesize additional samples from this distribution.

4. Implementation and Experimental Results

Performance of the proposed inpainting method is demonstrated by some visual examples. We compare the obtained results with the ones obtained by the methods in which the image is not decomposed, and just one algorithm (either structure inpainting method or texture synthesis technique) is applied. Also, a comparison between our method and the proposed approach by Bertalmio et al (2003) is made, as the proposed algorithm considers simultaneous structure and texture inpainting.

We have used the parameters in the proposed approach unchanged for all the examples considered here. We applied the image decomposition method with the number of numerical steps equal to 5, and for each step we computed the estimates using 30 iterations. The value of λ and μ were set to 0.03 and 0.01, respectively.

In the texture synthesis algorithm, the size of template window Ψ is set to 9×9 pixels. This size should be slightly larger than the largest distinguishable texture element or "texel", in the source region (we defined this size to be two times the texel size). During initialization, the function $C(p)$ was valued to be $C(p) = 0$, $\forall_P \varepsilon \Omega$, and $C(p) = 1, \forall_{\,p} \varepsilon f - \Omega$.

Fig. 1-3 shows the results obtained by our method in comparison with the proposed methods by Bertalmio et al (2003) and Marcelo Bertalmio (2009).

Experiments are carried out on the various natural scene images. Each input image is shown with inpainting domain. These regions are highlighted in black color. We found out that the restored images look plausible in general. It is obvious that the structure inpainting methods tend to blur the inpainted image, while the texture synthesis techniques fail to reconstruct areas having additional geometric information, as being observed in Fig. 2

The presented results, clearly demonstrate that the algorithm introduced in this paper succeeds effectively in inpainting large regions from images that consists of textures and surrounded by distinctive image structure. The execution time required for the inpainting process depends on the size of the image and the regions to be inpainted, and it ranges from few seconds to several minutes for large images.

5. Conclusion

We presented a new approach by combining structure inpainting method and texture synthesis technique in a decomposition framework. The combination of these two powerful approaches enables us to simultaneously recover texture and structure information. We demonstrated the quality of the results obtained by our method on a variety of defected input images and compared them to the results obtained by several other methods. In all cases, we could verify higher quality for inpainted images using our approach.

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Fig. 1-3 shows the results obtained by our method in comparison with the proposed methods in [9] and [25]. Each figure has (a) original image (b) image with occlusion part (c) Result of [9] (d) result of [25] (e) result of our method.

Fig. 1

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