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Image Inpainting Based on Wavelet Decomposition

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Abstract

Image inpainting is an important problem image processing. It is a difficult problem to simultaneously fill-in the texture and structure in regions of missing image information. In order to inpaint the damaged image with both missing the structure and texture information, an image inpainting algorithm based on wavelet decomposition is presented. First the damaged image is decomposed into structure sub-image and texture sub-image using the wavelet transformation. Then, the sub-image with the region of missing information in the structure is reconstructed by Curvature-Driven Diffusions (CDD) algorithm, while the same region in the texture sub-image is filled-in with the improved texture synthesis based on exemplar; Finally, the restored image is given by recombining the structure and texture restored results. A large number of experiments show that the proposed algorithm can quickly and efficiently restore the structure and texture information at the same time, and the visual effects and the Peak Signal to Noise Ratio (PSNR) is better than the similar algorithms.

Keywords: Image inpainting; image decomposition; texture synthesis

1. Introduction

Image inpainting is an important research topic in the area of image restoration[1, 2]. This paper focuses on image inpainting based on image decomposition. Recently, many algorithms for the simultaneous filling-in of texture and structure in regions of missing image information were presented[3-5]. Although the DCT-based image decomposition inpainting method which decomposed the input image into the frequency domain process easier than variation decomposition, it requires user intervention to adjust parameters repeatedly to get the best decomposition, which will result that the damaged area may cause a

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false edge and introduce unnecessary noise in the decomposition process. On the other hand, restore the sub-structure image and sub-texture image using single-pixel which will result in slower speed. According to these analyses, we propose an image inpainting algorithm based on wavelet decomposition. First the damaged image is decomposed into structure sub-image and texture sub-image using the wavelet technique. Then, the sub-image with the region of missing information in the structure is reconstructed using image inpainting by CDD[6] algorithm, while the same region in the texture sub-image is filled-in with texture synthesis based on exemplar algorithm; Finally, the restored image is given by recombining the structure and texture restored results. A large number of experiments show that the proposed algorithm can quickly and efficiently restore the structure and texture information at the same time, and the visual effects and the Peak Signal Noise Ratio (PSNR) is better than the similar algorithms.

2. The Proposed Algorithm

The proposed algorithm has three main building blocks, including Image decomposition, image (structure) inpainting, and texture synthesis. The original image is first decomposed into the sum of four images by wavelet transformation, one capturing the basic texture image and three capturing the image structures. Because the wavelet transform is the transfer of energy, image information has not any loss of information during the decomposition process and the wavelet transform has capability to perfect reconstruction. Therefore, in this paper we overlay the three structure images as one structure image. Then, the structure image is inpainted following the work by Chan T F.and Shen J H. described in [4], while the texture image is filled-in with a texture synthesis algorithm based on exemplar. The two reconstructed images are then added back together to obtain the reconstruction of the original data. In the next three sections we briefly describe the particular techniques used for each one of them.

2.1. Image Decomposition

In this section, we review the image decomposition approach based on wavelet transformation proposed in [5]. We first decompose the input image using wavelet transform and obtain the corresponding four wavelet coefficient matrix. Then we apply inverse wavelet transform to each wavelet coefficient matrix, respectively, we will get four images, including one texture image, one horizontal structure image, one vertical structure image and one diagonal structure image. Finally, the three structure image overlay as one structure image.

The two-dimensional discrete wavelet transform is defined as [7]:

$$W_\varphi(j_0,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}f(x,y)\varphi_{j_0,m,n}(x,y)\quad m,n=0,1,2,\ldots,2^j-1 \tag{1}$$

$$W_\phi^i(j,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}f(x,y)\phi_{j,m,n}^i(x,y)\quad i=\{H,V,D\} \tag{2}$$

where $f(x,y)$ is the 2D function being of $M\times N$. $W_\varphi(j_0,m,n)$ is the approximate component, $W_\phi^i(j,m,n)$ is the detail component $\varphi(x,y)$ is the 2D scaling function, while $\phi(x,y)$ is the 2D wavelet function. Further, we get

$$\varphi(x)=\sum_n h_\varphi(n)\sqrt{2}\varphi(2x-n) \tag{3}$$

$$\phi(x)=\sum_n h_\phi(n)\sqrt{2}\varphi(2x-n) \tag{4}$$

where $h_{\varphi}(n)$ is the coefficient of the 1D scaling function $\varphi(x)$ and h_{φ} is the scale vector, while $h_{\phi}(n)$ is the coefficient of the 1D wavelet function $\phi(x)$ and h_{ϕ} is the wavelet vector.

The corresponding inverse two-dimensional discrete wavelet transform is defined as:

$$f(x,y)=\frac{1}{\sqrt{MN}}\sum_{m}\sum_{n}W_{\varphi}(j_0,m,n)\varphi_{j_0,m,n}(x,y) + \frac{1}{\sqrt{MN}}\sum_{i=H,V,D}\sum_{j=j_0}^{\infty}\sum_{m}\sum_{n}W_{\phi}^{i}(j,m,n)\phi_{j,m,n}^{i}(x,y)\quad i=\{H,V,D\} \tag{5}$$

If $f(x,y)$ represents the input image, the wavelet transformation is equivalent to filter the image with $h_{\phi}(n)$ and $h_{\varphi}(n)$ and down-sampling as a factor of 2, then filter the two sub-images with $h_{\phi}(\mathrm{m})$ and $h_{\varphi}(\mathrm{m})$ and down-sampling as a factor of 2, finally four quarter-size sub-images (wavelet coefficients) are obtained. If the corresponding filter coefficient matrix of $h_{\phi}(n)$ and $h_{\varphi}(n)$ are represented as *Hn* and *Ln*, F represents the image matrix, then Wavelet transform can be simplified as

$$\begin{cases} C_{j+1}=L_n F L_m \\ D_{j+1}^{h}=L_n F H_m \\ D_{j+1}^{v}=H_n F L_m \\ D_{j+1}^{d}=H_n F H_m \end{cases}\quad j=0,1,\ldots,J-1 \tag{6}$$

where, C is the approximate component, D is the detail component. *h*, *v, d* represent the horizontal direction, vertical direction and diagonal direction of the detail component, respectively. On the contrary, the inverse wavelet transform can be simplified as

$$\begin{cases} F_{j-1}^{0}=L_m^{'} C_j L_n^{'} \\ F_{j-1}^{h}=H_m^{'} D_j^{h} L_n^{'} \\ F_{j-1}^{v}=L_m^{'} D_j^{v} H_n^{'} \\ F_{j-1}^{d}=H_m^{'} D_j^{d} H_n^{'} \end{cases}\quad j=J,J-1,\ldots,1 \tag{7}$$

$$F_{j-1}^{1}=F_{j-1}^{h}+F_{j-1}^{v}+F_{j-1}^{d}\quad j=J,J-1,\ldots,1 \tag{8}$$

Based on the above steps for layer wavelet decomposition, the image is decomposed into structure image F^0 and texture image F^1. Because it may look damaged boundary as the edge during the decomposition process which will intrudece the cumulative error, in this paper, in order to avoid the cumulative error, we first use the structural elements m=[0,1,0;1,1,1;0,1,0;] to expand the binary mask image, and then multiply the expanded binary mask image with each sub-images.

2.2. Image Inpainting

We now describe the second key component of our proposed scheme, the algorithm used to fill-in the region of missing information in the structure image. In this paper we use the technique developed in [6]. That is, using CDD model to inpaint the structure image. The CDD inpainting model, like the TV and BSCB models, is based on the PDE method. Therefore, it is directly applicable to structure images. CDD inpainting model define as[4]:

$$\frac{\partial u}{\partial t}=div\left[\frac{g(|k|)}{|\nabla u|}\nabla u\right] \tag{9}$$

where $k = div[\nabla u / |\nabla u|]$ represents the curvature which describes the local bending of the image, and

$$g(k) = k^p \qquad k > 0, p \geq 1 \tag{10}$$

The numerical implementation of CDD model not only discrete the gradient value in TV model, but also discrete the curvature of the image.

2.3. Texture Synthesis

In this paper, we adopt the improved texture synthesis based on exemplar [8] to fill-in texture information. This method is based on the literature [7]. We denote the known region by Φ, the unknown area by Ω and the boundary of Ω by $\partial\Omega$. Therefore, our approach proceeds as follows:

(1) Getting image mask of the region to be filled.

(2) Computing the main direction of image texture. Repeat the following four steps until the whole region is filled.

(3) Specifying the size of the template window ϕ_p for computing priorities. [9] provides a default window of 9×9 pixels, but in practice requires the user to set it according to the features of the image. The window size, for the points on boundary, is a tradeoff between the geometry shape of filled region around points and texture distribution in known region around them.

(4) Computing patches priorities. The priority computation is biased toward those patches which are on the continuation of strong edges and which are surrounding by high confidence pixels. In this way, we can get more information to fill the unknown region and preserve the image structure simultaneously.

(5) Adaptively propagating texture and structure information. We find a point $\hat{p} \in \partial\Omega$ with the maximum priority, and generate a template window $\Psi_{\hat{p}}$ adaptively based on the literature [8], then find the exemplar $\Psi_{\hat{q}} \in \Phi$ in the direction θ neighborhoods of $\hat{q}$ that minimizes $d(\Psi_{\hat{p}}, \Psi_{\hat{q}})$, and finally fill the unknown points in $\Psi_{\hat{p}}$ with the corresponding points in $\Psi_{\hat{q}}$.

(6) Updating priority values. After the patch $\Psi_{\hat{p}}$ has been filled with new pixel values, the priority is updated in the area delimited by $\Psi_{\hat{p}}$.

3. Experimental Results

In this section, our proposed algorithm and the DCT-based image decomposition algorithm are simulated on Matlab7.0.1 platform. We use objective criteria and visual effects to illustrate the superiority of our method. The objective criteria used in this paper is the Peak Signal to Noise Ratio (PSNR).

For comparison purpose, we apply two algorithms: DCT-based image inpainting and our inpainting, to the standard gray images. The simulation results are shown in Fig.1, where (a) is the original image, (b) is the damaged image, (c) is the reconstructed images by DCT-based image inpainting which PSNR=39.07dB and (d) is our reconstructed images which PSNR=42.78dB. From these images, we can see that the two methods can both reconstruct images from damaged images efficiently, but our results compare favorably to those obtained by DCT-based image inpainting.

4. Conclusions

We have presented an image inpainting algorithm based on wavelet decomposition. The proposed algorithm has three main building blocks, including Image decomposition, image (structure) inpainting, and texture synthesis. The original image is first decomposed into the sum of four images by wavelet transformation, one capturing the basic texture image and three capturing the image structures. Then, the structure image is inpainted following the work by Chan T F.and Shen J H. described in [4], while the texture image is filled-in with a an improved texture synthesis algorithm based on exemplar. The two reconstructed images are then added back together to obtain the reconstruction of the original data. A large number of experiments show that the proposed algorithm can quickly and efficiently restore the structure and texture information at the same time, and the visual effects and the Peak Signal Noise Ratio (PSNR) is better than the similar algorithms.

(a) (b) (c) PSNR=39.07dB (d) PSNR=42.78dB

Fig. 1. Restoration of damaged block. (a) the original image; (b) damaged image; (c) the result of DCT-based algorithm; (d) the result of our proposed algorithm

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