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A Novel Image Inpainting Method based on Image Decomposition

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Abstract

In posed years, Researchers proposed many algorithms which restored damaged images along isophate direction. These methods cause texture broken while inpainting texture image with complex structure. We advance a novel method which decomposes the texture image into cartoon image and texture image, then inpaints structure based on boundary restoration and use texture synthesis to inpaint texture image. The experimental result shows that it is effective to inpaint texture image with complex structure.

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Keywords: Image inpainting; Image decomposition; Texture segmentation; Texture synthesis; Boundary restoration

1. Introduction

Bertalmio proposed an algorithm using the partial differential equations(PDEs) to solve the inpainting problem in 2000^[1]. The method is only fitted for inpainting light scratches, little areas or blots etc, and computing is time consuming. Some people applied texture synthesis to inpaint the image^[2]. These methods are effective in replicating consistent texture, but they have difficult to restore images consisting of structures and textures. Some researchers proposed algorithms which simultaneously propagate texture and structure information^[3,4]. Reference[4] use TV to decompose the image into functions with structure and texture characteristics, and then reconstruct each one of these functions separately with structure and texture recovering algorithms. References[3] proposed example-based image inpainting method which

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can simultaneously propagate texture and structure information based on the theory of isophate-driven and the principle of the best matching exemplar patch.

Preceding algorithms have done well on boundaries in damaged image with linear structure and texture. We proposed a novel method which decomposes the image into two parts. One of them is cartoon image which sharp boundary and smooth region, while the other contains the texture of image. We inpaint the cartoon image firstly by boundary reconstruction. Then we do texture synthesis to texture image guided by boundary reconstruction. The method aims at inpainting structure and texture simultaneously and produces good results for texture with complex structure.

2. Image Decomposition

The cartoon image can be gained by texture segment. The result is the contour image. The texture image can be got by using the original image to cut the contour image.

There are many algorithms to segment the texture image. We propose a method to segment image based on PCNN. For the PCNN-based method is a parallel method, it can fast the algorithm.

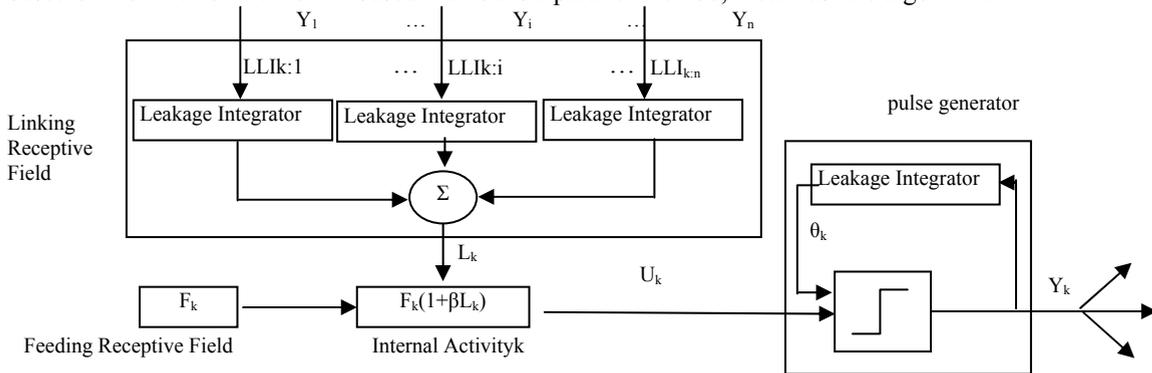


Fig.1 Pulse Coupled Neuron

A traditional PCN[6] consists of four parts: feeding receptive field, linking receptive field, internal activity field, and the pulse generator (shown as fig.1). The Feeding receptive field (marked as F_{ij}), in simplified PCNN model, only receive input from outside; while the Linking receptive field (marked as L_{ij}) only receive the pulse output from interconnected PCN. The model is given by:

$$F_{ij}[n] = I_{ij} \tag{6}$$

$$L_{ij}[n] = \sum W_{ijkl} \times Y_{kl}[n-1] \tag{7}$$

$$U_{ij}[n] = F_{ij}[n](1 + \beta L_{ij}[n]) \tag{8}$$

$$Y_{ij}[n] = \begin{cases} 1, & U_{ij}[n] > \theta_{ij}[n] \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

$$\theta_{ij} = \begin{cases} V_k & t = 0 \\ V_k \exp\left(\frac{-(t-t_1)}{\tau}\right) & 0 < t < t_1 \\ V_k & t = t_1 \end{cases} \tag{10}$$

Where L_{ij} stand for response of Linking receptive field caused by PCN_i stimulate PCN, W_{ijkl} is the

inverse value of Euclidean distance between center pixel (i,j) and its neighbor pixels. W is a 3*3 matrix which records values. Here we choose a common W:

$$W = \begin{pmatrix} 0.5 & 1 & 0.5 \\ 1 & 0 & 1 \\ 0.5 & 1 & 0.5 \end{pmatrix}$$

I_{ij} is a constant inputted from outside into feeding reception field; $Y_{ij}(t)$ is firing signal; $\theta_{ij}(t)$ is threshold of point (i,j) at time t; V_{ij} is initial threshold of point (i,j); T is the firing time; τ is error rate of threshold function. U_{ij} is the result of linking input L_{ij} and feeding input F_{ij} modulation and is inputted to the pulse generator field. C is the linking strength, it provides a simple and effective means of controlling the influence of the net linking input on the neuron's internal activity. At first, θ_{ij} is greater than threshold U_{ij} . Pulse generator is turned off and stops firing pulse. The threshold begins decreasing until U_{ij} is greater than its threshold. At this time, pulse generator is turn on and the PCN fire is activated and output a serial of pulses. Meanwhile the threshold of PCN rapidly increases to U_{ij} . A pulse output generated by a pixel activating will cause other similar neighbor pixels activate the PCN generate outputs of serial pulse. After having computing several times, an image will be partitioned into different regions. The segmentation boundary can be acquired by performing exclusive or operating on matrixes at different firing mode.

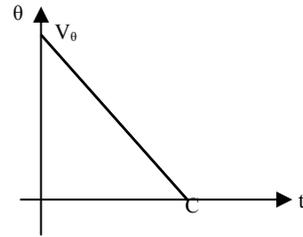


Fig.2 linear attenuated thresholdfunction

For threshold decrease function is exponent, this cause the traditional PCNN model cannot meet various kinds of application. This paper proposes a linear attenuated threshold mechanism and combines the flexibility of the threshold with the simple implementation(shown as fig. 2). Descent gradient of threshold is controlled by the slop of linear function.

Expression (9) is changed to expression (11):

$$\theta_{ij}(t) = \begin{cases} V_{\theta} & t = 0 \\ V_{\theta}(1 - \frac{t}{C}) & 0 < t < T \\ \infty & t = T \end{cases} \quad (11)$$

Expression (10) is changed to expression (12):

$$Y_{ij}[t] = \begin{cases} 0, & U_{ij}[t] < \theta_{ij}[t] \\ \frac{1}{\sigma \cdot |D|} \sum_{ij \in D} F_{ij}, & U_{ij}[t] \geq \theta_{ij}[t] \end{cases} \quad (12)$$

Where: $D = \{ij \mid U_{ij}(t) \geq \theta_{ij}(t)\}$, T is the firing time

While a image is segmented based on PCNN, the number of PCN is the same as pixels of the image. The eiginvector of a pexel is used to input to PCN. When there are similar eiginvectors in internal linking matrix W, A pulse output generated by a pixel activating will cause other similar neighbor pixels activate the PCN generate outputs of serial pulse.

Since the traditional PCNN is a two dimension matrix and the input image from extracted feature image is a three dimension matrix, we should regulate the PCNN. The input is a pexil in traditional PCNN, which is replaced by a 1-dimention vector. Then the similarity between eiginvectors is valued by a vector distance $d(i,j)$. The distance $d(i,j)$ between eiginvector i and j in feature space is given by :

$$d(i, j) = \sum_m \sum_n d_{mn}(i, j)$$

$$d_{mn}(i, j) = \left| \frac{\mu_{mn}^{(i)} - \mu_{mn}^{(j)}}{\alpha(\mu_{mn})} \right| + \left| \frac{\sigma_{mn}^{(i)} - \sigma_{mn}^{(j)}}{\alpha(\sigma_{mn})} \right| \tag{13}$$

Where $\alpha(\mu_{mn})$, $\alpha(\sigma_{mn})$ is standard variance.

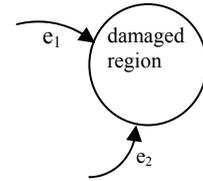


Fig.3 edge's direction

3. Image inpainting

For the cartoon image u , we use a method which inpaint image based on boundary reconstruction. The algorithm consists of three main steps.

In the first step, we use a method based PCNN to segment image. We can get the boundary and region information. Based on the information of boundary and damaged region, we achieve the edges around the damaged region, which abide with the principle that an edge must keep one side inside the damaged region and the other side outside the damaged region(that means they are interacted with damaged region.). After calculating their center points, and curvatures, edges are defined as positive edges or negative edges according to their radians(shown as fig.3).

In the second step, edges are distributed to three groups. One group is called matched-edge group(shown as fig.4), where the two matched edges are strongly related with each other. The second group is called coupled-edge group(shown as fig.5), where the two coupled edges are moderately related with each other. The third group is called single-edge group(shown as fig.6), where the edges are not related with each other at all(referred to[9] for more detail). The interpolation is employed when we connect the edges. The point to be interpolated is always affected more by the point near it.

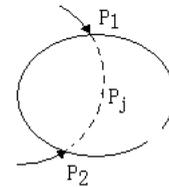


Fig.4 matched edge restoration

For matched-edge group, a radian is used to connect a couple matched-edges. The grey value of point in the radian is given by:

$$\lambda^{p_i} = \frac{w_1 \lambda^{p_1} + w_2 \lambda^{p_2}}{w_1 + w_2} \tag{14}$$

where λ^{p_i} is the value of a point to be inpainted, λ^{p_j} ($j \in \{1,2\}$) are the value of the end points which connects the edges to be inpainted, and w_j ($j \in \{1,2\}$) are their powers. W_j are defined as $w_j=1/d_j$, where d_j is the Euclidian distance between point i to j .

For the coupled-edge, firstly we find out their intersection point X , the grey value of the point X is given by:

$$\lambda^X = \frac{w_1^a \lambda^{p_1} + w_2^a \lambda^{p_2}}{w_1^a + w_2^a} \tag{15}$$

Where w_i^a ($i \in \{1,2\}$) are powers. They are the Reciprocal of the Euclidian distance between point X to P_i ($i \in \{1,2\}$).

then we interpolated on each arc. For arc P_1 - X , the grey value of interpolated point is given by:

$$\lambda^{p_j} = \frac{w_1^b \lambda^{p_1} + w_X^b \lambda^{p_2}}{w_1^b + w_X^b} \tag{16}$$

Where w_i^c , $i \in \{1,X\}$ are the powers, They are the Reciprocal of the Euclidian distance between point

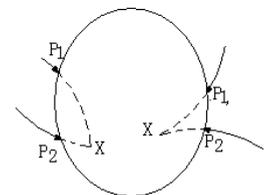


Fig.5 coupled edge restoration

P_j to P_1 or P_j to X . for arc P_2 - X , the grey value of point P_j is given by:

$$\lambda^{P_j} = \frac{w_2^c \lambda^{P_1} + w_X^c \lambda^{P_2}}{w_2^c + w_X^c} \tag{17}$$

Where w_i^c ($i \in \{2, X\}$) are the powers, They are the Reciprocal of the Euclidian distance between point P_j to P_2 or P_j to X .

For the single edge, the restoration method is similar with the coupled-edge. The single edge may be interconnected with the edge to be restored well (shown as fig.6, the edge e_6 is connected with e_4 - e_5). After finding out the point X , the function (15) is applied to calculate the interpolation point. Sometimes, two single edges may be interconnected to (shown as fig.6, single edge e_2 is interconnected with e_3), the interpolation method is same as the above. If the single edge isn't interconnect with any other edge (the edge e_1 shown as fig.6), we find out the point P_2 which the edge is intersect to boundary of damaged region. Based on the points P_1 and P_2 , the function (15) is applied to interpolate.

In the third step, the algorithm performs inpainting based on interpolation guided by boundary reconstruction. After having inpainted counter image u , we now describe the method inpainting the texture image v . Here we employ the exemplar-based texture synthesis as the main algorithm used to fill in the region of missing information in v . We use the algorithm developed in [4] to perform texture synthesis. Let I be the image, Ω be the region to be filled in. Let $\partial\Omega$ be the border of Ω , and Ψ be the known region. The image I has been segmented into several region with the edges inpainted. The $p \in \partial\Omega$ is the center of a square block $W(p)$. Choose a block $W(q)$ from the region which is same region as $w(p)$. The q if the center of block $W(q)$. $W(q)$ is similar with $W(p)$. This measure of similarity is calculated by the L2 distance (Euclidean distance) between pixels corresponding to neighborhood window. The function is given by :

$$d(N_1, N_2) = \frac{\sum_{p \in N} (I_1(p) - I_2(p))^2}{n^2} \tag{18}$$

If the $W(q)$ is similar with $W(p)$, We replace p with q . Then choose the next pixel neighbor to p to precede the algorithm until all damaged pixels to be repaired.

4. Experimental Results and Conclusion

We compare our algorithm with other methods (shown as fig.7) by the experimental results. Algorithm [6] decided which patch to be inpainted based on value of patch priority. Since the choice of priority is associated with the isophote, the blur is occurred when there is curve structure included in damaged region. Algorithm [5] decomposes the original image into structure image and texture image at first, and then uses the method proposed in [1] to inpaint the structure image. The texture image is restored by exemplar-based method. This algorithm is an isophate-driven method too, so it has the problem during inpainting when the curvature of boundary is variable. The results show that algorithm [3][4] can inpaint the texture, but make the boundary blur, while our algorithm can inpaint the boundary and texture well.

As preceding mention, our algorithm is a method which simultaneously inpaint image texture and

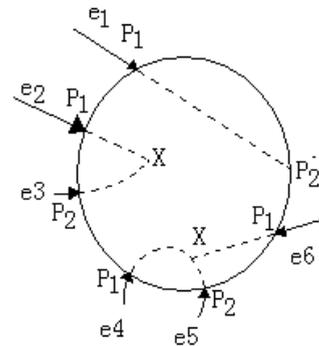


Fig.6 single edge restoration

structure. The algorithm ensures the boundary to be repaired well. The adaptive texture restoration based on region segmentation gets fast and accurate result.

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(a)original image to be restored



(b)result by our algorithm



(c) result by M.Bertalmio



(d) result by A.Criminisi]

Fig.7 experimental results