A Fast Image Inpainting Method Based on Hybrid Similarity-distance

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***Abstract*—A fast image inpainting method based on hybrid similarity-distance is proposed in this paper. In Criminisi et al.'s work[1], similarity distance are not reliable enough in many cases and the algorithm performs inefficiently. To solve these problems, we propose a new searching strategy to accelerate the algorithm. In addition, we modify the confidence-updating rule to make more reasonable the distributions of the confidences in source region. Besides, taking account of the stationarity of texture and the reliability of the source regions, we present a hybrid similarity-distance, which combines the distance in color space with the distance in spatial space by weight coefficients related to the confidence value. A more reasonable patch will be found out by this hybrid similarity-distance. The experiments verify that the proposed method yields qualitative improvements compared to Criminisi et al.'s work[1].**

Keywords-image inpainting; texture synthesis; hybrid similarity-distance; accelerated searching strategy;

I. INTRODUCTION

An increasingly popular area of research in the field of image processing is image inpainting. Inpainting is a very useful practice. The purpose is to fill in the missing areas or modify the damaged parts of the image in a non-detectable way for an observer not familiar with the original image [2]. Moreover, it can also be applied to video applications such as fixing scratches or blots, removing logos or subtitles and error concealment.

Many of the traditional works in image inpainting focus on filling in missing regions through the diffusion of local information [2-4]. These works fill holes in images by iteratively propagating color information from the surrounding neighborhood into the target region.

There are also other approaches to solve the problem of image inpainting by the concept of exemplar-based synthesis [1, 5-7]. The exemplar-based model copies the best match sample from the source region to fill the target region. Wong et al. [7] introduces the concept of nonlocal-means to exemplar-based inpainting. Cao et al. [5] endow the exemplar-based inpainting method with a geometric guide.

The inspiration for our work comes from the work of Criminisi et al.[1]. They propose a novel algorithm which combines the advantages of texture synthesis with image inpainting method. However, there still are some difficulties to be solved as follows:

- The algorithm performs inefficiently since the source region is so redundant.
- The distance, which measures similarity of two patches, is not reliable enough. Only using the distance of color space, the algorithm cannot often found a reasonable patch to human eyes.
- The confidence-updating rule is too simple to make a difference between good match and bad match.

To solve these problems, a fast image inpainting method based on hybrid similarity-distance is proposed in this paper. The major contributions of our approach are as follows:

- Accelerated searching strategy. By this strategy, the source region is delimitated to a smaller region surrounding the repaired patch. As Criminisi et al.'s work[1], the confidence term reflects a measure of the amount of reliable information surrounding the pixel p. Therefore, our method adaptively adjusts the size of source region based on the confidence of the center point of the repaired patch in order to guarantee that the source region is adequate and small.
- A novel hybrid similarity-distance. It combines the distance in color space with the distance in spatial space by weight coefficients related to the confidence value. Guaranteeing stationarity and continuity of the texture, more reasonable source exemplar will be found out from reliable enough source region by this distance.
- Modified confidence-updating rule. Since this rule make a difference between good match and bad match, the distributions of the confidences in the source region are more reasonable.

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II. IMAGE INPAINTING ALGORTHM

A. Exemplar-based Inpainting

In this section, we briefly review the exemplar-based inpainting approach proposed by Criminisi et al. [1], which is employed as a fundamental inpainting algorithm in our algorithm. The overall process can be presented as follow steps:

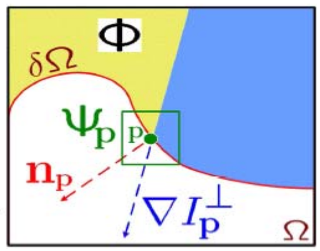

Figure 1. Exemplar-based inpainting diagram

Step 1:
Initialization:

$C(p)=0, \forall p \in \Omega$ and $C(p)=1, \forall p \notin \Omega$

where Ω is the region which will be filled, $C(p)$ is the confidence of the patch ψ_p centered at p.

Step 2:
For each point p in the fill front $\delta\Omega$, compute

- $\nabla I_p^{\perp}$, the isophote of intensity at p.
- n_p, the normal to the contour $\delta\Omega$ at p.
- Data term: $D(p)=|\nabla I_p^{\perp} \bullet n_p|$
- Confidence of the patch ψ_p centered at p:

$$C(p)=\sum_{q\in\Psi_p\cap\bar{\Omega}} C(q)$$

where the confidence term $C(p)$ may be thought of as a measure of the amount of reliable information surrounding the pixel p.

- The inpainting priority of p: $P(p)=C(p)D(p)$

Step 3:

Select point p of highest priority in the fill front, and search in the image domain to find out a patch Ψ_q which is most similar to Ψ_p in color space, and then the unknown pixels in Ψ_p are set to the values of the corresponding pixels in $\Psi_{q'}$,

Then the confidence $C(p)$ is updated as follow:

$$C(q)=C(\hat{p}) \qquad \forall q \in \Psi_{\hat{p}} \cap \Omega$$

Step 4:

Repeat Step 2 and Step 3 until all points in the inpainting domain have been repaired.

B. New Searching Strategy

In the work of Criminisi et al.[1], the source region Φ is defined as: $\Phi = I - \Omega$. I denotes the entire image and Ω denotes the region which will be filled. However, the most similar patch to the repaired patch ψ_p usually is located near ψ_p. Searching in the entire source region for the most similar patch to ψ_p is unnecessary and time-consuming. Thus, under the assumption that the source exemplar more likely lies in near areas than far areas, a novel strategy to determine the source region is proposed in this paper.

As Criminisi et al.'s work[1], the confidence term $C(p)$ reflects a measure of the amount of reliable information surrounding the pixel p. Therefore, in our method, the size of source region Φ is supposed to be inversely proportional to $C(p)$ and defined to be as:

$$\Phi = \Phi' \cap (I-\Omega) \tag{1}$$

where Φ' is an rectangular region centered at the point p, the center of the Ψ_p. Its size is inversely proportional to $C(p)$. The region Φ' is defined as follows:

$$X_{\Phi start} = X_{\Psi start} - \lambda \times Size_{\Psi} \tag{2}$$

$$Y_{\Phi start} = Y_{\Psi start} - \lambda \times Size_{\Psi} \tag{3}$$

$$X_{\Phi end} = X_{\Psi end} + \lambda \times Size_{\Psi} \tag{4}$$

$$Y_{\Phi end} = Y_{\Psi end} + \lambda \times Size_{\Psi} \tag{5}$$

where $(X_{\Phi start}, Y_{\Phi start})$ and $(X_{\Psi start}, Y_{\Psi start})$ denote the top-left coordinate of Φ' and Ψ_p respectively; $(X_{\Phi end}, Y_{\Phi end})$ and $(X_{\Psi end}, Y_{\Psi end})$ denote the bottom-right coordinate of Φ' and Ψ_p respectively; $Size_{\Psi}$ denotes the size of Ψ_p; λ is defined as:

$$\lambda = \begin{cases} \dfrac{1}{confidence} \times \eta + \delta & if\ \dfrac{1}{confidence} > \varepsilon \\ k & otherwise \end{cases}$$

In our experiments, we set $\eta = \dfrac{4}{7}$, $\delta = \dfrac{7}{20}$, $k = 8$ according to our experiences.

C. Hybrid Similarity-distance

The most similar source exemplar in color space is not necessarily the most reasonable exemplar to human eyes. Taking account of the stationarity of texture and the reliability of the source regions, a novel hybrid similarity-distance is proposed in this paper, which combines the distance in color space with the distance in spatial space by weight coefficients related to the confidence value. By the hybrid similarity-distance, the similar patch will be searched in reliable source region while stationarity and continuity of the texture is guaranteed. Therefore, more reasonable source exemplar to the human eyes would be found out.

The proposed hybrid similarity-distance $Dis_{sim}(p,q)$ between two patches centered at point p and q is defined as:

$$Dis_{sim}(p,q) = \alpha \times Dis_{ss}(p,q) + \beta \times Dis_{cs}(p,q) \tag{6}$$

Where $Dis_{ss}(p,q)$ is the Euclidean distance in spatial space between patches centered at point p and q, its role is to guarantee stationarity and continuity of the texture; $Dis_{cs}(p,q)$ is the Euclidean distance in color space between patches centered at point p and q; α and β are corresponding Weight Coefficients, They are defined as:

$$\alpha = \sqrt{1 - C(p)}$$
$$\beta = 2 - C(q)$$

α is inversely proportional to $C(p)$. In early period of filling, confidence values in the source region are relatively high. This reflects that the source region is reliable. Thus, α is low, and then Dis_{cs} dominates Dis_{sim}. As filling proceeds, confidence values in the source region decay and the source region becomes more and more unreliable. Therefore, Dis_{cs} is not longer a reliable measure of similarity. To guarantee stationarity and continuity of the texture, α, the weight coefficient of Dis_{ss}, should be strengthened.

Meanwhile, the role of β is to guarantee that the high-confidence patches are more likely to be the source exemplar.

D. *Modified Confidence-updating Rule*

After the patch Ψ_p has been filled with pixels of the source exemplar Ψ_q, the confidences of new pixels in Ψ_p are updated as:

$$C(\hat{p}) = \min(C(p) \times \gamma, 1) \qquad \forall \hat{p} \in \Psi_p \cap \Omega \tag{7}$$

where γ is an attenuation coefficient and defines as:

$$\gamma = \begin{cases} \tau \times e^{-\tau \times (\log_\theta Dis_{sim}(p,q) - \upsilon)} & \text{if } \log_\theta Dis_{sim}(p,q) - \upsilon \geq 0 \\ \omega & \text{otherwise} \end{cases}$$

γ is inversely proportional to $Dis_{sim}(p,q)$. $Dis_{sim}(p,q)$ reflects similarity between Ψ_p and Ψ_q. The smaller $Dis_{sim}(p,q)$ is, the higher confidences of new pixels in Ψ_p are, and vice verse. As we known, the hybrid similarity-distance encourages searching for the source exemplar in more reliable source region. Therefore, during next iteration, these new high-confidence pixels repaired with good match are more likely to be pixels in source exemplar than those repaired with bad match.

we set $\tau = 1.5$, $\theta = 10$, $\upsilon = 3.2$, $\omega = 1.5$ according to our experiences in our experiments.

III. RESULTS

Test images containing large and complex holes are used to evaluate the effectiveness of the proposed method. By adaptively propagating neighborhood information, our method smoothly generates texture patterns without blurring important feature curves. For comparison, the patch size is set to 9*9, the same size as that used in the work of Criminisi et al. [1].

A. *Comparisons of Visual Quality*

The comparisons of visual quality between our method and that of Criminisi et al. are shown in Fig. 2 and Fig. 3.

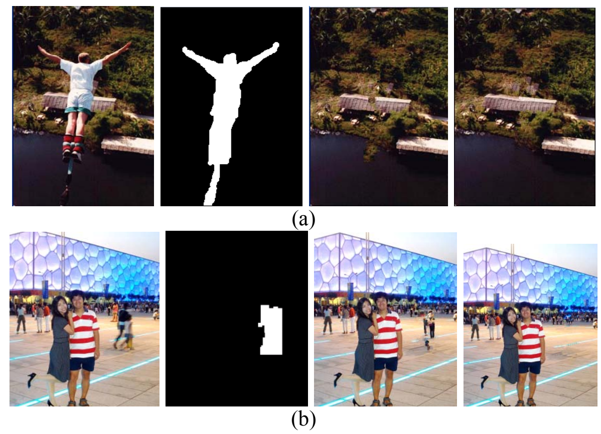

Figure 2. From left to right. First: Original images, Second: Masks, Third: The results by Criminisi's method, Fouth: our results

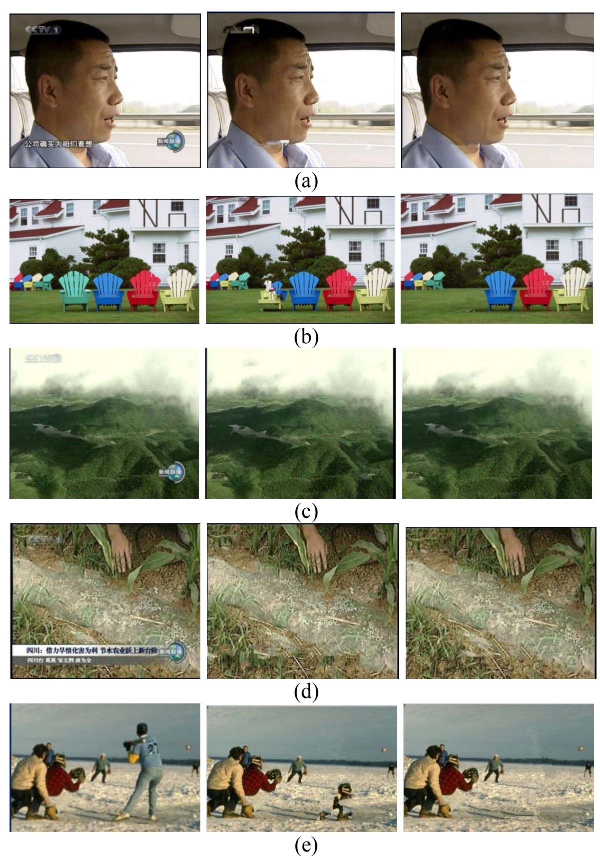

Figure 3. From left to right. First: Original images, Second: The results by Criminisi's method, Third: our results

It is obvious that the results by the method of Criminisi et al. are unnatural in some cases, while the results by our method are well reconstructed. Two factors account for this. Firstly, the modified confidence-updating rule ensures that the pixels repaired with good match are more likely to be pixels in the source exemplar than those repaired with bad match during next iteration. Secondly, taking account of the stationarity of texture and the reliability of the source regions, the hybrid similarity-distance combines the distance in color space with distance in spatial space so that more reliable source exemplar will be found out.

B. Comparisons of Running Time

The comparisons of running time between our method and that of Criminisi et al.[1] are shown as Table I.

The running time depends on the image texture and hole complexity. We notice that the running time is approximately a quarter of Criminisi et al.'s in the tests of Fig. 2 (b) and Fig. 3 (a). As shown in table 1, our method runs much faster. It is mainly because that the new searching strategy adaptively decreases the source region so that the redundancy of the source region in traditional methods is eliminated.

TABLE I. TIME (SECONDS) OF IMAGE INPAINTING

	Criminisi's method	Our method
Figure 2 (a)	35	19
Figure 2 (b)	47	12
Figure 3 (a)	597	127
Figure 3 (b)	38	12
Figure 3 (c)	17	5
Figure 3 (d)	17	10
Figure 3 (e)	16	10

IV. CONCLUSION

A fast image inpainting method based on hybrid similarity-distance is proposed in this paper, which is composed of a new searching strategy, a modified confidence-updating rule and a novel hybrid similarity-distance. By using this searching strategy, our algorithm can adaptively delimitate the source region to a small region. Therefore, it runs much faster. In addition, by utilizing this hybrid similarity-distance and this modified confidence-updating rule, the source exemplar will be searched in high-confidence source region and more reasonable source exemplar will be found out. The experiments verify that improved visual quality and efficiency can be achieved over the approach used in tradional exemplar-based inpainting technique[1].

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REFERENCES

[1] Criminisi A, Perez P, Toyama K. Region filling and object removal by exemplar-based image inpainting. IEEE Transactions on Image Processing,13(9):1200-12, 2004.

[2] Bertalmio M, Sapiro G, Caselles V, Ballester C. Image inpainting. *Siggraph 2000 Conference Proceedings*:417-24 547, 2000.

[3] Chan T, Shen J. Mathematical models for local nontexture inpaintings. *SIAM Journal on Applied Mathematics*,62(3):1019-43, 2001.

[4] Rane SD, Sapiro G, Bertalmio M. Structure and texture filling-in of missing image blocks in wireless transmission and compression applications. *IEEE Transactions on Image Processing*,12(3):296-303, 2003.

[5] Cao F, Gousseau Y, Masnou S, Pérez P. Geometrically guided exemplar-based inpainting. to appear.

[6] Wu J, Ruan Q. Object Removal By Cross Isophotes Exemplar-based Inpainting. *Proceedings of the 18th International Conference on Pattern Recognition - Volume 03*:810-3, 2006.

[7] Wong A, Orchard J. A Nonlocal-Means Approach to Exemplar-Based Inpainting. *2008 15th IEEE International Conference on Image Processing, Vols 1-5*:2600-3 3231, 2008.