Image Completion Using Global Patch Matching and Optimal Seam Synthesis

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Abstract—This paper presented a global exemplar-based image completion method for filling large missing or damaged regions in an image. Based on three proposed completion rules, the image completion problem is formulated as a global discrete optimization problem with a well-defined energy function. The energy function can evaluate image consistency globally and is minimized with an expectation-maximization (EM) like algorithm, which considers patch matching and patch synthesis in a unified way. In the algorithm, M step and E step are achieved by fast coherent searching and optimal seam synthesis respectively. Moreover, E step combines image patch synthesis and coherent correction simultaneously. We analyzed our global energy function and optimization method in theory. Simulation comparisons with other state-of-the-art methods show the superiority of our proposed method in ensuring global coherent and avoiding image blurring.

Keywords—Enhancement, restoration and filtering; Signal, image and video processing; Texture and color analysis

I. INTRODUCTION

Image completion, also known as image inpainting, involves the issue of filling missing or unwanted parts in images in a visually satisfactory manner. The methods can mainly category into diffusion-based methods and exemplar-based methods.

Diffusion-based methods [1-4] usually perform in pixel level and solve partial differential equations (PDE) or similar diffusion systems in order to propagate the information into the missing regions from undamaged or available parts. These methods work well for small defect region or structure image. They lead to blurred results when dealing with large defected region or complex texture due to lack of semantic texture or structure synthesis.

Exemplar-based methods [5-16] perform more effectively for large missing regions or holes. The basic idea behind these methods is to first match the patches in the unknown region with the patches in the known region, and then copy or synthesis the known content to complete the unknown region under some coherence constraints in color, texture, and structure. These methods involve two key issues: (1) Completion priority: how to determine the completion orders of the unknown patches; (2) Texture generation: how to select a best matching patch to fill the unknown region, which refers to the process of searching, matching and synthesis. Many techniques were developed to address the two key issues.

Completion priority determines the order of each patch to be completed, thus can remain the structure information of texture boundaries. The methods to address this issue perform completion in greedy or global fusions. Criminisi et al [5] and Drori et al. [6] calculate the confidence of pixels to determine synthetic sequence of unknown completion patches using PDE or variation method. But these methods are greedy, synthesis patches cannot be changed once they are placed, which will leads to color and structure incoherent. To ensure structure continuity, Jia et al. [7] performed image segmentation and edge connection to complete image structures. The completed results are dependent on image segmentation. Sun et al. [8] interactively provided significant structure information by drawing some curves from the known region to unknown region, which guides structure propagation in completion process. Shen et al. [9] proposed a two-phase method that construct gradient maps through a patch based filling algorithm firstly and use it to complete the image through a Poisson equation. Xu et al. [10] used structure sparsity to determine the patch priority. All the methods above perform completion in greedy fusions by determine the completion priority of image patch with gradient calculation, edge segmentation, or human assistance. The stability of empirical calculation of gradient or edge is difficult to guarantee and guidance with human assistance reduces the degree of automation. Besides, the methods with greedy fusions cannot correct the synthesized patches backwardly, which results in error propagation.

Unlike methods with greedy fusions, some methods perform completion in global fusions. Komodakis et al. [11] use belief propagation algorithm to optimize a global energy function. Wexler et al. [12] define and optimize a spatial and temporal coherence function to complete video. The cost energy functions defined in these methods usually encourages that each patch in the completed region is as similar as possible to a certain known patch, thus help to yield more coherent completion results. But because the cost functions inherently have multiple disconnected local optima, these methods are sensitive to initialization and to the optimization strategy. Pritch et al.[13] characterize the completion problem by a shift-map where the relative shift of every pixel in the output image from its source in an input image, and indeed treat it as a global optimization on the entire image. However, the shift-map may miss user's intensions. To employ the fast image completion, Kwok et al. [14] decomposed exemplars into the frequency coefficients and select some most significant to evaluate the matching score and developed a local gradient-based algorithm to fill the un-known pixels in a query image block. He et al. [15] proposed an ap-

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proach to constrain the selection of known patches through statistics of patch offsets. Because offsets for matching similar patches are sparsely distributed, and a few dominant offsets provide reliable information for completing the image. Broll et al. [16] presented an approach for high quality real-time image and video inpainting which allows for the manipulation of live video streams.

Texture generation is used to generate larger similar texture to extend unknown region by means of texture patches sampled from the known region, which performs the process with iterative matching and synthesizing. During the process of texture generation, overlapped regions lead to matching error, which makes the transitions of color or structure unnatural. To reduce synthesizing errors, Efros et al. [17] performed quilting to ensure similar overlap existing in adjacent patches. Kwatra et al. [18] dealed with overlapped areas using graph cut based optimization. Agarwala et al. [19] corrected the color difference between overlapped regions using gradient domain fusion [20]. Ge et al. [21] performed seamless stitching with total variation gradient fusion.

In this paper, we proposed a global exemplar-based image completion method to restoring the large missing or damaged areas in an image. Based on three defined completion rules, we posed the completion problem as a global discrete optimization problem with a well-defined energy function. An EM-like algorithm was introduced to solve the optimization problem. The algorithm performs completion by iteratively patch matching and optimal seam synthesis. The theory analysis on the global energy function and the optimization method was introduced. Simulation experiments compared with diffusion-based method [1], greedy exemplar-based completion method [5] and several state-of-the-art image completion methods [12-16] demonstrate the advantages of our method in ensuring globally coherent of completion results.

II. Global Optimization of Completion Problem

A. Basic concepts

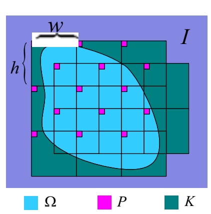


Figure 1. Discrete model of completion problem

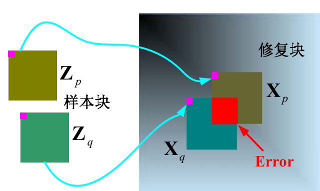


Figure 2. Matching error during patch synthesis

As Fig.1 illustrates, the target patches are sampled discretely from the unknown region Ω in the image I with a $h \times w$ scanning window. The neighborhood target patches are overlapped with $h/2 \times w/2$. Each target patch is indicted with its top-left point (called anchor point), thus all anchor points form an anchor point set P. X_p is denoted as one target patch with corresponding anchor point $p \in P$. The two anchor points p and q are called neighbors if patches X_p and X_q are overlapped. K is the overlapped region between the set of target patches and source region $I - \Omega$. Source patches are sampled from $I - \Omega$ with the same size as target patches and form source patch set S. The goal of image completion is to select an optimal group of patches $\{Z_p\}$ from S and synthesize them to corresponding target patches $\{X_p\}$ under the condition of visual integrity and consistency.

B. Completion Rules

We introduce three rules to complete an image:

Rule 1: Every target patch $X_n^i \in \{X_p\}$ in which the subscript $n \in \Omega$ represents the corresponding anchor point and the superscript $i = 1,...,m$ represents index of the target patch. Target patch X_n^i should be similar to Z_n^i selected from $\{Z_p\}$, thus making $\max sim(Z_n^i, X_n^i)$ in which $sim(\bullet,\bullet) \in (0,1]$ measures the similarity between two patches, and equals to 1 when two patches are just the same.

Rule 2: Each target patch in $\{X_n^i\}$ should be similar to each other, thus making $\max sim(X_n^i(n), X_n^j(n))$. If similarity is 1, the pixels at n are just the same in all the target patches which contain n.

Rule 3: The pixel value of point n should be picked just from one single patch to avoid blurring rather than weight several patches to get the average pixel value.

Rule 1 defines how to select source patches for completing unknown region. Rule 2 and rule 3 define how to synthesize target pixels. As shown in Fig.2, under non-ideal condition, synthesizing two patches will produces matching errors. For greedy exemplar-based methods, the completed patches cannot be corrected after they are copied or synthesized. Thus, once an error occurs, it will propagate and result in unexpected completion result.

C. Global Energy Function

To evaluate the completion results I^*, the coherence is defined as the product of the similarity between every target patch and the corresponding source patch, that is,

$$Coherence(I^* \mid S) = \prod_{p \in P} \max_{Z_q \in S} sim(Z_q, X_p) \tag{1}$$

The completion process is to select a group of patches $\{Z_p\}$ corresponding to $\{X_p\}$ and synthesize them to get I^*, thus obtaining maximum coherence. Similarity $sim(\bullet,\bullet)$ is measured by the sum of squared differences (SSD) of image color difference:

$$sim(Z_q, X_p) = \exp\left(-d(Z_q, X_p)/2\sigma^2\right) \tag{2}$$

where the parameter σ controls the error smoothness and $\sigma = \sqrt{hw}$, $d(\bullet,\bullet)$ is local weighted difference function. The global coherent function is turned into a global error function:

$$Error(I^* \mid S) = \sum_{p \in P} \min_{Z_q \in S} d(Z_q, X_p) \tag{3}$$

Then the completion problem can be formulated as a global discrete optimization problem which can be solved by minimizing the global energy function E:

$$E(X) = E_X(X;\{Z_p\};\{W_p\}) + \lambda E_C(X;X^C) \quad (4)$$

where X is the pixel set in all target patches, $X = \bigcup_{p\in P} X_p$, W_p is weighted mask, X^C is the pixel set in the region K. The global energy function E consists two sub-functions, parameter λ is used to balance the influence of two energy sub-functions. $\|\bullet\|$ is Euclid norm.

(1) Similarity energy function E_S is used to measure the similarity between selected source patches and the synthesized results (based on rule 1 and rule 2), where using weighted mask W_p can optimize pixels (based on rule 2 and rule 3).

$$E_S(X;\{Z_p\};\{W_p\}) = \sum_{p\in P} d(Z_p, X_p) = \sum_{p\in P} \left\| W_p(X_p - Z_p) \right\|^2 \quad (5)$$

(2) Constrained energy function E_C is used to constrain the smoothness between target region and source region. M_p is used to indicate whether the pixel belongs to the region K.

$$E_C(X;X^C) = \sum_{k\in K} \left\| X(k) - X^C(k) \right\|^2 = \sum_{p\in P} \left\| M_p(X_p - Z_p) \right\|^2 \quad (6)$$

And the matching error between two patches is

$$d(Z_p, X_p) = \left\| W_p(X_p - Z_p) \right\|^2 = \sum_{k\in N_p} \left[W_p(k)(X_p(k) - Z_p(k)) \right]^2$$

where N_p is the corresponding region of anchor point p.

III. Optimization Methods

A. Process Algorithm

To minimize the global energy function in (4), it is difficult to optimize patch matching and patch synthesis simultaneously. To address this issue, we use an EM-like algorithm to perform completion by two-step iterative optimization. Patch matching and patch synthesis can be achieved by coherent searching and optimal seam algorithm respectively. The algorithm 1 lists the process steps.

B. Initialization

EM algorithm is sensitive to the initial values, so $\{Z_p^0\}$ should be initialized appropriately. The target patches are sorted according to their shortest distances (denoted as patch orders) to the boundaries $\partial\Omega$ of target region in ascending order. Then we search the corresponding source patches $\{X_p\}$ and denote them as the initial target patches $\{Z_p^0\}$. The algorithm 2 lists the process steps.

Algorithm 1. Process algorithm of completion method

Step 1: Initialize $\{Z_n^0\}, \forall p \in P$: set maximum iteration time T, and set calculator $t = 0$.

Step 2: Iteration:

E step: fix $\{Z_p^t\}$, get $\{X_p^t\}$ and $\{W_p^t\}$ by optimization seam method;

M step: fix $\{X_p^t\}$ and $\{W_p^t\}$, seek the matching patch in S by minimization global energy function (4) by coherent searching.

Step 3: If $Z_n^{t+1} = Z_n^t, \forall p \in P$ or $t > T$, stop; otherwise, $t = t+1$, return to step 2.

Algorithm 2. Initialization in completion method

Step 1: Sort $\{X_p\}$ in descending order according to patch priority and put them into the sequence Q; initialize the binary mask M, if X_p belongs to Ω, M is 1, otherwise 0.

Step 2: If Q is not empty, do the following until the sequence Q is empty:

(1)Get the first patch X_p from Q; (2)Search Z_p^0 in S, which has the least difference from the effective area in X_p, duplicate X_p to Z_p^0 ; (3)Update the mask, set $M_p = 1$; delete X_p from Q.

C. Optimal seam algorithm

As illustrated in Fig.3, two overlapped patches usually generate visible seams in the overlapped region because of color difference. Optimal seam method is good at synthesizing texture seamlessly [17][18]. The idea is seeking for a cut with minimal color difference between two overlapped patches as optimal seam.

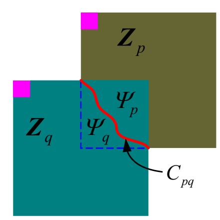


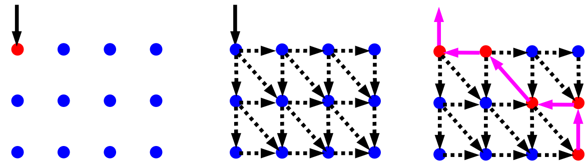
Figure 3. Optimal Seam

Dynamic programming (DP) algorithm is used to find optimal seam [17]. We synthesize the target pixels with similar idea. As shown in Fig.3, as for target patches Z_p and Z_q , the overlapped region is Ψ , optimal seam algorithm is to find a cut with minimal error to split Ψ into Ψ_q , Ψ_p and optimal seam C_{pq} . The problem can be considered as a shortest path problem. We define a color error as

$$e(k) = \begin{cases} 0 & if\ k \in K \\ \left\| Z_p(k) - Z_q(k) \right\|^2 & otherwise \end{cases}, \forall k \in \Psi \quad (7)$$

To search for a shortest path, we determine the start point and build all seams from that start point in the error image with DP algorithm and finally find a seam with minimum cumulative error in all these seams as the optimal seam. The procedure is shown in Fig.4 and the cumulative error $A(x, y)$ can be calculated with:

$$e(x, y) + \min\{A(x-1, y), A(x-1, y-1), A(x-1, y+1)\}$$



(a) Initialization (b) Extension (c) Tracing back

Figure 4. Implementation procedure of finding optimal seam

And solutions for other overlapped directions are similar.

After obtaining the optimal seam, based on completion rule 3, only the pixels on the optimal seam are replaced by the weight average while other pixels in the target region are replaced by the source pixels to avoid blurring. W_p and X_p are:

$$W_p(k) = \begin{cases} 1, & if\ k \in \Psi_p \\ 0, & if\ k \in \Psi_q \\ 0.5, & if\ k \in C_{pq} \end{cases}$$
$$X_p(k) = \begin{cases} X^C(k) & if\ k \in K \\ W_p(k)Z_p(k) + (1 - W_p(k))Z_q(k) & else \end{cases} \quad (8)$$

D. Coherent searching

1) Matching criterion

Constrained energy $E_C(X; X^C)$ does not depend on $\{Z_p\}$ directly, while $\{Z_p\}$ depends on X indirectly. The synthesized patch Z_p is similar to X_p after E step and the patch obtained in source patch set S is coherent with the constrained energy in M step. If constrained energy of Z_p is small, so is X_p. Similar to [22], we find the corresponding patch with:

$$Z_p = \arg\min_{V \in S}\left[\left\|W_p(X_p - V)\right\|^2 + \lambda E_C(Y; X^C)\right]$$
$$where\ Y(q) = \begin{cases} V(q - p + r) & if\ q \in N_p \\ X(q) & else \end{cases}, r = \left(\frac{h}{2}, \frac{w}{2}\right) \quad (9)$$

Coherent searching is used to find the best matching patch. The target patches are classified into two categories: one is inner patch, which is disjoint with the source region $I - \Omega$ and the other is boundary patch, which has overlapped pixels with $I - \Omega$. From (9) we know that the constrained energy E_C of inner patch is 0 while the boundary patch needs the error of the overlapped pixels. So (9) can be rewritten as:

$$Z_p = \begin{cases} \arg\min_{V \in S}\left[\left\|W_p(X_p - V)\right\|^2\right], & X_p \in Inner \\ \arg\min_{V \in S}\left[\left\|(W_p + I_\lambda)(X_p - V)\right\|^2\right], & X_p \in Boundary \end{cases} \quad (10)$$

I_λ is 1 if the pixel belongs to region K, otherwise is 0.

2) Sample space searching

Sometimes patches are discretely sampled only from $I - \Omega$ to reduce the number of source patches, which improves the completion speed. Coherent searching can be solved as a nearest neighbor searching (NNS) problem in high dimension space containing patches with the same shape and size [23]. Using hierarchical tree [22] we obtain a hierarchical tree with points in S and search for Z_p that satisfies (9) with X_p.

3) Image space searching

If full searching in source region is applied in patch matching, coherent searching deals with the image space directly without sample selection. SSD measures matching error and Fast Fourier Transform (FFT) speeds up matching searching. Denote $f(x), x \in I$ as the sample image, and J as the corresponding weighted mask of X_p. Given a fixed offset x_0, patch matching error is calculated with:

$$\begin{aligned} e_p(x_0) &= \sum_x J(x)\left(f(x + x_0) - X_p(x)\right)^2 \\ &= \sum_x J(x)X_p{}^2(x) + \left(-2(h \circ f) + J \circ f^2\right)(x_0) \end{aligned} \quad (11)$$

where $h(x) = J(x)X_p(x)$, and $\circ$ is correlation operation, i.e. $(h \circ f)(x_0) = \sum_x h(x)f(x + x_0)$. The first term in (11) is constant. The main computation cost of patch matching error comes from the two correlation operations. FFT makes the correlation operation easy with a complexity of $O(n \log n)$ where $n = |I|$ is the number of pixels in sample image [24].

IV. Methods Analysis

A. Global energy function analysis

Our global discrete optimization is equivalent to graph optimization. A graph $G = \{P, \Gamma\}$ is defined, vertices are anchor point set P, and edge set Γ is the set of pairs of adjacent vertices. Consider the similarity energy function E_S in (5) and two definitions in (8), we have:

$$\begin{aligned} E_S &= 2\sum_{(p,q)\in\Gamma}\sum_{k \in C_{pq}}\left\|\left(Z_q(k) + Z_p(k)\right)/2 - Z_p(k)\right\|^2 \\ &= \frac{1}{2}\sum_{(p,q)\in\Gamma}\sum_{k \in C_{pq}}\left\|\left(Z_q(k) - Z_p(k)\right)\right\|^2 = E_S\left(\{Z_p\}; \{C_{pq}\}\right) \end{aligned} \quad (12)$$

External energy function $V_{p,q}$ and internal energy function V_p can be defined:

$$\begin{aligned} V_{p,q}(Z_p, Z_q) &= \frac{1}{2}\sum_{k \in C_{pq}}\left\|\left(Z_p(k) - Z_q(k)\right)\right\|^2 \\ V_p(Z_p) &= \lambda\left\|M_p(X_p - Z_p)\right\|^2 \end{aligned} \quad (13)$$

Energy function (4) is equivalent to a Markov random field (MRF) energy function defined on the graph G :

$$E(\{Z_p\}) = \sum_{(p,q)\in\Gamma} V_{p,q}(Z_p, Z_q) + \sum_{p\in P} V_p(Z_p) \quad (14)$$

The energy E_S measures the coherence of two overlapped patches, which ensures smooth transition between images. The total color difference in overlapped region is used to measure the coherence, but there usually exists apparent seams at the boundaries of overlapped region [18][19]. In contrast, we use coherence of optimal seam error in overlapped region. Our method combines synthesis with coherence correcting simultaneously, which eliminates seams effectively. Unlike the method in [21] weighting all the pixels in overlapped region, our method copies the pixels directly from source patches, which avoid being blurred.

B. Optimization algorithm analysis

The optimization algorithm is equivalent to the statistical estimation method in graph model. Global visual coherent function in (1) can be regarded as the likelihood function while EM algorithm can be regarded as maximum likelihood estimation. We first consider the likelihood function in a statistical graph model,

$$L = \sum\nolimits_{(Z_1, Z_2, \ldots, Z_N)\in S^N} \prod_{n=1}^{N} sim(X_n, Z_n) \quad (15)$$

In MLE (Maximum Likelihood Estimation), the summation can be represented by the maximum item since $sim(\bullet,\bullet) \in (0,1]$. Moreover, the corresponding matching patches are independent with each other, so the maximum likelihood function is

$$\max L \approx \max_{(Z_1,\ldots,Z_N)} \prod_{n=1}^{N} sim(X_n, Z_n) = \prod_{n=1}^{N} \max_{Z_n} sim(X_n, Z_n) \quad (16)$$

MLE is equivalent to obtaining maximum coherence (1). Unlike the methods in [8][11] using belief propagation algorithm for optimization and having time complexity $O(2TDMN^2)$, our energy optimization method uses EM algorithm with hierarchical tree searching [22] in M step and has the time complexity $O(2TD\log N)$, where T is iteration times.

V. EXPERIMENTAL RESULTS

To verify the effectiveness of our proposed method, we simulated all experiments on the PC with Pentium IV 2.6G and 2G memory. The images mainly come from the internet and references. The parameters are set λ = 100, T = 50. We compared our method with diffusion-based method [1] and exemplar-based method proposed in [5]. Parts of the results are given here.

Fig.5 is compared with completion method based on PDE [1]. As for larger texture areas, the PDE-based method deals with pixels, and produces blur in the result image, while the method in this paper can avoid image blurring by synthesis image patches. Fig.5 (e) and (f) are the comparison of local zoom-in results, the PDE-based method makes smoothness in the target region, which leads to blur, while our method remains the texture clear.

(e)local zoom-in of PDE results (f) local zoom-in of our results

Figure 5. Comparison with diffusion-based completion method

Fig.6 shows some results compared with Criminisi's exemplar-based completion method in [5]. Even though greedy methods determine the completion order according to the image structure, the synthesis patch cannot be corrected afterwards, so the greediness will lead to fracture of image structure. We use discrete optimization and obtain better results in structure and color coherence by repeated iterations. Greedy methods may have color artifacts, while our method eliminates the seams and improves the coherence of color.

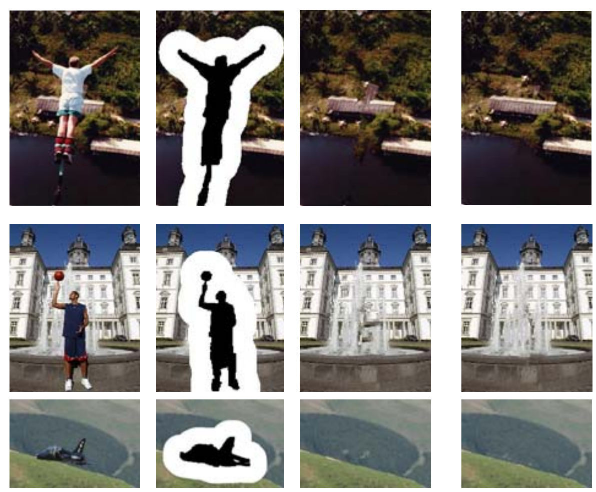
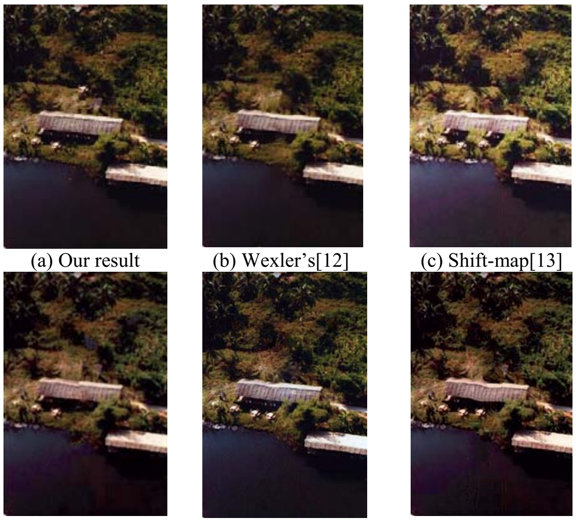

(a) Input image (b) Target region (c) Criminisi's (d) Our results

Figure 6. Comparison with greedy exemplar-based completion method.

Fig.7 shows some comparisons of state-of-the-art image completion methods of bungee jumper. (b) and (c) are the results of Wexler's [12] and shift-map [13] respectively. They appear false illusions and show more blurry. (d), (e) and (f) are the results of Kwok's[14], He's [15] and PixMix[16] respectively, the structure is not coherent. By contrast, (a) is our result, it gets rid of the false illusions and gains coherent simultaneously.



(a) Our result (b) Wexler's[12] (c) Shift-map[13]

(d) Kwok's[14] (e) He's[15] (f) PixMix[16]

Figure 7. Comparisons with other exemplar-based methods

VI. CONLUSION

In this paper, we posed the completion problem as a global discrete optimization problem, which defines an energy function that evaluates the image consistency globally based on three defined completion rules. We used an EM-like algorithm to solve two key problems, patch matching and patch synthesis. M step and E step are achieved by fast coherent searching and optimal seam approach, respectively. Moreover, E step is combined with patch synthesis and coherent correction. The theory analysis for proposed global energy function and optimization method was introduced. Compared with diffusion-based method, greedy exemplar-based method and other exemplar-based methods using shift-map, statistics, or PixMix, our completion method based on global discrete optimization can ensure global coherent and avoid image blur.

Next we will consider the gradient of image and structure information to complete complex structure in energy function and will practice the method in the fields of video and scene completion.

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